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The 4th Annual
Magnolia Finance Conference

Mississippi State University

April 28, 2017

MISSISSIPPI STATE UNIVERSITY™
INSTITUTE FOR MARKET STUDIES

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Dear Magnolia Finance Conference Attendee:

Welcome to Mississippi State University and the 4th Annual Magnolia Finance Conference. In addition to being known as "The Magnolia State," Mississippi is also known for its rich history of traditions and hospitality. The Magnolia Finance Conference is a two-day event designed to promote academic research and treat our guests to some southern hospitality.

We are fortunate to welcome six distinguished speakers to our beautiful campus for this year's conference. I am grateful to each of them for their participation, and I also appreciate you taking the time to attend our conference and share your expertise with our faculty and graduate students.

Finally, the Magnolia Finance Conference would not be possible without the support of the Mississippi State University Department of Finance and Economics, The Nutie and Edie Dowdle Professorship Endowment, and The Mississippi State University Institute for Market Studies.

I hope you enjoy the conference and your time in Starkville.

Hail State!

Sincerely,

Brandon N. Cline
Nutie and Edie Dowdle Professor of Finance

4th Annual Magnolia Finance Conference

April 28, 2017
The Mill Conference Center
Mississippi State University

Schedule:
8:00 AM – Registration & Breakfast

9:00 AM – Naveen Daniel, Drexel University

Causal Impact of Risk Oversight Functions on Bank Risk: Evidence from a Natural Experiment

10:00 AM – Tong Yao, University of Iowa

Costly Information Production, Information Intensity, and Mutual Fund Performance

11:00 AM – Harley "Chip" Ryan, Jr., Georgia State University

The Influence of Learning and Bargaining on CEO-Chair Duality: Evidence from Firms that Pass the Baton

12:00 PM – Lunch

12:45 PM – David Denis, University of Pittsburgh

Persistent Operating Losses and Corporate Finance Policies

1:45 PM – Jarrad Harford, University of Washington

Analyst Effort Allocation and Firms' Information Environment

2:45 PM – Coffee Break

3:15 PM – David Yermack, New York University

Digital Currencies, Decentralized Ledgers, and the Future of Central Banking

4:15 PM – Panel Discussion, "Publishing and Perishing in Finance: Navigating the Changing Landscape"

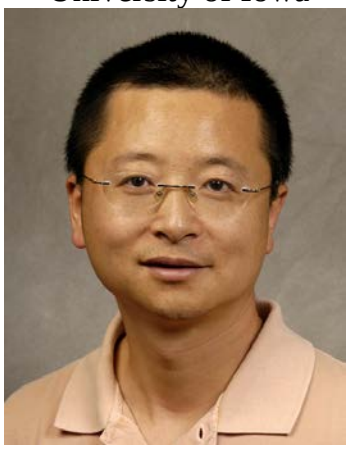
Naveen Daniel
Drexel University

Naveen D. Daniel is Associate Professor of Finance at Drexel University, where he joined the faculty in 2007. Professor Daniel taught previously at Georgia State University and Purdue University.

Professor Daniel did his Chemical Engineering and M.B.A. in India. He worked as an equity analyst before deciding to pursue his Ph.D. degree. He received his Ph.D. in 2001 from Arizona State University.

Dr. Daniel's primary research interest is in the area of corporate governance. His research has been awarded research grants and best paper awards. He has published academic papers in premier journals, including the *Journal of Finance*, *Journal of Financial Economics*, *Review of Financial Studies*, and *Journal of Accounting and Economics*. His work has been featured in business publications, such as the NY Times, Forbes, and Business Week.

Tong Yao
University of Iowa

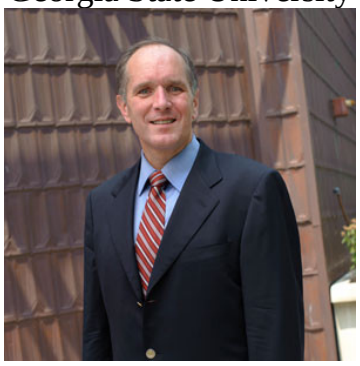


Tong Yao is an associate professor of finance, and Henry B. Tippie research fellow, at the Tippie College of Business, University of Iowa. He obtained his PhD degree in finance from Boston College and previously taught at the Eller College of Management, University of Arizona. He conducts research on stock valuation, stock return predictability, as well as performance and investment management issues faced by institutional investors such as mutual funds, insurers, and pensions.

In addition to the academic positions, he had short stints at investment firms and banks such as Numeric Investors, State Street Research and Management, Bank of Communications, and China Investment Corporation.

Harley "Chip" Ryan, Jr.

Georgia State University



Harley E. Ryan, Jr. (Chip) is the SunTrust Professor of Capital Markets and associate professor of finance at the J. Mack Robinson College of Business at Georgia State University in Atlanta, Georgia. Professor Ryan has been at Georgia State since 2005 and was the associate dean for curriculum and teaching from 2014-2016, the assistant dean for flex and professional MBA programs from 2013-2014, and the coordinator of the finance Ph.D. program from 2005-2012.

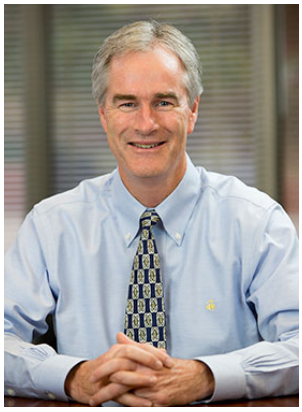
Professor Ryan has a Ph.D. in finance and an MBA from Georgia State University, and a bachelor of electrical engineering from the Georgia Institute of Technology in Atlanta, Georgia. Before joining Georgia State University, he was the Louisiana Department of Insurance professor and associate professor of finance at Louisiana State University in Baton Rouge, LA (1998-2005), assistant professor of finance at Northeastern University in Boston, Massachusetts (1994-1998) and an instructor at Georgia State University in Atlanta, Georgia (1992-1994). He also has been employed as a research assistant at Georgia State University (1989-1992) and as a sales engineer for the Westinghouse Electric Corporation (1983-1989).

Professor Ryan's research interests span a wide array of topics in finance and capital markets including compensation and incentive systems, corporate governance, mergers and acquisitions, the role of financial intermediaries in corporate decision-making, capital investment decisions, and insurance. He has published papers in journals such as *Journal of Financial Economics*, *Journal of Business*, *Journal of Financial and Quantitative Analysis*, *Review of Finance*, *Financial Management*, *Journal of Corporate Finance*, *Journal of Risk and Insurance*, *Journal of Financial Research*, *Journal of Business Finance and Accounting*, and *Quarterly Review of Economics and Finance*.

Professor Ryan has made numerous presentations at national and regional conferences such as the American Finance Association Meetings, the Western Finance Association Meetings, the European Finance Association Meetings, the Financial Management Association Meetings, and the Conference on Financial Economics and Accounting. He has also presented his research to the Office of Economic Analysis at the Securities and Exchange Commission and at the National Bureau of Economic Research. Professor Ryan has served as an expert witness in valuation and security arbitration cases, and is a senior advisor to Financiere Monceau, Paris, France. He has also provided executive education to numerous professional groups including the Graduate School of Banking at LSU, the Turnaround Management Society Certification Review Course, the LSU Executive Program, and the Georgia State University Munich Re Program.

David Denis

University of Pittsburgh



Professor Denis is the Roger S. Ahlbrandt, Sr. Chair and Professor of Finance at the University of Pittsburgh's Katz Graduate School of Business. Professor Denis earned a B.S. degree in finance and managerial statistics from Syracuse University in 1982, an MBA from the University of Michigan in 1984, and a Ph.D. in finance from the University of Michigan in 1988. Prior to joining the Katz faculty in 2011, Professor Denis was a faculty member at Virginia Polytechnic Institute and State University from 1989 to 1995 and at Purdue University's Krannert School of Management from 1995 to 2011.

Professor Denis' primary teaching and research interests are in the area of corporate finance. He is the author of over 50 published articles in leading peer-reviewed journals on topics related to corporate governance, corporate financial policies, corporate organizational structure, corporate valuation, and entrepreneurial finance. He has also co-edited a book on corporate restructuring. He is currently an Editor of the *Review of Financial Studies*, has served as a Co-Editor of the *Journal of Corporate Finance* and is currently an Associate Editor of the *Journal of Financial Research.* He served as an Associate Editor of the *Journal of Finance* from 2001 to 2003, an associate editor of the *Journal of Applied Finance* from 2002-2008, and an associate editor of the *Review of Financial Studies* from 2010-2013.

Professor Denis has served as a member of the Board of Directors of Futuragene Corporation (2002-2003) and has served as a consultant to law firms, corporations, and government agencies on various aspects of financial markets and securities including bankruptcy reorganization, payout policy, credit ratings, corporate restructuring, stock prices, corporate valuation, corporate governance, capital acquisition, executive compensation, mortgage backed securities (MBSs), and collateralized mortgage obligations (CMOs).

Jarrad Harford

University of Washington

Jarrad Harford is the Paul Pigott - PACCAR Professor of Finance and Chair of the Finance and Business Economics Department at the University of Washington's Foster School of Business. He earned his PhD in Finance with a minor in Organizations and Markets at the University of Rochester. His teaching focuses on core finance and acquisition analysis.

Professor Harford currently serves as a Managing Editor of the *Journal of Financial and Quantitative Analysis* and as an Associate Editor for the *Journal of Financial Economics* and the *Journal of Corporate Finance*. His primary research areas are mergers and acquisitions, corporate governance and payout policy, and he has published more than 20 papers on these topics in top finance journals. In 2017, Pearson-Prentice Hall published the fourth edition of an undergraduate finance textbook co-authored by Prof. Harford.

David Yermack

New York University

David L. Yermack is the Albert Fingerhut Professor of Finance and Business Transformation at New York University Stern School of Business. He serves as Chairman of the Finance Department and Director of the NYU Pollack Center for Law and Business. Professor Yermack teaches joint MBA - Law School courses in Restructuring Firms & Industries and Bitcoin & Cryptocurrencies, as well as PhD research courses in corporate governance, executive compensation, and distress and restructuring.

Professor Yermack has been with NYU Stern since 1994. His primary research areas include boards of directors, executive compensation, and corporate finance. Professor Yermack has published more than 25 articles in leading academic journals in Finance, Accounting, Economics, and Law. He is a Faculty Research Associate of the National Bureau of Economic Research and has been a Visiting Scholar at the U.S. Federal Reserve Bank.

Professor Yermack received his Bachelor of Arts in Economics (1985), Master of Business Administration (1991), Juris Doctor (1991), Master of Arts in Business Economics (1993), and Doctor of Philosophy in Business Economics (1994) from Harvard University.

Don Chance

Louisiana State University

Don M. Chance, Ph.D., CFA, holds the James C. Flores Endowed Chair of MBA Studies and is Professor of Finance at the E. J. Ourso College of Business at Louisiana State University. He previously held the William H. Wright, Jr. Endowed Chair for Financial Services at LSU, and the First Union Professorship in Financial Risk Management at Virginia Tech. Prior to his academic career, he worked for a large southeastern bank, now part of Regions Bank. He has been a visiting scholar at universities in Hong Kong, Australia, Korea, Singapore, Scotland, and in the U. S.

Professor Chance has had numerous articles published in academic and practitioner journals and has authored three books: *An Introduction to Derivatives and Risk Management*, 10th ed. co-authored with Robert Brooks, *Essays in Derivatives: Risk Transfer Tools and Topics Made Easy* (2nd ed.), and *Analysis of Derivatives for the CFA Program*.

His current research is on foreign exchange risk management, dividend rights as executive compensation, the performance of random securities analysts, the measurement of alphas from option strategies, corporate boasting, and companies that move from the NYSE to Nasdaq. He has extensive experience conducting professional training programs, and his consulting practice (Omega Risk Advisors, LLC) serves companies, organizations, and law firms. He is also involved in the development and authorship of the derivatives and risk management curriculum in the CFA program. In 2015 he received the C. Stewart Shepard Award for his many years of service to the CFA Institute in the development of its educational programs.

In his spare time, he plays guitar, sings, composes music, performs as a solo guitar & vocal act. He has traveled to approximately 50 countries, and in March, 2016 he completed a 26-mile hike on the Inca Trail to Machu Picchu.

Magnolia Finance Conference 2018 Keynote Speaker
April 19th & 20th, 2018

Andrew Karolyi
Cornell University

Professor Karolyi is an internationally-known scholar in the area of investment management, with a specialization in the study of international financial markets. He has published extensively in journals in finance and economics, including the Journal of Finance, Journal of Financial Economics and Review of Financial Studies, and has published several books and monographs. His research has been covered extensively in print and electronic media, including The Wall Street Journal, Financial Times, The Economist, Time, New York Times, Washington Post, Forbes, BusinessWeek, and CNBC.

Karolyi currently serves as executive editor of the *Review of Financial Studies*, one of the top-tier journals in finance. He is and has also served as an associate editor for a variety of journals, including the *Journal of Finance*, *Journal of Financial Economics*, *Journal of Empirical Finance*, *Journal of Banking and Finance*, *Review of Finance* and the *Pacific Basin Finance Journal*. He is a recipient of the Fama/DFA Prize for Capital Markets and Asset Pricing (2005), the William F. Sharpe Award for Scholarship in Finance (2001), the Journal of Empirical Finance's Biennial Best Paper Prize (2006), the Fisher College of Business' Pace Setter Awards for Excellence in Research and Graduate Teaching and Johnson's Prize for Excellence in Research in 2010.

He joined Johnson in 2009, after teaching for 19 years at the Fisher College of Business of the Ohio State University. He leads various executive education programs in the U.S., Canada, Europe, and Asia, and is actively involved in consulting with corporations, banks, investment firms, stock exchanges, and law firms. He currently chairs the board of trustees and is past president of the Financial Management Association International and has served as a director of the American Finance Association.

Karolyi received his BA (Honors) in economics from McGill University in 1983 and worked at the Bank of Canada for several years in its research department. He subsequently earned his MBA and PhD degrees in finance at the Graduate School of Business of the University of Chicago.

Causal Impact of Risk Oversight Functions on Bank Risk: Evidence from a Natural Experiment

Lakshmi Balasubramanyan[a]
Naveen D. Daniel[b]
Joseph G Haubrich[c]
Lalitha Naveen[d]

April 2017

Abstract

Our goal is to document the causal impact of having a board-level Risk Committee (RC) and a management-level executive designated as Chief Risk Officer (CRO) on bank risk. The Dodd Frank Act requires bank holding companies with over $10 billion of assets to have an RC, while those with over $50 billion of assets were additionally required to have a CRO to oversee risk management. The innovation that allows us to document a causal impact is our research design. First, we use the passage of the Dodd Frank Act as a natural experiment that forced firms that were not compliant to adopt a RC and appoint a CRO. Thus, we adopt the difference-in-difference approach to estimate the change in risk following RC and CRO adoption. Second, we use the regression discontinuity approach centered around the $10 billion and $50 billion thresholds whereby firms that were just below the threshold were not required by the law to install a RC and to recruit a CRO, while those just above the thresholds had to comply with the regulation. Our contribution is to document that neither the RC nor the CRO have a causal impact on risk. However, we do find strong evidence of risk reduction following the passage of the law.

Keywords: Bank Holding Companies, Risk, Chief Risk Officer, Risk Committee, Dodd Frank Act, Bank Risk

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We thank Marco Elia, Jasmine Lidhar, and especially Charlotte DeKoning for outstanding research assistance. We are grateful to participants at the 2016 Temple/Lehigh/Drexel/University of Delaware Research Symposium for helpful comments.

Causal Impact of Risk Oversight Functions on Bank Risk:
Evidence from a Natural Experiment

In this paper, we examine whether the presence of a board-level Risk Committee (RC) and a Chief Risk Officer (CRO) has a causal impact on risk management at banks. We exploit the passage of the Dodd-Frank Wall Street Reform and Consumer Protection Act (DFA, hereafter) that required banks, based on their size, to adopt an RC and a CRO. We assess the causal impact of the RC and CRO using difference-in-difference and regression discontinuity methodologies. Our main takeaway is that the presence of an RC or CRO has no causal impact on bank risk. Our findings are relevant not only in the context of the recent DFA regulation, but also in view of the fact that the current incoming political regime in the U.S. plans to unravel the DFA.[1]

The DFA regulation was signed into law in July, 2010 with the purpose of promoting financial stability in the US banking sector. We focus on two aspects of DFA that are relevant to our study. All publicly traded bank holding companies (hereafter, simply banks) with at least $10 billion of consolidated assets were required to have a Risk Committee comprised of members from the board of directors. Additionally, those with at least $50 billion in assets must designate an executive specifically as Chief Risk Officer. The stated purpose of these two institutions—RC and CRO—is to oversee the risk management function at the bank at the board level and the management level. The key requirements of the RC are that: (i) it should be a stand-alone risk committee; (ii) its Chair should be an independent director; (iii) it should meet at least once a quarter; (iv) all of its members should understand risk management; and (v) it should have at least one expert with experience in risk management. For the CRO, the requirements are that: (i) the technical expertise of the CRO should include experience in evaluating the bank's risk profile, and

[1] "Donald Trump's Transition Team: We Will 'Dismantle' Dodd-Frank," Wall Street Journal, 11/10/2016.

(ii) the CRO should report directly to the CEO and the RC. The CRO provides all the reports necessary for the RC to oversee the risk management policies of the bank.

In terms of our hypothesis, it is possible that RC and CRO have no real impact on risk for two reasons. First, it is possible that banks comply with the DFA, but treat these regulatory requirements for RC and CRO as nothing more than a nuisance. This is similar to the argument in Ellul and Yerramilli (2013) who hypothesize that risk management function may have no impact because "banks appoint risk managers, without giving them any real powers, merely to satisfy bank supervisors." Second, even if banks take these mandates seriously, the risk committee members and the CRO may not be qualified enough to catch serious problems. After all, JP Morgan had both an RC and a CRO but still sustained a $6 billion loss due to the London Whale. According to JP Morgan CEO Jamie Dimon, "It's a little unrealistic to expect the risk committee to capture something like this."[2]

Alternatively, it is possible that, by putting the spotlight on risk, DFA forced banks to take a closer look at risk. The word "risk" is mentioned, on average, 170 times in banks' 10K statement in 2005. This number nearly doubled to 322 in 2015 (see Figure 1). The increased focus on risk could mean that some banks that were not taking risk seriously might realize that they were taking more-than-optimal risk and scale down their risk. Finally, it is possible that some banks will realize that they were not taking enough risks and, given the increased confidence that they have because of the oversight of the RC and CRO, might actually increase risk following the passage of the law. The overall effect of RC and CRO on risk, therefore, is an empirical issue.

We use the passage of DFA to estimate the causal impact of having an RC and a CRO on risk. As part of the DFA, all publicly-traded banks with assets ≥ $50 billion had to install an RC

[2] See http://www.bankdirector.com/magazine/archives/4th-quarter-2012/what-s-the-risk/

and designate an executive as CRO while banks with assets ≥ $10 billion (but less than $50 billion) had to install only an RC. The deadline for compliance with the law for firms with assets ≥ $50 billion was January 1, 2015, while banks with assets ≥ $10 billion (but less than $50 billion) had to comply by July 1, 2015. The relevant asset size was that as of Jun 30, 2014.

We modify the difference-in-difference (hereafter "diff-in-diff") research design to allow for the fact that (i) banks were given almost 5 years to comply with the law after its passage, (ii) some banks that were affected by the law were compliant even before the law was passed, (iii) some banks that were not affected by the law were compliant even before the law was passed and some of these banks become compliant after the law was passed.

Thus, our treated sample of firms consists of banks that were shocked by the law to adopt risk oversight functions, rather than those that were simply affected by the law because they were above the size threshold. That is, the treated firms that were subject to the law, but were not compliant as of the signing of the law ("treated" firms). It is reasonable to assume that the treated firms that were forced to comply subsequently did so only because of the law, and would not have an RC and a CRO had it not been for the law.

Banks were given 5 years to comply with the law. To account for this, we exclude the years between the passage of the law and their compliance with the law. For example, for a treated bank that installed an RC only in 2012, we exclude the year 2011 from the analysis. Thus, for this hypothetical treated bank, the years 2010 and earlier constitute the pre-treatment period and the years 2013 and onwards constitute the post-treatment period.

As far as the control sample is considered, there are several different ways to form the control group; each has its pros and cons. The ideal control group would be one that is similar in characteristics to the treated group, but is not shocked by the law. Thus, our baseline control group

is the set of banks that were subject to the law but were already compliant as of the passage of DFA as of June 2010. One advantage of this control group is that banks could have changed their risk, not directly in response to the addition of the RC or CRO, but in response to other regulations contained in the DFA (such as the Volcker Rule provisions, for example). As long as the compliance with respect to these additional regulations were distributed equally across our treatment and control groups, changes in risk due to these other regulations are netted off using our diff-in-diff analysis and we are able to isolate changes in risk due to the RC and CRO. We use several alternative controls, which are discussed in Section I. For the control firms, the years 2010 and earlier constitute the pre-period and the years 2011 and onwards constitute the post-period.

A second innovation in research design we employ is the regression-discontinuity approach, which is as close as it gets to a pure randomized experiment. This tackles the potential endogeneity of the intervention itself, which in our case, is the passage of the DFA. The idea behind regression discontinuity is that banks that are just below the threshold ($10 billion for RC and $50 billion for CRO) are similar to those that are just above the threshold. However, those above the threshold are subject to regulations regarding RC and CRO while those below are not. Thus, this analysis limits our sample to firm-years after the passage of the law, that is, from 2011 and onwards.

As with the diff-in-diff, we modify the regression discontinuity design to account for the lag between the passage of the law and its implementation. Our treated sample of firms are exactly the same as with the diff-in-diff. That is, these are firms that were subject to the law but were not compliant as of the signing of the law. As with the diff-in-diff, we exclude the years between the passage of the law and their compliance with the law. The control firms are those that were below the asset threshold and were not compliant. (In a typical regression discontinuity design, we would

include all firms under the threshold because none of these firms would be compliant with the law). We also exclude the years for these control firms once they choose to voluntarily comply with the law. To study the impact of RC, we pick a bandwidth of $7 billion because the tier of banks that the Federal Reserve monitors starts at $3 billion. Thus to be included in our sample, firms must have assets between $3 and $17 billion. To study the impact of CRO, we pick a bandwidth of $30 billion, so firms must have assets between $20 and $80 billion to be included in our sample.

We use data on bank holding companies and financial holding companies from 2005 to 2015. We consider all years for a given bank as long as its assets are greater than $3 billion in any of the 11 years of our sample period.

Using the diff-in-diff approach, we find that that the presence of an RC has no causal impact on risk. There is, however, weak evidence that CRO has led to an increase in risk. With the regression discontinuity approach, we find no evidence of either RC or CRO on risk.

Overall, we conclude that the presence of a risk committee and chief risk officer has no significant causal impact on risk. Our paper is closest to Ellul and Yerramilli (2013), who find that a "strong and independent risk management function can curtail risk exposures at banks." Our paper differs from theirs, however, in two important ways. First, while Ellul and Yerramilli examine the impact of the *strength* of risk management function, *broadly defined*, on risk, we examine the specific impact of the presence of RC and CRO on risk, as well as the impact of having an RC and CRO as defined under Dodd-Frank Act. Ellul and Yerramilli construct a Risk Management Index (RMI) for each firm-year observation, which is the first principal component of six variables formed based on RC and CRO characteristics. Their definitions of RC and CRO, however, are not as per the strict definition of DFA and much more broad. For example, they

assume that the bank has a CRO if the bank has a Chief Lending Officer, Chief Compliance officer, or a Chief Credit Officer with enterprise-wide responsibility. Because of this broad definition, 100% of the firms in Ellul and Yerramilli sample had a CRO by 2008 even though the DFA was passed only in 2010 and banks were given until 2015 to comply with the regulation. Similarly, the authors characterize the strength of the board committee (measured by directors' financial expertise and the frequency of board meeting) designated with overseeing risk. This could be the Risk Management Committee or the Audit and Risk Management Committee. Thus, as per their broad definition, all firms have an RC in every year of their sample (1994-2009) even though DFA was passed only in 2010. The second key difference is that the authors examine the 15-year period ending 2009 while the law was passed only in 2010. Thus, our research design (difference-in-difference and regression discontinuity) provides a cleaner test of causation. The authors address the endogeneity of RMI using the average change in RMI of peer firms as the instrument in a two-stage least squares setting. They also consider a dynamic GMM by including lagged values of risk to control for the possibility that the bank's prior risk somehow determines both current RMI and current risk.

The main takeaway of Ellul and Yerramilli (2013) is that a better risk management function lowers risk. Our paper finds that the presence of an RC and a CRO has no impact on risk. Thus our findings complement theirs and suggest that other aspects of risk management may be more important than having an RC or a CRO.

I. Data

We start with the set of firms from the Federal Reserve NIC database with the following entity types: BHC (Bank Holding Companies), FHD (Financial Holding Company/BHC), and

DEO (Domestic Entity Other). We limit ourselves to publicly traded institutions because we need stock returns to estimate risk. We obtain data from 2005 (5 years before DFA was passed) to 2015. We also limit the sample to firms with book value of assets greater than or equal to $3 billion in any of our sample years. That is, even if a bank grows in size to cross the $3 billion threshold in, say, 2008, we include all the years of this bank from 2005-2015. We choose the $3 billion threshold so as to limit our sample size and thus ensure that hand collecting data from proxy statements is not too onerous. The starting sample is 114 banks. We drop Santander Holdings USA because our focus is on domestic banking organizations. CIT Group and Goldman Sachs Incorporated were listed as DEO from 2005 to 2008 before acquiring FHD and BHC status, respectively. We drop all firm-years of firms that failed or were acquired. Our final sample consists of 94 banks and 980 bank-years.

We obtain financial information on the banks from the FR Y-9C reports filed with the Federal Reserve System. The FR Y-9C provides a detailed breakdown of BHC portfolio, security holdings, regulatory risk capital and derivative usage information. The financial information is presented on a calendar year basis.

A. RC and CRO

The information on RC, CRO, and other relevant data were collected by hand from the 10-K and proxy statements filed by the banks with the SEC. As mentioned in the Introduction, the key requirements of the RC are that: (i) it should be a stand-alone risk committee; (ii) its Chair should be an independent director; (iii) it should meet at least once a quarter; (iv) all of its members should understand risk management; and (v) it should have at least one expert with experience in risk management. We collect the names of the RC members, the experience and independence of

the members of the RC, the details about Chair of the RC, and the frequency of the RC meetings. We collect the experience of risk committee members using the biographical information supplied by the company. While it is possible to code the first three requirements of RC objectively, we found it impossible to objectively decide whether all of its members understand risk management and whether it has at least one expert in risk management. Thus, we form two indicator variables:

RC Present = 1 if the firm has a RC
= 0 if the firm has no RC

RC Compliant = 1 if the firm has a RC that meets the first 3 requirements
= 0 if the firm has no RC or the RC does not meet the first 3 requirements

We also collect data on the presence of a Chief Risk Officer (CRO) the position of the CRO in the executive hierarchy.

For the purposes of this paper, a bank is considered to have a CRO if there is an executive whose title contains the word "risk." Examples includes "Chief Risk Officer," "Executive Risk Management Officer," and "Chief Credit Risk Officer." Officers whose positions may include some risk management, but whose focus is not sufficiently risk-oriented to warrant such a title (e.g. "Chief Credit Officer", "Chief Compliance Officer", etc.) are not considered CROs and thus are not coded as such.

For a CRO to be compliant with DFA, the requirements are that: (i) the technical expertise of the CRO should include experience in evaluating the bank's risk profile, and (ii) the CRO should report directly to the CEO and the RC. Again, it is impossible to figure out from the biographical information whether the CRO has the technical experience to evaluate the bank's risk profile and whether the CRO reports directly to the CEO and RC. Thus, we only have one indicator variable:

CRO Present = 1 if the firm has a CRO
= 0 if the firm has no CRO

That is, we do not have *CRO Compliant* dummy.

B. Risk Measures

We use two main proxies for bank risk: *Aggregate Risk* and *Tail Risk*. Ellul and Yeramilli use *Tail Risk* as the main proxy. Their logic for this is as follows: "As banks are in the business of taking risks, the main purpose of the risk management function is to mitigate the risk of large losses, that is, to mitigate tail risk. Accordingly, our main risk measure of interest is Tail Risk." As in their paper, we define *Tail Risk* as the negative of the mean return on the 5% worst-return days in the year.

In our opinion, tail risk does not capture all of the risks that firms care. For example, in JP Morgan's 2014 Annual Report, they provide a table of the various risks that are inherent in the firm's business and they are: principal risk, credit risk, capital risk, market risk, liquidity risk, structural interest rate risk, model risk, legal risk, country risk, compliance risk, operational risk, fiduciary risk, and reputational risk. While some of these risks are systematic in nature (example: interest rate risk), some are idiosyncratic (example: compliance risk), while others could be considered a mix between the two (example: credit risk). Thus, our main proxy for risk is *Aggregate Risk*, which is given by the volatility of daily returns and is estimated each year.

C. Control Variables

We follow EY for the control variables. We winsorize all our variables at the 1st and 99th percentile levels. All functional transformations (example: logs) are made on the winsorized variables.

Figure I
Frequency of Risk in Proxies

The figure plots the mean and median number of times the word "risk" is mentioned in the proxy statements.

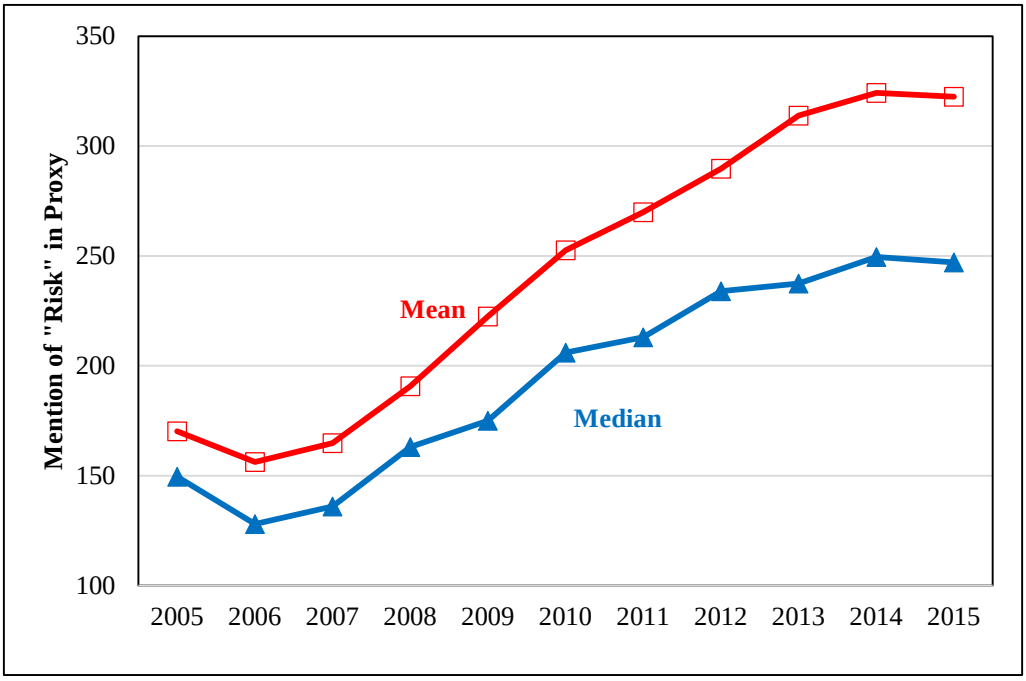
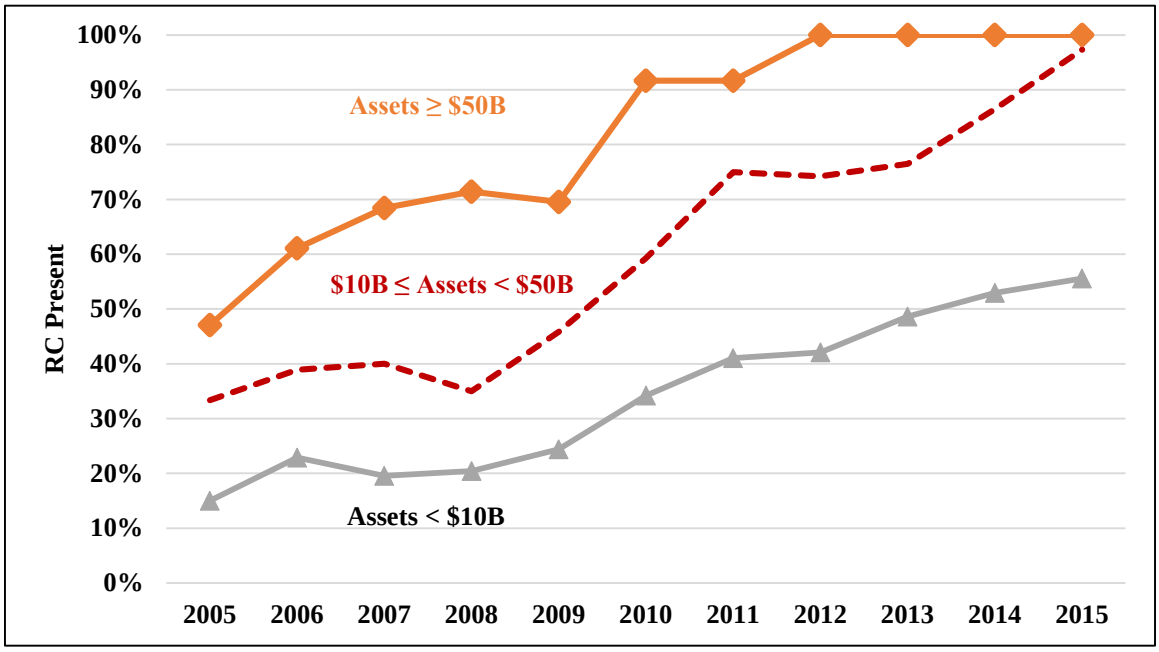


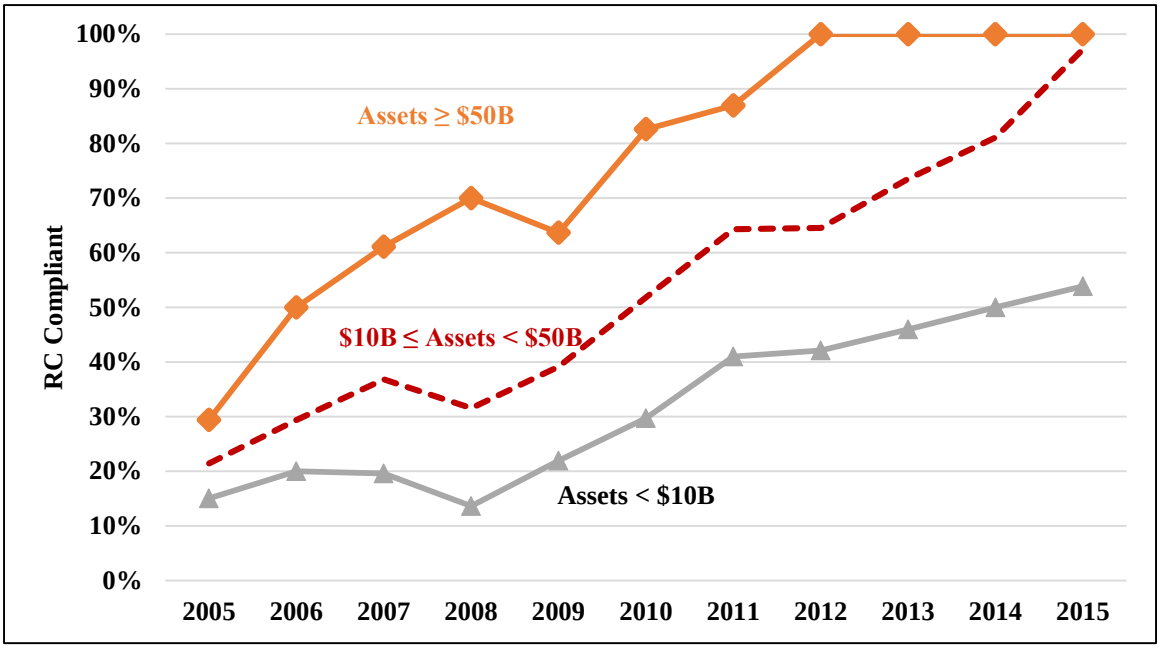
Figure II
RC and CRO Time Series

The figures plot the mean of three indicator variables. (i) *RC Present*, which equals 1 if the firm has a RC, and equals 0 otherwise. (ii) *RC Compliant*, which equals 1 if the firm has a RC that satisfies 3 requirements imposed by the DFA, and equals 0 otherwise. (iii) *CRO Present*, which equals 1 if the firm has a CRO, and equals 0 otherwise.

Panel A: RC Present



Panel B: RC Compliant



Panel C: CRO Present

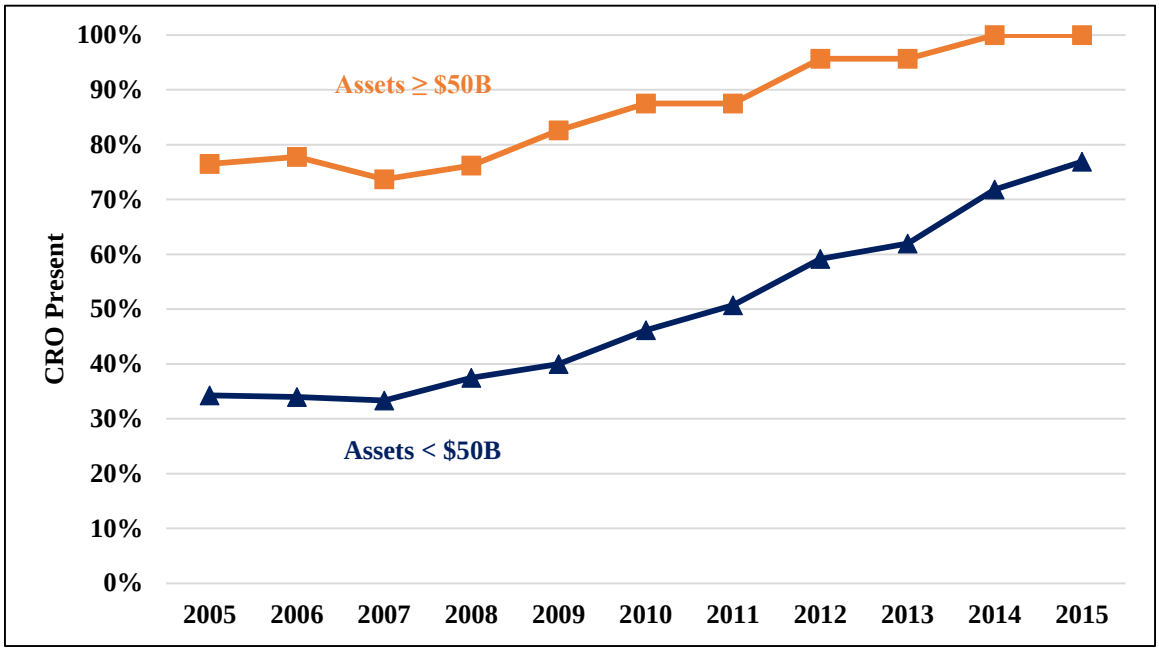
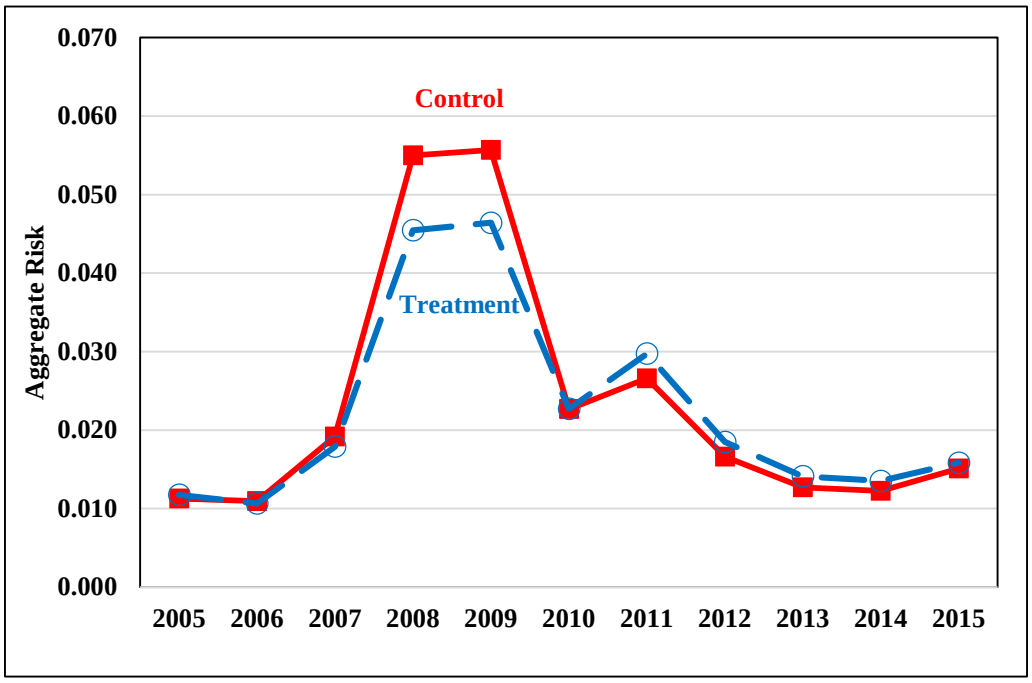


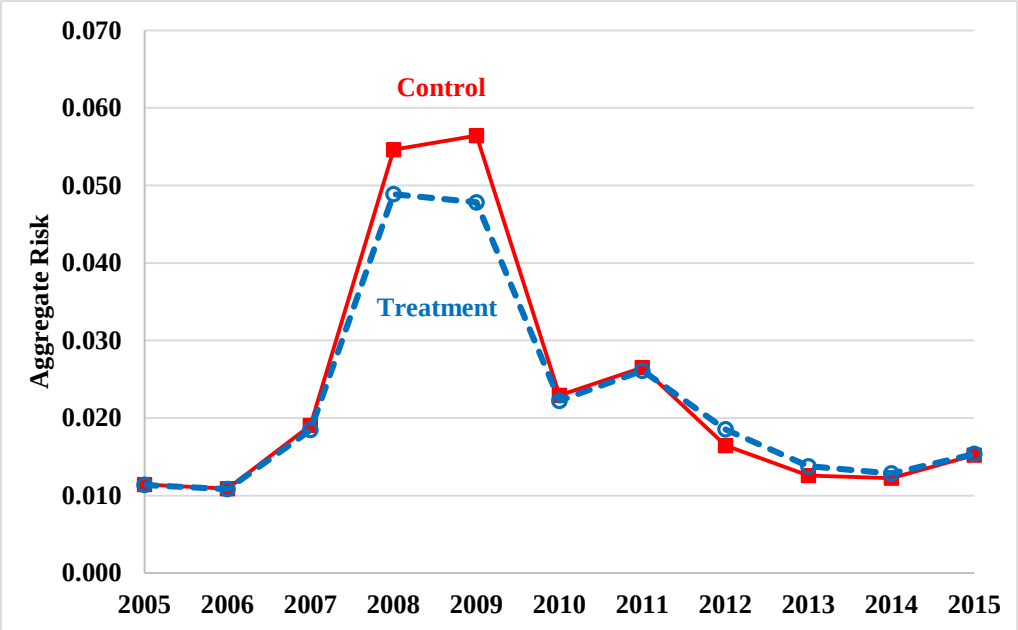
Figure III
DID: Parallel Trends

The figure plots the mean of *Aggregate Risk* of treated banks and control group. The treated firms are those that that were shocked by the law. That is, they were non-compliant as of the passage of the law. Control group is the set of firms that were affected by the law but were already compliant as of the passage of the law.

Panel A: RC Present



Panel B: RC Compliant



Panel C: CRO Present

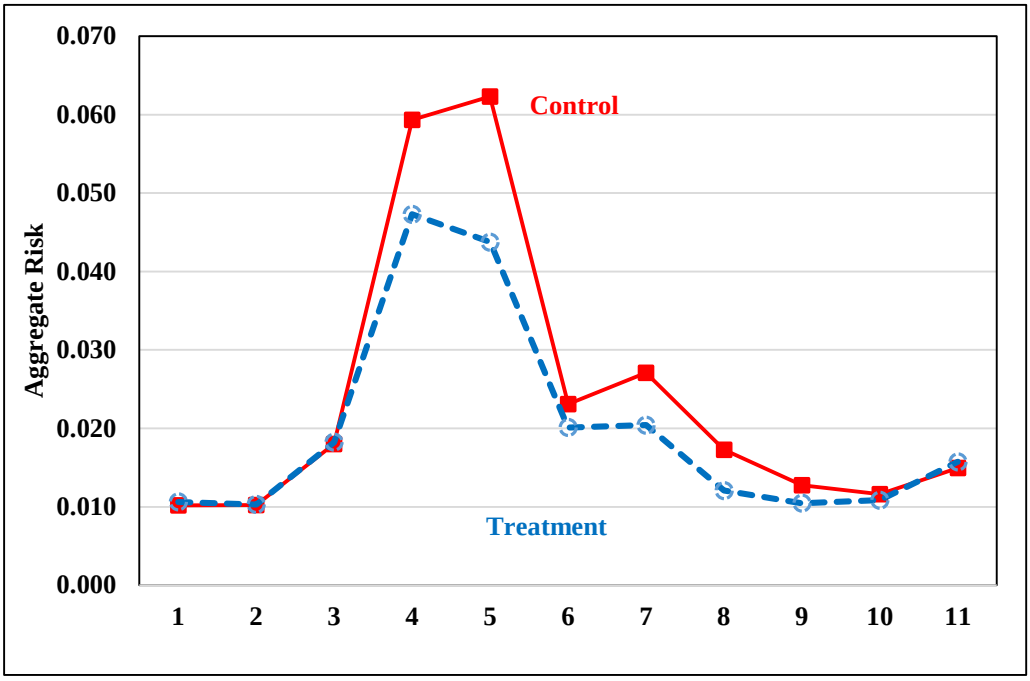
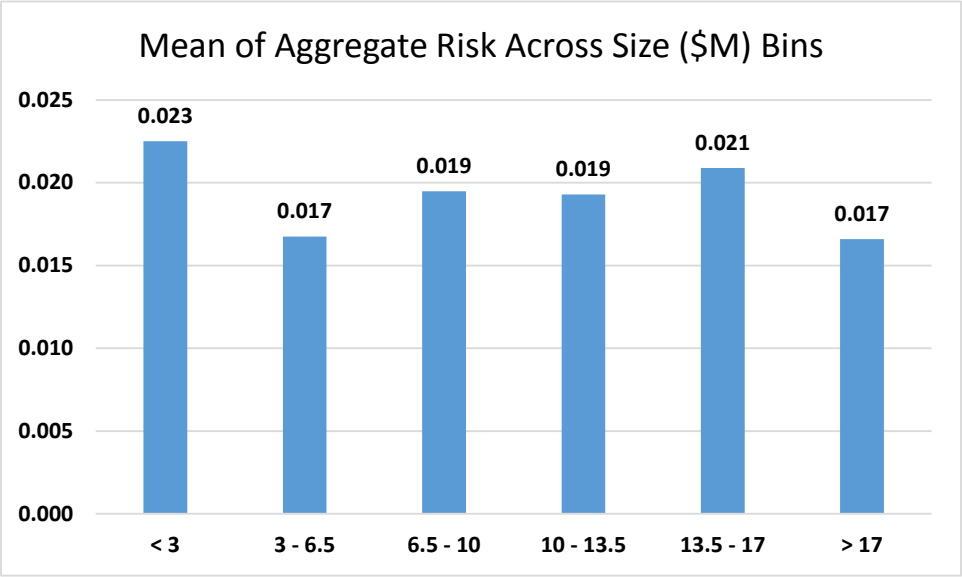


Figure IV
Regression Discontinuity: Univariate (Risk around the threshold)

The figure plots the mean of *Aggregate Risk* of banks around the $10 billion threshold for RC Present and RC Compliant. We do not present the figure for CRO Present because there are very few relevant observations around the $50 billion threshold (2 between $30 and $50 billion and 1 between $50 and $70 billion).

Panel A: RC Present



Panel B: RC Compliant

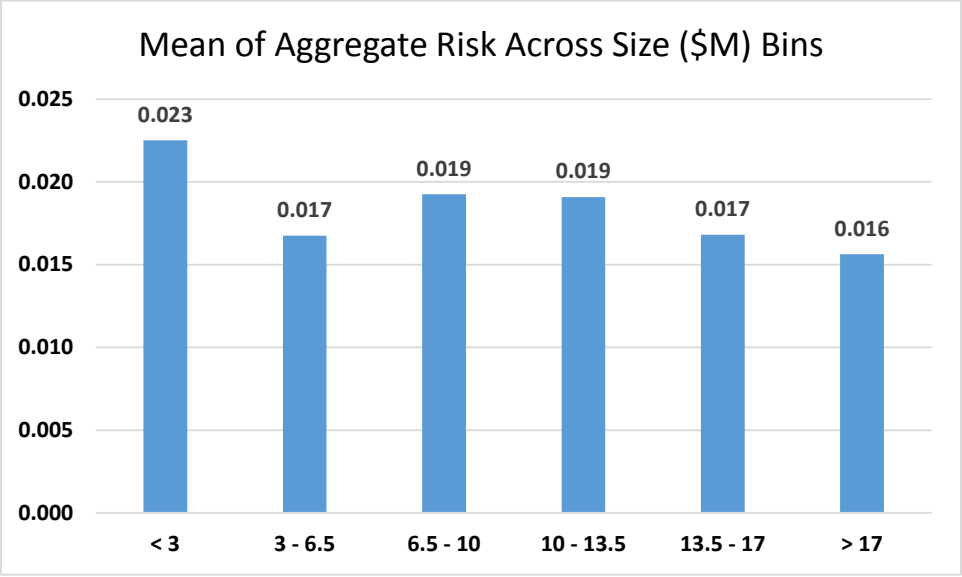


Table I
Summary Statistics

The table provides the summary statistics for the key variables. We have two risk measures. (i) *Aggregate Risk* and (ii) *Tail Risk*. *Aggregate Risk* is the standard deviation of daily returns during the year. *Tail Risk* is the negative of the mean return on the 5% worst-return days during the year. We have three risk oversight measures. (i) *RC Present*, which equals 1 if the firm has a RC, and equals 0 otherwise. (ii) *RC Compliant*, which equals 1 if the firm has a RC that satisfies 3 requirements imposed by the DFA, and equals 0 otherwise. (iii) *CRO Present*, which equals 1 if the firm has a CRO, and equals 0 otherwise. The control variables used in our risk regressions are defined as in EY and are defined almost verbatim below. *Assets* is the book value of total assets (BHCK2170). *ROA* is the ratio of income before extraordinary items (BHCK4300) to assets. *Annual Return* is the buy-and-hold return on the BHC's stock over the calendar year. Deposits/Assets is the ratio of total deposits (BHDM6631+BHDM6636+ BHFN6631+BHFN6636) to assets. *ST Borrowing/*Assets is the ratio of assets financed by commercial paper and other short-term non-deposit borrowing to assets. *Tier-1 Capital/Assets* is the ratio of Tier-1 capital (BHCK8274) to assets. *Loans/Assets* is the ratio of total loans (BHCK2122) to assets. *Bad Loans/Assets* is the ratio of the sum of loans past due 90 days or more (BHCK5525) and nonaccrual loans (BHCK5526) to assets. *Non-Interest Income/Income* is the ratio of noninterest income (BHCK4079) to the sum of interest income (BHCK4107) and noninterest income (BHCK4079). *Deriv. Trading/Assets* is the ratio of the total gross notional amount of derivative contracts held for trading, obtained by adding amounts on interest rate contracts (BHCKA126), foreign exchange contracts (BHCKA127), equity derivative contracts (BHCK8723), and commodity and other contracts (BHCK8724) to assets. *Deriv. Hedging/Assets* is the ratio of the value of derivatives used for hedging purposes (obtained by adding the following variables: BHCK8725, BHCK8726, BHCK8727, and BHCK8728) to assets. *Large M&A* equals 1 if book assets grew more than 20%, and equals 0 otherwise. *CEO Turnover* equals 1 if there is a change in the CEO, and equals 0 otherwise.

	Obs	Mean	Std. Dev.	Median	IQR
Risk Measures					
Tail Risk		0.023	0.015	0.017	0.013
Aggregate Risk		0.049	0.031	0.036	0.031
Risk Oversight Measures					
RC Present		0.567			
RC Compliant		0.525			
CRO Present		0.603			
Firm Measures					
Assets ($000,000)		127	370	1,210	4,230
ROA		0.005	0.005	0.005	0.003
Annual Return		0.070	0.290	0.061	0.319
Deposits/Assets		0.704	0.137	0.733	0.118
ST Borrowing/Assets		0.033	0.034	0.022	0.045
Tier-1 Capital/Assets		0.090	0.021	0.086	0.025
Loans/Assets		0.626	0.157	0.667	0.160
Bad Loans/Assets		0.011	0.011	0.007	0.013
Non-Interest Income/Income		0.275	0.168	0.241	0.173
Deriv. Trading/Assets		1.852	7.696	0.002	0.149
Deriv. Hedging/Assets		0.085	0.147	0.030	0.105
Large M&A		0.136			
Governance Measures					
Institutional Ownership		0.598	0.189	0.629	0.273
G-Index		10	3	9	4
CEO Delta ($000)		477	921	130	393
CEO Vega ($000)		162	340	30	111
CEO Turnover		0.089			
CEO Tenure		9.0	7.4	6.6	9.6

Table II
OLS Regressions of Risk

The table presents the OLS regression results where the dependent variable is *Aggregate Risk* and the key independent variable is one of three Risk Oversight measures. (i) *RC Present*, which equals 1 if the firm has a RC, and equals 0 otherwise. (ii) *RC Compliant*, which equals 1 if the firm has a RC that satisfies 3 requirements imposed by the DFA, and equals 0 otherwise. (iii) *CRO Present*, which equals 1 if the firm has a CRO, and equals 0 otherwise. The first three columns do not have firm FE while the last three columns include firm FE. Table I defines the control variables.

	Dependent Variable = Aggregate Risk					
	Risk Oversight =					
VARIABLES	RC Present	RC Compliant	CRO Present	RC Present	RC Compliant	CRO Present
Risk Oversight	-0.000	-0.000	0.002***	-0.000	-0.000	0.002*
	(-0.5)	(-0.6)	(3.7)	(-0.1)	(-0.3)	(1.8)
Size	0.004	0.004	0.002	0.032***	0.033***	0.031***
	(0.8)	(0.8)	(0.4)	(3.5)	(3.6)	(3.4)
$Size^2$	-0.000	-0.000	-0.000	-0.001***	-0.001***	-0.001***
	(-0.7)	(-0.7)	(-0.3)	(-3.3)	(-3.3)	(-3.1)
ROA	-0.371***	-0.363***	-0.337***	-0.174*	-0.168*	-0.174*
	(-4.2)	(-4.2)	(-3.8)	(-1.9)	(-1.9)	(-1.9)
Annual Return	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***
	(-8.6)	(-8.6)	(-8.7)	(-8.4)	(-8.3)	(-8.4)
Deposits/Assets	0.001	0.001	0.001	-0.007	-0.007	-0.007
	(0.3)	(0.3)	(0.3)	(-0.8)	(-0.8)	(-0.8)
ST Borrowing/Assets	0.016	0.015	0.018*	-0.003	-0.003	-0.002
	(1.4)	(1.3)	(1.7)	(-0.2)	(-0.3)	(-0.1)
Tier1 Capital/Assets	0.033**	0.033**	0.033**	-0.066**	-0.064**	-0.066**
	(2.0)	(2.0)	(2.1)	(-2.5)	(-2.4)	(-2.5)
Loans/Assets	0.002	0.002	0.000	-0.002	-0.002	-0.004
	(0.5)	(0.5)	(0.1)	(-0.4)	(-0.3)	(-0.6)
Bad Loans/Assets	0.092***	0.089***	0.085***	0.065	0.060	0.059
	(3.1)	(2.9)	(2.7)	(1.6)	(1.5)	(1.5)
Non-Interest Income/Income	-0.003	-0.003	-0.004	-0.003	-0.003	-0.004
	(-1.1)	(-1.1)	(-1.6)	(-0.6)	(-0.6)	(-0.7)
Deriv. Trading/Assets	0.000	0.000	0.000	-0.000	-0.000	-0.000
	(1.1)	(1.0)	(1.0)	(-0.5)	(-0.5)	(-0.6)
Deriv. Hedging/Assets	0.002	0.002	0.002	0.001	0.001	0.001
	(0.6)	(0.6)	(0.5)	(0.4)	(0.4)	(0.5)
Large M&A	0.001**	0.001**	0.001*	-0.000	-0.000	-0.000
	(2.1)	(2.2)	(2.0)	(-0.4)	(-0.3)	(-0.4)
Year FE	Y	Y	Y	Y	Y	Y
Firm FE	N	N	N	Y	Y	Y
Observations	769	758	770	769	758	770
R^2	0.842	0.842	0.846	0.877	0.877	0.878

Table III
DID (Univariate): Mention of "Risk" In Proxies

The table presents mean of the number of times the word "risk" is mentioned in the proxy statements. The treated firms are those that that were shocked by the law. That is, they were non-compliant as of the passage of the law. Control firms are those that were affected by the law but were already compliant as of the passage of the law.

Panel A: RC Present

	Control	Treated	Difference
Before	261	173	-88***
After	426	306	-120**
Difference	165***	133***	
Diff-in-Diff			-32

Panel B: RC Compliant

	Control	Treated	Difference
Before	258	202	-56**
After	427	357	-70**
Difference	169***	155***	
Diff-in-Diff			-14

Panel C: CRO Present

	Control	Treated	Difference
Before	360	107	-252***
After	564	338	-225**
Difference	204***	231***	
Diff-in-Diff			27

Table IV
DID (Univariate): Aggregate Risk

The table presents mean of the number of *Aggregate Risk*, which is the standard deviation of daily returns during the year. The treated firms are those that that were shocked by the law. That is, they were non-compliant as of the passage of the law. Control firms are those that were affected by the law but were already compliant as of the passage of the law.

Panel A: RC Present

	Control	Treated	Difference
Before	0.029	0.026	-0.003*
After	0.016	0.017	0.001
Difference	-0.013***	-0.009***	
Diff-in-Diff			0.004

Panel B: RC Compliant

	Control	Treated	Difference
Before	0.029	0.027	-0.002
After	0.016	0.016	0.000
Difference	-0.013***	-0.011***	
Diff-in-Diff			0.002

Panel C: CRO Present

	Control	Treated	Difference
Before	0.032	0.025	-0.007
After	0.017	0.013	-0.004
Difference	-0.015***	-0.012*	
Diff-in-Diff			0.003

Table V
DID: Multivariate

The table presents the DID regression results where the dependent variable is *Aggregate Risk* and the key independent variable is one of three Risk Oversight measures. (i) *RC Present*, which equals 1 if the firm has a RC, and equals 0 otherwise. (ii) *RC Compliant*, which equals 1 if the firm has a RC that satisfies 3 requirements imposed by the DFA, and equals 0 otherwise. (iii) *CRO Present*, which equals 1 if the firm has a CRO, and equals 0 otherwise. The treated firms are those that that were shocked by the law. That is, they were non-compliant as of the passage of the law. Control firms are those that were affected by the law but were already compliant as of the passage of the law. Table I defines the control variables.

	Dependent Variable = Aggregate Risk		
	Risk Oversight =		
	RC Present	RC Compliant	CRO Present
Risk Oversight	-0.001	0.001	-0.006*
	(-0.3)	(0.3)	(-2.0)
After	-0.011***	-0.011***	-0.009***
	(-7.7)	(-7.6)	(-3.9)
Risk Oversight × After	0.001	-0.001	0.004***
	(0.8)	(-0.8)	(3.5)
Size	0.016	0.018*	0.010
	(1.6)	(1.9)	(0.3)
$Size^2$	-0.000	-0.000*	-0.000
	(-1.5)	(-1.8)	(-0.4)
ROA	-0.229	-0.175	-0.095
	(-1.3)	(-0.9)	(-0.3)
Annual Return	-0.019***	-0.020***	-0.026***
	(-7.3)	(-7.7)	(-10.6)
Deposits/Assets	-0.008	-0.006	-0.015
	(-1.0)	(-0.8)	(-1.4)
ST Borrowing/Assets	0.001	0.002	0.044
	(0.0)	(0.1)	(0.8)
Tier1 Capital/Assets	-0.026	-0.020	-0.076
	(-0.8)	(-0.6)	(-1.1)
Loans/Assets	0.002	0.002	-0.011
	(0.3)	(0.4)	(-1.7)
Bad Loans/Assets	0.077	0.075	0.146
	(1.4)	(1.3)	(1.2)
Non-Interest Income/Income	-0.013**	-0.013**	-0.027***
	(-2.2)	(-2.3)	(-2.8)
Deriv. Trading/Assets	0.000	0.000	0.000
	(0.7)	(0.9)	(0.0)
Deriv. Hedging/Assets	-0.001	-0.001	-0.002
	(-0.3)	(-0.3)	(-0.4)
Large M&A	0.001	0.001	-0.000
	(0.2)	(0.3)	(-0.0)
Observations	414	407	200
R^2	0.38	0.39	0.46

Table VI
Regression Discontinuity: Multivariate

The table presents the RD regression results where the dependent variable is *Aggregate Risk* and the key independent variable is Above Threshold. Only firm-years 2011 are included because the law was passed in 2010. *Aggregate Risk* is the standard deviation of daily returns during the year. *Above Threshold* is an indicator variable which equals 1 if the size is above the threshold ($10 billion for RC and $50 billion for CRO), and equals 0 otherwise. We consider three Risk Oversight measures. (i) *RC Present*, which equals 1 if the firm has a RC, and equals 0 otherwise. (ii) *RC Compliant*, which equals 1 if the firm has a RC that satisfies 3 requirements imposed by the DFA, and equals 0 otherwise. (iii) *CRO Present*, which equals 1 if the firm has a CRO, and equals 0 otherwise. The treated firms are those that that were shocked by the law. That is, they were non-compliant as of the passage of the law. Control firms are those that were not affected by the law and had not voluntarily complied with the law even though they were not subject to the law. For the treated firms, only the firm-years post-compliance are included. For the control firms, we exclude the firm-years after they chose to voluntarily comply. Table I defines the control variables.

	Dependent Variable = Aggregate Risk					
	Risk Oversight =					
	RC Present	RC Compliant	CRO Present	RC Present	RC Compliant	CRO Present
Above Threshold	-0.000	-0.002	-0.003	-1.157	1.616	9.486
	(-0.1)	(-0.5)	(-0.2)	(-0.4)	(0.5)	(0.4)
Size	0.001	0.001	-0.000	-0.293	-0.290	-3.104***
	(0.4)	(0.2)	(-0.0)	(-1.0)	(-1.0)	(-5.7)
$Size^2$				0.010	0.009	0.090***
				(1.0)	(1.0)	(5.8)
Above Threshold × Size				0.163	-0.169	-0.878
				(0.4)	(-0.5)	(-0.3)
Above Threshold × $Size^2$				-0.006	0.004	0.019
				(-0.4)	(0.4)	(0.3)
Observations	69	75	12	69	75	12
R^2	0.004	0.004	0.096	0.018	0.027	0.646

Costly Information Production, Information Intensity, and Mutual Fund Performance

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Costly Information Production, Information Intensity, and Mutual Fund Performance

Abstract

This study examines the concentration of active mutual fund managers' research efforts toward information-intense stocks and the degree to which they are successful in such efforts. Information intensity of a stock is proxied by the contribution of jumps to stock return variance. We find that both skilled and unskilled fund managers are attracted to stocks with high information intensity. Moreover, the well-known phenomenon of performance persistence is only observed among funds aggressively investing in high information intensity stocks. The effect of fund information intensity on performance persistence is robust to the control of characteristics of fund holdings such as market cap, illiquidity, and return volatility, and is different from the effect of existing measures of fund activeness. Finally, information intensity increases fund flow sensitivity to past performance. These findings suggest that, with costly information production, information intensity is an important dimension of active investment decision by fund managers and an important dimension of fund selection decision by investors.

Keywords: Mutual fund performance; costly information production; information intensity

1 Introduction

In oil exploration, prospectors must first narrow down the promising locations before they start their costly drilling operations. Much the same can be said about information production in the stock market. When stock selection information is scarce, investors have to be smart about where to deploy their costly efforts and limited resources in their search for information.

Such decisions are important in today's market, where investment managers increasingly rely on costly information to generate performance. Consider the evolution of fundamental research, the most popular approach used by equity mutual fund managers to produce stock selection information. The traditional form of fundamental research, espoused as early as by Graham and Dodd (1934), involves parsing publicly available information such as corporate financial statements to identify undervalued stocks. The cost of performing such research during recent decades has become relatively low and, perhaps as a result, its potential rewards appear to be disappearing. Over time, the focus of fundamental research has shifted toward uncovering information not yet publicly available. For example, many fund managers engage in "channel-checking", i.e., gathering information about a company (e.g., Apple) by talking to its suppliers and customers.[1] Some fund managers rely on interactions with corporate executives (e.g., face-to-face talks or conference calls) to assess their professional qualities and incentives, and to capture "soft" information not apparent from reading financial statements or news releases.[2] Indeed, several investment firms (e.g., Fidelity) attempt to derive competitive advantage from having large troops of analysts who frequently visit firms and meet with corporate managers. Such efforts to uncover non-public information are considerably more costly than poring over financial statements.

Costly information production is rewarded in the efficient-market equilibrium described

[1]Similar to channel-checking, investors have also attempted to obtain information from franchisees about franchising companies such as McDonald's. Anecdotally, some funds send analysts to count the lights of hotel rooms at night, or to count the cars parked outside shopping malls, in order to predict the revenues of hotels and department stores.

[2]For example, according to a recent Barron's report (Bary 2015), Fidelity Contrafund manager William Danoff talks to over 1000 corporate managers a year.

by Grossman and Stiglitz (1980).[3] In today's market, the effectiveness of such information production efforts could well be the deciding factor of investment performance. However, fund manager efforts, and the associated costs, are either unobservable or difficult to quantify, which perhaps explains why, so far, there is no direct empirical mechanism to examine their private-information production.[4]

In this study, we focus on a key decision in mutual fund costly information production – how fund managers allocate their research efforts across stocks. We ask: do skilled fund managers concentrate their research on stocks that are informationally intense, so that their research efforts are more likely to be rewarded? Further, are fund managers that aggressively pursue information-intense stocks successful in producing information and delivering performance? And, if so, how do we characterize their information production processes? These are relevant questions for fund managers and for fund investors. The active investment management industry faces serious challenges in coming up with valid investment strategies, and fund investors face an ever shrinking pool of active investment managers who can deliver consistent performance (Barras, Scaillet, and Wermers, 2010; Fama and French, 2010).

We quantify the potential reward to private-information production using a measure of information intensity, or a stock's tendency to produce large surprises to investors when significant corporate events or news arrives. Such events include, for example, earnings announcements, mergers and acquisitions, product launches or failures, and executive turnover. Intuitively, if certain information causes a large investor surprise, it should be valuable to obtain beforehand. Note that this notion of information intensity is different from the concept

[3]In equilibrium, the expected return of the marginal information gatherer just equals the cost of gathering such information. An investor with more cost-effective information production technique than the marginal investor, however, may reap positive net present value from their information production efforts.

[4]Two recent studies indirectly showcase the importance of private-information production by fund managers. Wermers, Yao, and Zhao (2012) find that stock selection information extracted from the portfolio holdings of skillful fund managers has a low correlation with a set of public signals – stock characteristics indicative of mispricing – but is significantly related to future corporate earnings. They conjecture that successful fund managers generate their own private information about future corporate fundamentals. In addition, Kacperczyk and Seru (2007) show that funds relying more on analyst recommendation changes – a source of public information – have worse performance, implying that such managers have less private information to rely upon.

of mispricing, which is defined relative to public information.[5]

To measure large information surprises and information intensity, we draw on the literature of nonparametrically estimating stock price jumps (e.g., Barndorf-Nielsen and Shephard, 2006). Specifically, the information intensity of a stock is the proportion of total stock return variance attributable to jumps. This measure can be intuitively understood as the amount of significant information relative to the total amount of available information and noise combined.[6] Further, we quantify the information intensity of a fund portfolio based on the weighted average of the stock-level information intensity across the fund's stock holdings. A high level of fund information intensity suggests that the fund aggressively invests in information-intense stocks.

We perform analysis on a large sample of U.S. equity mutual funds over the period from 1980 to 2014. We show that the information intensity (hereafter "II") of a fund is related to various fund characteristics indicative of investment activeness. For example, funds with higher II tend to be younger, smaller, trading more frequently and charging higher fees. They also tend to have higher ActiveShare (Cremers and Petajisto, 2009). Furthermore, fund II is highly persistent over time, suggesting that high information intensity is likely related to the conscious efforts by funds, rather than due to random chance.

Stocks with high information intensity represent opportunities for skilled active fund managers. But can funds successfully produce information on these stocks? We conjecture that high-II stocks may attract all sorts of active funds, not all of them having the necessary skills to produce stock-selection information. That is, among high-II funds, only those that are skilled have the potential to deliver good performance. Indeed, our analysis shows that fund II, per se, does not predict performance. However, among high-II funds, there is

[5]In addition, the information intensity measure should be technically better than traditional proxies for mispricing in quantifying potential rewards to information production. Traditional mispricing proxies, such as illiquidity and firm size, are based on market frictions. But high frictions in the form of information costs or trading costs could overwhelm any expected reward to information, defeating the purpose of measuring the reward.

[6]The relation between stock price jumps and significant corporate events has been documented in existing studies; see, for example, Lee and Mykland (2008), Lee (2012), and Jiang and Yao (2013). Although, conceptually, both information and noise could cause large price movements, these studies show that most stock price jumps are related to significant corporate events or macroeconomic news.

a particularly large dispersion in performance, and such performance differences are highly predictable by fund skill proxies, such as past fund alphas. For example, among funds ranked in the top II quintile, those in the top quintile of past four-factor alpha subsequently generate a significantly positive after-expense monthly four-factor alpha of 0.20%, while those in the bottom past four-factor alpha quintile generate a significantly negative monthly four-factor alpha of -0.25%. Their performance difference, 0.448% per month, or, equivalently 5.376% per year, is both economically and statistically significant. Moreover, an interesting contrast is that, among funds in the bottom II quintile, past fund alphas do not significantly predict subsequent performance. That is, the well-known phenomenon of performance persistence is concentrated among high-II funds.

We extend the analysis in several dimensions to gain further perspectives on the effect of fund information intensity. First, we show that the results are robust to alternative fund performance measures such as fund net returns and the characteristics selectivity measure of Daniel, Grinblatt, Titman, and Wermers (1997), to the use of alterative proxies for fund skills such as the similarity-based fund performance measure of Cohen, Coval, and Pastor (2006) and the return gap measure of Kacperczyk, Sialm, and Zheng (2008), and to the use of fund information intensity measures lagged by as many as four quarters.

Second, we compare the effect of fund information intensity on fund performance with several competing effects of fund characteristics, including the effect of the return volatility of fund holdings, the effect of fund investments in small and illiquid stocks, and the effect of fund activeness. Our key findings are highlighted below.

a) Stock return volatility. Since the measure of information intensity relies on a particular decomposition of stock return volatility, we are curious about how the effect of information intensity differs from the effect of stock return volatility. We find that funds holding more volatile stocks tend to have worse performance, consistent with the recent findings of Jordan and Riley (2015). However, the negative relation between fund stock holdings' return volatilities and fund performance mainly exists among potentially unskilled funds, i.e., funds with poor past alphas. Among potentially skilled funds (i.e., those with

good past alphas), the return volatility of stock holdings does not predict performance. In contrast, the effect of information intensity is mainly observed among potentially skilled funds. That is, among funds with high past alphas, those with higher II exhibit significantly better performance, but among funds with low past alphas, II does not predict performance. This contrast suggests that the relation of fund performance with the volatility of fund stock holdings is not driven by fund decisions to produce costly information, but rather has a different underpinning – for example, preference for lottery-like stocks.[7]

b) Market frictions. Although we argue that information intensity is conceptually different from misvaluation of stocks relative to public information, empirically information intensity may have an intricate relation with various forms of market frictions that are indicative of mispricing. On the one hand, stocks with large frictions, such as small stocks and illiquid stocks, tend to be neglected stocks and thus are more likely to cause large surprises when they have significant news. On the other hand, investors could experience large surprises for reasons unrelated to market frictions. For example, to avoid competition a firm may provide little voluntary disclosure but instead release a large amount of information at the time of mandatory disclosure (e.g., earnings announcements). Therefore, it is interesting to see to what extent the information intensity effect on fund performance is related to, and different from, the effect of market frictions. Using both a sorted portfolio approach and multivariate regressions, we show that the effect of information intensity on fund performance persistence is not subsumed by fund tendency to invest in small and illiquid stocks.

c) Fund activeness. Several recent mutual fund studies have examined the activeness of fund investment strategies, where fund activeness is measured by the departure of either fund portfolio weights or fund returns from those of the benchmark portfolios (Cremers

[7]Stocks with high volatility tend to have positively skewed returns, therefore may attract managers with lottery preferences. Such stocks may be particularly appealing to managers with tournament-like incentives (e.g., Brown, Harlow, and Starks, 1996; Chevalier and Ellison, 1997; and Huang, Sialm, and Zhang, 2011). We have also performed analysis on funds chasing lottery-like (high-skewness) stocks. We find that the intensity of chasing lottery stocks has an impact on fund performance that is very different from the impact of chasing information intense stocks. Chasing lottery stocks does not affect fund performance persistence, does not affect performance of funds with high past alphas, but significantly affects the performance of funds with low past alphas, in a way similar to the effects of holding volatile stocks.

and Petajisto, 2009; Amihud and Goyenko, 2013; Cremers, Ferreira, Matos, and Starks, 2015). While active funds may engage in strategies that exhibit both large departure from benchmarks and high information intensity in their stock holdings, we find that the relation of information intensity with fund performance is different from that of two activeness proxies in the existing literature that measure departure from benchmarks – ActiveShare and fund return R2. After controlling for these activeness measures using either the sorted portfolio approach or multivariate regressions, we find that the effect of information intensity on performance persistence remains significant. Thus, relative to departure from benchmarks, information intensity captures another important dimension of active investment strategies, which could be valuable in guiding the fund selection decisions of investors.

Third, we look into the nature of information that skilled high-II funds are able to produce. We focus on two types of corporate events – earnings announcements and M&A announcements. Previous studies have shown that such events often lead to large investor surprises. Further, the importance of the ability in predicting corporate earnings to fund performance has also been documented in existing studies (e.g., Baker, Litov, Watcher, and Wurgler, 2010; Jiang and Zheng, 2015). We find that funds with high past alpha and high II have substantially higher returns during the short windows around these corporate events, relative to funds with high past alpha but low II, or relative to funds with high II but low past alpha. This provides corroborative evidence that skilled funds successfully uncover private information from information-intense stocks, and that earnings and M&A events are the relevant types of private information these funds successfully uncover.

Finally, we examine the behavior of fund flows to see if fund investors take information intensity into account when they make fund investment decisions. We find that the relation of fund flows with past performance is significantly more sensitive among those high-II funds, than among those low-II funds. This result is robust to the control of various fund characteristics, including the effect of fund investments in small stocks and illiquid stocks, the volatility characteristics of fund holdings, and the effect of fund activeness. Thus, it seems that investors' fund selection decisions are affected by how fund managers allocate their costly

information production efforts and the impact of such allocation on fund performance.

The rest of the paper is organized as follows. Section 2 introduces the measure of information intensity at both the stock level and at the fund level. Section 3 describes data. Section 4 presents the empirical results. Section 5 concludes.

2 Measuring Information Intensity

An informationally-intense stock is one that is likely to cause large surprises to investors. Various factors can affect the level of information intensity. Some firms' business operations are more uncertain in nature than others – for example, the operating performance of technology companies is typically more unpredictable than that of utilities companies. Also, some firms may hold off voluntary disclosure until the time of mandatory disclosure (e.g., earnings announcements), at which time they lease information in lump sum. Alphabet (Google), Coke-Cola, AT&T, and Costco are well-known examples of firms withholding earnings guidance. Information intensity is also likely related to market frictions – for stocks with higher information costs or trading costs, there is likely more information out there not fully impounded into stock prices, resulting in investor surprises when such information ultimately arrives in a conspicuous way, e.g., via corporate announcements. It is likely that these factors interact with each other to shape up the level of information intensity of a stock.

In econometric terms, these large surprises are represented by stock price jumps – large discrete movement in stock prices. Various econometric methods have been developed to identify jumps in asset prices or to quantify the statistical properties of jumps. The estimation techniques range from maximum likelihood, GMM, Bayesian, to non-parametric. In this study, we use the non-parametric approach developed in the recent literature (e.g., Barndorff-Nielsen and Shephard, 2004 and 2006) to estimate the contribution of jumps to overall stock return variance. The idea behind this approach is that a quantity known as bi-power variation represents the contribution by the continuous diffusion component of stock price movement to the stock return variance, while the remaining variance can then

be attributed to the jump component. Specifically, consider a general, continuous-time, jump-diffusion process for stock price:

$$\frac{dS_t}{S_t} = \mu_t dt + \sigma_t dW_t + dJ_t \tag{1}$$

where μ_t is the instantaneous drift, σ_t is the instantaneous diffusion volatility, dW_t is a standardized Brownian motion, J_t is a pure jump Lévy process with increments $J_t - J_s = \sum_{s \leq \tau \leq t} \kappa_\tau$, and κ_τ is the jump size. Suppose the stock prices are observed altogether N+1 times at discrete times n, with n = 0, 1, ..., N. The discretized log-return from time n-1 to n is then $r_n = ln(S_n) - ln(S_{n-1})$, for n=1, ..., N. Define the *realized variance* as

$$\text{RV} = \sum_{n=1}^{N} r_n^2 \tag{2}$$

And the *bi-power variation* is defined as

$$\text{BPV} = \frac{\pi}{2} \frac{N}{N-1} \sum_{n=2}^{N} |r_n||r_{n-1}| \tag{3}$$

The bi-power variation measure is similar to the realized variance measure, except that the quadratic term of return r_n^2 in RV is replaced by by the product term of the absolute values of two consecutive-observed returns, $|r_n||r_{n-1}|$, in BPV. The key idea is that the diffusion volatility affects the magnitude of both r_n and r_{n-1}, while a jump may have a large impact on either r_n or r_{n-1}, but not both. Thus, in the limit, BPV is not affected by jumps. Indeed, under reasonable assumptions, as data sampling frequency increases, i.e., N $\rightarrow \infty$, the discretely sampled RV and BPV converge respectively to the continuous-time measures of integrated variance and integrated diffusion variance. For notional convenience, we normalize the time span so that t$\in$[0,1]. We have,

$$\lim_{N\rightarrow\infty}\text{BPV} \rightarrow \int_{t=0}^{1} \sigma_t^2 dt \tag{4}$$

$$\lim_{N\rightarrow\infty}\text{RV} \rightarrow \int_{t=0}^{1} \sigma_t^2 dt + \sum_{j=1}^{K} \kappa_j^2 \tag{5}$$

where K is the total number of jumps during the period and κ_j is the size of the j-th jump. Now define the jump variance as JV=Max(0, RV-BPV).[8] It is easy to see that

$$\lim_{N\to\infty}\text{JV} \to \sum_{j=1}^{K} \kappa_j^2 \tag{6}$$

That is, JV is a consistent estimator of the contribution of pure jumps to the integrated variance. Further, the ratio JV/RV can be interpreted as the percentage contribution of jumps to the total return variance. Both JV and the ratio JV/RV have been used in existing studies to test the presence of jumps. See, e.g., Barndorff-Nielsen and Shephard (2004 and 2006), Andersen, Bollerslev, and Diebold (2004), and Huang and Tauchen (2005).[9]

In this study, we define the information intensity of a stock based on the ratio:

$$\text{SII} = \frac{\text{JV}}{\text{RV}} \tag{7}$$

We estimate the information intensity following the above equation (7) for each individual stock every quarter, using daily stock returns from CRSP for the period from 1980 to 2014. RV and BPV are estimated following equations (2) and (3) respectively. It is noted that many studies (with the exception of Jiang and Yao, 2013) estimate jumps using the intra-day data. We focus on daily data in our study for two reasons. First, intra-day data are not available for the earlier half of our sample period. Second, intra-day stock returns are known to subject to severe market microstructure effect. Christensen, Oomen and Podolskij (2014) show that jumps in asset prices are far less as frequent as suggested by tests based on high-frequency data. Many intra-day large returns are simply the effect of market microstructure noise or illiquidity and are often quickly reversed. By contrast, our main interest is on stock price jumps associated with important informational events. If a jump only has impact on stock return at the intra-day level but does not affect daily return with economically significant magnitude, it is not important for the purpose of this study.

[8] RV-BPV is non-negative in the continuous limit, but may be negative in the discrete-time estimates. Here we replace the negative estimate of RV-BPV by zero. Our results are not substantially altered if we simply define JV as RV-BPV.

[9] An alternative non-parametric approach for jump identification is based on the variance swap idea (e.g., Jiang and Oomen, 2008; Jiang and Yao, 2013). The variance swap approach identifies jumps based on their contributions to the return skewness instead of return variance.

After obtaining estimates of information intensity SII_{it} for each stock i during each calendar quarter t, we measure the information intensity of fund j during quarter t as:

$$\text{QII}_{jt} = \sum_{i=1}^{N_j} w_{ijt-1}\text{SII}_{it} \tag{8}$$

where N_j is the number of stocks held by fund j, and w_{ijt-1} is the weight of stock i in all of fund j's equity holdings at the beginning of a quarter (or the end of the previous quarter). That is,

$$w_{ijt-1} = \frac{V_{ijt-1}}{\sum_{i=1}^{N_j} V_{ijt-1}} \tag{9}$$

where V_{ijt} is the dollar value of fund j's holding of stock i in quarter t.[10]

In any given quarter, a fund may have high or low information intensity due to either its intentional pursuit of certain investment strategies or random chance. To reduce the influence of random chance, we further take the rolling four-quarter average of the quarterly-measured fund information intensity:

$$\text{II}_{jt} = \sum_{s=0}^{3} \text{QII}_{jt-s} \tag{10}$$

We require at least two QII observations for the above II estimate to be valid.

3 Mutual Fund Data and Sample

The data on mutual funds are from two sources – CRSP and Thomson Reuters. Our sample includes actively-managed US domestic equity funds during the period from 1980 to 2014. The Thomson-Reuters data provide quarterly snapshots of mutual fund portfolio holdings. The CRSP database reports fund net returns, flows, investment objectives and other fund characteristics. Funds in these two datasets are matched via the MFLINKS file (available from Wharton Research Data Services, WRDS). We combine multiple share classes of a fund in the CRSP database into a single portfolio (value-weighted, based on beginning-of-quarter

[10] We have performed analysis using an alternative QII definition where the beginning-of-quarter weight w_{ijt-1} is replaced by the end-of-quarter weight w_{ijt} in the above expression. The results we obtain are quite similar. Intuitive, this is due to the fact quarterly fund turnover is relatively low, and the fact that at the stock level, SII is quite persistent over time.

total net assets of each share class) before matching the CRSP data with the Thomson-Reuters data. Our focus is on the U.S. actively managed diversified equity funds that mainly invest in domestic stocks. We exclude index funds, international funds, municipal bond funds, bond and preferred stock funds, and sector funds. To ensure data accuracy, we exclude fund-quarter observations if a fund has less than 10 stock holdings with valid SII measures, and fund-quarter observations when the value of stock holdings with valid SII measures is less than 50% of the portfolio value. We further exclude fund-quarter observations if the total net assets are below $10 million dollars. We address the incubation bias (e.g., Evans 2010) by removing fund-quarter observations prior to the first offer date of the earliest share class of a fund reported in CRSP.

Funds report holdings at the end of their fiscal quarter (as indicated by the variable "rdate" in the Thomson data), which may not always be the end of a calendar quarter. In order to facilitate cross-sectional comparison, if the date of the reported holdings is not at a calendar quarter end, we assume that the holdings remain valid at the end of that calendar quarter, with adjustment for stock splits using the CRSP share adjustment factor. In addition, SEC's mandatory reporting frequency of mutual fund holdings is quarterly prior to 1985, semi-annual between 1985 and May 2004, and quarterly again afterwards. When a fund reports holdings at the semi-annual frequency and for the quarter it does not report its holdings, we assume that its holdings are the same as in the prior quarter.

Our final sample includes 3,348 unique funds and 159,480 fund-quarter observations during the 35-year period. Table 1 provides summary statistics for the mutual fund sample. For each sample year, we report the number of funds, the averages of the numbers of stocks held, the net assets (TNA), expense ratio, turnover, and the information intensity measure II. These numbers are as of the end of each year, and if in a given year, a fund ceases to exist in the data before the end of the year, we use its latest available information during that year. In 1980, the beginning of our sample, there are 216 funds, holding an average of 57 stocks per fund, with an average TNA of $192 million, an average expense ratio of 0.96% and an average annual turnover of 70%. By the end of the sample period, in 2014, there

are 1,594 funds in the sample, holding 129 stocks on average, with an average TNA of $2.51 billion, an average expense ratio of 1.09% and an average turnover of 64%. The growth in the number of funds and the average TNA reflect the growth of the fund industry. The average fund TNA peaks in 2014. Before that, it peaked in 2007 and then took a large toll during the recent financial crisis of 2008 (and in 2002, after the burst of the internet bubble). By contrast, the number of funds does not fluctuate as dramatically around the crisis. The declining number of funds toward the end of the sample period is likely due to the time lag by Thomson-Reuters in updating the data.

The table also reports the cross-fund mean and standard deviation of our key variable of interest, fund information intensity (II). The average II hovers above 8% in the 1980s, drops below 8% during the early 1990s, late 1990s and early 2000s. It starts to pick up afterwards, reaching above 10% in the seven of the last 10 years of the sample period. Note that at the stock level, information intensity can be interpreted as the proportion of jump-induced variance in total stock variance. Thus, a 10% II at fund level means that on average, 10% of the return variances of stocks held by funds are due to jumps, or large information surprises. The cross-sectional standard deviation of II is more stable, but follows a similar pattern of time variation – it started high in the 1980s, trended lower in the 1990s and picked up again in recent years. In fact, the time series correlation between the mean and standard deviation of II is 51% during the 35-year sample period.

4 Empirical Results

4.1 Information Intensity and Fund Characteristics

We first attempt to understand the fund-level information intensity by relating it to various fund characteristics. In each quarter, we sort funds into quintiles based on its rolling four-quarter measure of information intensity II, and report the average characteristics for each fund quintile. In Panel A of Table 2, we first check the following characteristics: fund information intensity II, the weighted average of JV, RV, and return standard deviation

(during the past 12 months) of stocks held by funds. The average information intensity of the funds ranked in the top quintile of II is 11.77%, suggesting that among the stocks they hold, over 11% of stock return variance is realized in the form of large surprises. By contrast, large surprises only account for 6.87% of return variances for stocks held by funds ranked in the bottom II quintile. That is, the information intensity of top-II fund quintile is almost twice as high as that for the bottom quintile, indicating a large cross-sectional variation. In addition, the weighted average JV, RV, and return standard deviation for stocks held by funds in the top II quintile are also much higher than those for stocks held by funds in the bottom II quintile. This suggests that high-II funds invest in highly-volatile stocks; and more importantly, they invest in stocks that tend to generate large surprises.

In the same panel, we then look at two characteristics indicative of fund activeness: ActiveShare and R2. The measure of ActiveShare follows Cremers and Petajisto (2009) and the measure of R2 follows Amihud and Goyenko (2013).[11] Going from bottom to top II quintiles, ActiveShare increases monotonically, with a large difference between the top and bottom quintiles. This supports the notion that stocks with more intense information attract more active funds. The relation between II and R2, however, is virtually flat and not monotonic.

Panel A of Table 2 further reports the number of stocks held by funds and fund turnover. These two measures are related to the concentration of fund holdings and the intensity of fund trading, which to some extent are also related to fund activeness. The average number of stocks held by funds increases from 75 for the bottom II quintile to 102 for the fourth quintile, and drops to 99 for the top II quintile. Fund portfolio turnover exhibits a similar pattern – turnover increases from the bottom to the fourth II quintile, but drops off for the top II quintile. In other words, both low-II and high-II funds are more concentrated and trade less, and the relations of II with holding concentration and trading activeness are not monotonic.

[11] We thank Martjin Cremers for providing the ActiveShare data. The data on ActiveShare we obtain are for the period from 1981 to 2012. Thus, the analysis involving this variable is for that period. R2 is the R-square of regressing monthly fund returns during the past 24 months onto the Carhart (1997) four factors.

Panel B of Table 2 shows that funds with higher information intensity are smaller, younger, and charge higher fees. These characteristics also fit the profile of more active funds. The panel also reports the investment styles of funds in terms of size, book-to-market ratio, momentum, and illiquidity of stocks held by funds. The four style scores, SIZESCORE, BMSCORE, MOMSCORE, and ILLIQSCORE, are measured in the following way. First, we cross-sectionally standardize four stock-level characteristics – marketcap, book-to-market ratio, past 12-month returns, and the Amihud illiquidity ratio – across all stocks in a given quarter by subtracting the cross-sectional mean and then dividing by the cross-sectional standard deviation. We then take the weighted average of the standardized stock characteristics across the stocks held by a fund. The table shows that funds with higher II ranks hold more small stocks and illiquid stocks. But the relations of II with the value and momentum styles appear relatively weak.

Funds may have high IIs either due to their decisions to engage in private-information production, or due to sheer random chance. Fund IIs should be more persistent in the former case. Table 3 shows the averaged II during the subsequent four years after initial fund ranking, across the II quintiles. The persistence in information intensity is clear. For funds initially ranked in the top II quintile, their average II experiences a slight drop, from 11.77% at the initial ranking (reported in Table 2) to 11.61% during the subsequent year, but stays above 11% throughout the five years after the ranking. For funds initially in the bottom quintile, their average II increases from 6.87% at the initial ranking (reported in Table 2) to 7.71% during the first year, and continues to rise slightly each year, until it reaches 8.58% in year 5. It is noteworthy that by year 5, the difference in II between the initially-ranked top and bottom fund quintiles remain large (11.08% vs. 8.58%). Such persistence suggests that a substantial component of II is due to their stable, long-term, information production efforts.

4.2 Information Intensity and Performance

The empirical relations between information intensity and various fund characteristics suggest that active funds are attracted to information-intense stocks. However, the information intensity measure only captures the opportunities for fund information production. It does not yet tell us whether funds are successful in turning these opportunities into valid stock selection information. Discovering non-public information about corporate fundamentals is not mechanical work; it requires skills. Thus, we expect that skills matter particularly for the performance of funds investing in information intense stocks. To test this prediction, we examine the effect of information intensity on fund performance and performance persistence.

4.2.1 The Effects of Past Fund Alpha and Information Intensity on Subsequent Fund Performance

We first use the sorted fund portfolio approach to confirm the well-known phenomenon of performance persistence and to examine the relation between information intensity and fund performance. Specifically, in each month, we sort funds into quintiles based on either the past fund alpha or information intensity II. We then form equally weighted fund portfolios within the quintiles and look at the next-month performance of each quintile. Past fund alpha is estimated using the Carhart (1997) four-factor model over the past 12 months up to the end of the ranking month. When we rank funds by II in each month, we use the II estimate based on the rolling four-quarter average of quarterly information intensity (QII) up to the most recent quarter. We report the four-factor alpha of the fund portfolios in Table 4. The fund returns used in compute past fund alphas and the subsequent alphas of fund quintile portfolios are both net of fund expenses.

Panel A of the table shows the persistence of performance. Funds in the top past-alpha quintile significantly outperform those in the bottom quintile by 0.272% in terms of monthly four-factor alphas. By contrast, Panel B of the table shows that fund information intensity does not significantly predict fund performance. The difference in fund alphas between the top and bottom II quintiles is 0.079%, positive but statistically insignificant.

The table also reports the dispersion of fund returns within each fund quintile. The dispersion is measured by the cross-sectional standard deviation of monthly fund net returns for a given month, and then averaged over time. The return dispersion is 2.41% for the top II quintile and 1.96% for the bottom quintile, visibly higher than those of the three middle quintiles. Likewise, funds ranked in the top and bottom quintiles of past alphas exhibit high return dispersion.

The insignificant relation between II and subsequent fund performance, and the large performance dispersion among the top II funds, lead us to the conjecture that although information-intense stocks attract many active funds, not all such funds can successfully produce information. An analogy is the great American Gold Rush of the mid-1880s – many aspiring gold seekers went to California, but only a few made a fortune. Their different fortunes are perhaps due in part to luck, and in part to skills. We are more interested in the extent to which skills matter for private-information production in the stock market. This motivates our subsequent analysis.

4.2.2 Performance of Fund Portfolios Double-sorted by Information Intensity and Past Alpha

We now turn to a double-sorting approach to see if skill matters for successful information production. In each month, we sort funds independently by past four-factor alpha and information intensity (II) into 5 by 5 (25) groups. Fund alpha is estimated using rolling 12 months returns, and II is the four-quarter rolling average of information intensity up to the most recent quarter. Within each fund group, we form an equal-weighted portfolio and examine its next-month performance. To ensure the robustness of inference, we report post-ranking performance of the 25 portfolios using three performance measures – fund net returns, the four-factor alpha, and the characteristic selectivity measure (CS) of Daniel, Grinblatt, Titman, and Wermers (1997). Specifically, CS is the weighted average of stock return during a month in excess of the corresponding benchmark portfolio return, across all stocks held by a fund. The benchmark portfolios are formed quarterly, based on sequential

quintile sorts on market capitalization, book-to-market ratio, and the return during the past 12 months. Stocks in the benchmark portfolios are value-weighted. Note that the net returns and alphas are net of fund expenses, while the DGTW stock selectivity measure is before-expense.

Panels A, B, and C of Table 5 report the performance of the double-sorted fund portfolios under these three performance measures respectively. Since the patterns are similar across panels, we focus the discussion on the four-factor alpha (Panel B). Note that the last row of each panel reports the performance difference between the funds in the top and bottom past-alpha quintiles, across funds in different II quintiles. These numbers indicate the magnitude of performance persistence. For funds in the low II quintile, the monthly alpha difference between the top and bottom past-alpha quintile is 0.040%, statistically insignificant. Therefore, there is no performance persistence among low II funds. As we move to funds with higher IIs, performance persistence becomes more visible. Among funds in the top II quintile, those in the top past-alpha quintile outperform those in the bottom past-alpha quintile by 0.448% monthly, or 5.376% annually, with a large t-statistic. Thus, performance is strongly persistent among the top II funds.

The funds in the top past-alpha quintile and in the top II rank worth particular attention. These funds deliver a significantly positive alpha of 0.198% per month, or 2.376% annually. These funds invest in information-intense stocks, and they are skillful in producing information on such stocks. In contrast, the alpha of funds with the same top past-alpha rank but in the bottom II rank is -0.115%, underperforming the afore-mentioned fund group by 0.313% per month. Although these funds have good past performance, their past performance is not the result of intense information production efforts, and thus smacks of random chance that does not last long.

Among funds in the bottom past alpha quintile, those ranked in the top II quintile generate a significantly negative alpha of -0.250%, and those in the bottom II quintile generate a significantly negative alpha of -0.155%. The performance difference between these two groups, at -0.095%, is statistically insignificant. The former group has low information in-

tensity, and thus their poor past performance is more likely due to random chance, while the latter group has high information intensity, and thus their low past performance may be more likely attributable to their ineffectiveness in information production. It is also plausible that these funds are attracted to high II stocks for reasons not related to information production. As noted in the introduction of the paper, high-SII stocks tend to have positively skewed returns, and thus may attract investors with lottery preferences.

To give a quick summary, II has a significant impact on the performance among funds with good past performance, and insignificant impact on the performance of funds with poor past performance. Further, performance persistence mainly exists among funds with high II, and non-existent among low-II funds. These results are consistent with the notion that when funds engage in costly information production and focus their efforts on information-intense stocks, their skills matter for performance; but when funds do not substantially engage in costly information production, their performance has more of a random element and thus lacks persistence.

4.2.3 Performance of Fund Portfolios Double-sorted by Information Intensity and Alternative Fund Skills Proxies

In addition to using past fund alpha as a proxy for fund skills, we consider two alternative skill proxies. One is the performance measure based on similarity of fund holdings proposed by Cohen, Coval, and Pastor (2006), and another is the return gap of Kacperczyk, Sialm, and Zheng (2008). The measure ("Similarity" hereafter) of Cohen et al. (2006) is based on the idea that due to scarcity of good investment ideas, skilled fund managers tend to hold similar stocks. Following their study, we construct this measure in two steps. First, we compute a stock quality measure, which is the weighted average of the alphas holding the funds, with weights proportional to the portfolio weight a fund has on the stock. The fund alpha used in this step is the Carhart (1997) four-factor alpha estimated with rolling 12 months of returns. Then, in the second step, the Similarity measure of a fund is the weighted average of the stock quality measure across stock holdings of the fund, with weights being

the portfolio weights. The return gap ("Return Gap" hereafter) is the difference between the reported fund return and the hypothetical return inferred from the beginning-of-period fund holdings. It follows the idea that unobserved actions by mutual funds (relative to the prior-disclosed portfolio holdings) matter for fund performance. Conceptually, this measure captures the interim trading skills of mutual funds, rather than the conventional notion of stock selection (i.e., picking stocks at the beginning of a period and holding them throughout the period). However, in analyzing the relation between GAP and subsequent fund performance, Kacperczyk, Sialm, and Zheng (2008) show that GAP is significantly related to the subsequent characteristic selectivity of Daniel, Grinblatt, Titman, and Wermers (1997). Thus, the interim trading skills are at least correlated with the stock selection ability of fund managers.

Table 6 reports the performance of fund groups double-sorted by II and one of the two alternative skill proxies. Again, we perform independent double-sorts monthly to form 25 (5 by 5) equal-weighted fund portfolios and examine their next-month performance. The performance measure reported in the table is the after-expense four-factor alpha. The patterns observed here are quite similar to those in Table 5. The subsequent performance difference between the top and bottom Similarity quintiles is significant only among funds in the top two II quintiles. And the subsequent performance difference between the top and bottom Return Gap quintiles is significant only among the funds in the top II quintiles. Further, despite being statistically significant, the results based on Return gap are overall weaker relative to those based on past four-factor alphas or Similarity. This is perhaps due to that GAP is related to both interim trading skills and stock selection skills, and more to the former.

4.2.4 The Effect of Lagged Information Intensity Measures

Fund information intensity measure II depends on fund holdings data, and information about fund holdings is typically available with delays. In this part, we examine whether delayed measures of fund information intensity is still useful to fund investors when they make fund

selection decisions.

There are at least two types of delays that are relevant here. The first is due to reporting lag of fund holdings – mutual funds have at most 60 days after the end of their fiscal quarter to disclose their holdings via SEC's EDGAR system. The second is that data vendors such as Thomson-Reuters may include the newly disclosed holdings into their datasets with a time lag.[12] By contrast, fund returns are reported in a more timely manner. Due to the requirement of daily pricing of fund net asset values (NAV), fund return is available at the daily frequency and by the end of a day.

Note that as described in Equations (8), (8), and (10), the latest fund holdings used to compute fund II for a given calendar quarter are those at the end of the previous calendar quarter. Thus, the results reported in Table 5 are based on fund holdings information already disclosed by funds at the time of fund ranking, and thus are not subject to the first type of delays described above. However, they may still be subject to the second type of delays on the part of data vendors. To address this concern, we use lagged fund IIs to repeat the double-sorting analysis performed in Table 5.

Panels A of Table 7 reports the performance of double-sorted fund portfolios where fund IIs are lagged by one quarter relative to the II measures used in Table 5. To give a concrete example, when we double-sort funds in July of a given year, past fund alphas are still estimated for the 12 months up to the end of July (assuming no reporting delays for fund returns), but fund IIs are estimated in March of that year, which involves fund holdings in the fourth calendar quarter of the previous year. The performance measure reported in the table is the after-expense four-factor fund alpha. The results show that among funds ranked in the top lagged-II quintile, the alpha difference between the top and bottom fund quintiles sorted on past alpha is 0.445%, comparable to the corresponding number reported in Table 5 (0.448%). The funds ranked in the top past-alpha quintile and top II quintile have an alpha of 0.201%, also comparable to the corresponding number reported in Table 5

[12] A small number of funds report their holdings to data vendors via direct data feeds shortly after their fiscal quarter-end or even at the monthly frequency. Thus, their holdings information may become available in the datasets before funds file their holdings disclosure via EDGAR. However, this is not the case for the majority of funds.

(0.198%). Thus, lagging fund IIs by one quarter does not significantly reduce the effect of fund II on performance persistence.

In Panels B to D of Table 7, we lag fund IIs by two to four quarters. The results show that when we take longer lags on II, its effect on performance persistence tends to become weaker. However, even after lagging fund IIs by four quarters, the effect of II on performance persistence remains significant. What we observe from this table is to a large extent consistent with the persistence of fund II reported in Table 3. These findings highlight the practical usefulness of the fund information intensity measure to fund investors when they make fund selection decisions.

4.2.5 Subperiod Analysis

Barras, Scaillet, and Wermers (2010) and Fama and French (2010) document that the proportion of truly skilled active funds in the market shrinks substantially over time. One possible reason for such a time trend is improved market efficiency. In theory, if market efficiency in both the semi-strong form and the strong form improves over time, any type of fundamental research, whether it is based on public information or private information, should exhibit reduced profitability. However, we note that there are countervailing factors in the market, which may keep the opportunities alive for private information production. One particular factor is the tightening regulations (e.g., Reg FD) on corporate disclosure and insider trading, which, for the purpose of fairness and investor protection, may have an effect of delaying the release of private information to the public. Such a slow-down of releasing private information creates profit opportunities for investors who can uncover information on their own means.[13] Therefore, it is interesting to see the time trend in the effectiveness of private information production by fund managers.

In Table 8, we break the entire sample period of 1980-2014 into two subperiods, 1980-1996 and 1997-2014, and repeat the double-sort analysis of Table 5 for each of the subperiod.

[13]Regulations may also affect the specific methods of uncovering private information. For example, some practices once popular among investors to uncover private information –e.g., expert network – have been essentially outlawed, while others –e.g., channel-checking – remain legitimate or in the grey area.

The performance measure reported in the table is the after-expense four-factor fund alpha. The results show that during the early subperiod, the relation between II and performance persistence is very strong. Among the funds in the top II quintile, the alpha difference between the top and bottom past-alpha quintiles is 0.532%. During the later subperiod, the alpha difference between the top and bottom past-alpha quintiles is lower, at 0.352%; however, such a performance difference remains statistically significant. Thus, improved market efficiency weakens, but does not completely wipe out the effectiveness of fund managers' private information production efforts during the more recent years. In other words, the more recent version of fundamental research remains useful as a stock selection approach.

4.3 Comparison with and Controlling for Alternative Effects

In this part of the analysis, we compare the effect of information intensity on fund performance with several competing effects. In Section 4.3.1, we document the effect of the fund holdings' volatility and the effect of fund return R-square (R2) on fund performance. In Section 4.3.2, we control for various competing effects using a triple-sorting procedure. In Section **??**, we use multivariate regressions to examine the effect of information intensity on fund performance while controlling for various competing effects.

4.3.1 Return Volatility and Skewness of Fund Holdings, and R2

The stock-level information intensity is based on a decomposition of return volatility – the return variance attributed to large price jumps relative to the total variance. It is natural to question how important it is to separate the jump component from the diffusion component in defining information intensity. Note that at the stock level, there is a well-known low volatility anomaly – stocks with high return volatility (idiosyncratic or total volatility) tend to have abnormally low subsequent returns (Ang, Hodrick, Xing, and Zhang, 2006). At the fund level, a recent study by Jordan and Riley (2015) reports a related phenomenon – funds with high return volatility tend to have poor subsequent performance. They attribute this fund level relation to the volatility of stocks held by funds. Finally, our Table 2 shows that

funds with high II also tend to hold stocks with high realized variance (RV) and high return standard deviation. Given all these considerations, it is important to understand the relation between the information intensity effect and the effect of return volatility of stocks held by funds.

To quantify this volatility effect, we use the variable reported in Table 2 – STDEV, which is the weighted average return standard deviation of stocks held by the fund. The weights are the portfolio weights at the beginning of a holding quarter. The return standard deviation of a stock is computed using daily returns during the quarter. Similar to the construction of fund II, we take the rolling 4-quarter averages of the quarterly weighted average return standard deviation to obtain STDEV. Then, in each month, we form 25 (5 by 5) equal-weighted fund portfolios independently double-sorted on past 12-month four-factor alpha and STDEV.

Panel A of Table 9 reports the performance of the 25 fund portfolios. Again, we focus on the four-factor alphas during the subsequent month. The results show that STDEV also has a significant impact on fund performance persistence. Specifically, performance persistence, as measured by the performance difference between funds in the top and bottom past-alpha quintiles, is stronger among funds with higher STDEV. Interestingly, a closer look at the results reveals that the volatility effect is different from that of information intensity. Recall that in Table 5 and discussed earlier, II affects performance persistence mainly through predicting the performance of funds with high past alphas. In contrast, the volatility effect here works mainly through its impact on the performance of funds with low past alphas. For example, among funds with the bottom past alpha rank, those with the top STDEV rank generate a significantly negative four-factor alpha of -0.390%. They significantly underperform those with the bottom STDEV rank, which have an insignificantly negative alpha of -0.072%. Meanwhile, among funds with the top past alpha rank, the relation between STDEV and performance is basically flat – those in the top STDEV rank generate a four-factor alpha of 0.062%, indifferent from the alpha generated by those with the bottom STDEV rank (0.016%).

This comparison suggests that the effects of stock holdings volatility and information intensity are different. The information intensity measure II captures the effect associated with costly information production, while the volatility effect likely represents a different phenomenon – for example, as discussed in the introduction of the paper, investors' preference for lottery-like stocks. It is worthwhile noting that we have also performed analysis using two other measures of volatility – the weighted RV and the weighted BPV of stocks held by funds. The effects of these two measures on fund performance persistence are similar to that of STDEV. This is perhaps largely due to the high correlation among RV, BPV, and STDEV at the fund level and at the stock level.

Next, we turn to another fund characteristic known to affect fund performance and performance persistence. Amihud and Goyenko (2013) report that their fund activeness measure R2 has a significantly negative relation with subsequent fund performance, and that its effect is particularly strong among funds with high past alphas. Panel B of Table 9 by and large confirms their results. Here, funds are independently double-sorted by past alpha and R2. As noted in Section 4.1, we follow Amihud and Goyenko (2013) to estimate fund R2 as the R-square obtained from the Carhart four-factor regression model based on past 24 months of fund returns. The results from the last row of the panel show that the performance difference between the top and bottom past-alpha fund quintiles, a measure of performance persistence, decreases with R2 quintile ranks. The top-bottom performance difference is 0.386% for the bottom R2 quintile, and 0.138% for the top R2 quintile. In addition, the last column of the panel shows that R2 does not significantly affect fund performance among funds in the lowest past-alpha quintile, but significantly affects fund performance among funds in the top past-alpha quintile. These observed effects of R2 on fund performance are similar, although at a weaker magnitude, to those reported for information intensity in Table 5.

The results reported in Panel B are also somewhat weaker relative to those reported by Amihud and Goyenko (2013). We conjecture that the difference is caused by further nuances in sample construction. In Panel C of Table 9, we repeat the analysis of Panel B by adopting

two additional sample restrictions of Amihud and Goyenko (2013): 1) censoring R2 at the top and bottom 1% each month, and 2) restricting the sample period to 1990-2010. The results are stronger.

Since the results here suggest that the effect of R2 is somewhat similar to that of II, it would be interesting to further disentangle these two effects. We do so in subsequent analysis. In addition to R2, we have performed similar double-sorting analysis involving another fund activeness measure, ActiveShare. We find that ActiveShare does not have a significant impact on fund performance persistence.

In addition, we also consider the return skewness of fund stock holdings. Since at individual stock level, positive jumps are more frequent than negative jumps (Jiang and Yao 2013), the stock-level information intensity measure SII is likely positively related to stock return skewness. This gives rise to the issue of whether the return skewness of fund holdings has an impact on fund performance similar to that of II. We examine this by constructing a fund level return skewness measure. Specifically, a quarterly measure of fund holding skewness is the weighted average of return skewness of the stocks held by a fund, where the weights are proportional to the portfolio weights. Stock return skewness is measured during the same quarter of measuring stock information intensity SII. Further, similar to the construction of fund information intensity II, we take the rolling four-quarter average of the quarterly fund holdings skewness measure. This measure is referred to as SKEW.

In Panel D of Table 9, we perform the alphas of funds double sorted by past alpha and SKEW, in a way similar to our double sorts in Panel A on past alpha and STDEV. The results show that performance persistence exists in each SKEW quintile – funds in the top past-alpha quintile significantly outperform funds in the bottom past-alpha quintile regardless of their SKEW quintile ranking. Thus, the SKEW does not have a significant impact on performance persistence. Further, the effect of SKEW on fund performance is most visible among the bottom past-alpha funds. There, low-SKEW funds significantly outperform high-SKEW funds. By contrast, for funds in the top past-alpha quintile, SKEW does not significantly affects fund performance. This pattern is likely related to the lottery preference

of certain fund managers. It has been well documented that due to lottery preference of certain investors, stocks with large positive skewness tend to be over-valued and have low future returns. Chasing such stocks tend to result in poor performance. This is particularly relevant for fund managers with poor past performance (an indication of lack of skills).

4.3.2 Controlling for Competing Effects Using Triple-sorted Fund Portfolios

In this part of the analysis, we use the triple-sorted portfolio approach to examine the effect of information intensity on performance persistence while controlling for various competing effects. The triple-sorting procedure works as follows. First, we sort funds into quintile by a fund characteristic representing a competing effect that is to be controlled. Then, within each quintile of the first sorting variable, we further use independent double sorts to rank funds into II quintiles and past four-factor alpha quintiles. This results into 125 fund groups. Finally, we combine funds with the same quintile ranks on II and past alpha but different quintile ranks of the first sorting variable into a single equal-weighted portfolio. This procedure results in 25 (5 by 5) fund portfolios, and within each portfolio, fund characteristic represented by the first sorting variable is distributed relatively evenly across fund portfolios. Thus, if we continue to observe significant impact of II on performance persistence across the 25 portfolios, then such an effect of II cannot be attributed to the competing effect represented by the first sorting variable. Note that similar procedures to control for competing effects have been used in previous studies, e.g., Ang, hodrick, Xing, and Zhang (2006).

We control for three sets of competing effects. The first set is related to market frictions. As pointed out in the introduction part of the paper, information intensity is conceptually different from mispricing, with the former pertaining more to private information and the latter relative to public information. However, information intensity may have an interwined relation with market frictions such as illiquidity, which may exacerbate mispricing. In particular, investors tend to pay low attention to small stocks and illiquid stocks, and as a consequence these stocks may surprise investors from time to time by significant news. However, stocks could also generate large surprises for reasons unrelated to market frictions –

for example, to avoid competition, a firm may provide little voluntary disclosure but instead release a large amount of information at the time of mandatory disclosure (e.g., earnings announcements). Therefore, we expect the effect of market frictions on fund performance to be related to, but do not subsume the effect of information intensity. We use two fund characteristics reported in Table 2 – SIZESCORE and ILLIQSCORE – to quantify the effect of market frictions a fund faces.

The second set of effects to control for is fund activeness, and we include two fund activeness measures – ActiveShare and R2. The last set of competing effect is the return volatility of fund stock holdings, and the variable to control for is the weighted average return standard deviation of stocks held by a fund, STDEV.

Panels A to E in Table 10 report the results of the triple-sorting analyses that control for the above-mentioned effects. The results show that the significant effect of II on performance persistence is not explained away by any of the competing effects.[14]

4.3.3 Multivariate Regressions

We further perform Fama-MacBeth multivariate regressions to analyze the impact of information intensity on fund performance while controlling for various fund characteristics affecting fund performance. The regressions are performed each month t across sample funds. The dependent variable is fund abnormal return during month t under the Carhart four-factor model (referred to as the "four-factor abnormal return"). Specifically, a fund j's four-factor abnormal return $\hat{\alpha}_{j,t}$ is estimated as:

$$\hat{\alpha}_{j,t} = r_{j,t} - r_{ft} - (\hat{\beta}_{j,1,t-1}\text{MKTRF}_t + \hat{\beta}_{j,2,t-1}\text{SMB}_t + \hat{\beta}_{j,3,t-1}\text{HML}_t + \hat{\beta}_{j,4,t-1}\text{UMD}_t) \quad (11)$$

where $r_{j,t}$ is fund j's month-t after-expense net return, r_{ft} is the riskfree rate, and MKTRF, SMB, HML, and UMD are the market, size, book-to-market, and momentum factors. $\hat{\beta}_{j,1,t-1}$, $\hat{\beta}_{j,2,t-1}$, $\hat{\beta}_{j,3,t-1}$, and $\hat{\beta}_{j,4,t-1}$ are the estimated fund loadings to the four factors. These loadings are estimated using past 36 months of data (month t-36 to month t-1) under the Carhart

[14] Again, since our data for ActiveShare is for the period of 1981-2012, the results in Panel C are based on that sample period.

four-factor model. We require a fund to have a minimum of 24 months of data for the factor loading estimates (and consequently, for the abnormal return estimates) to be valid.

The main explanatory variables include past fund alpha, the information intensity measure II, and the interaction between past alpha and II. Past alpha is estimated from the Carhart four factor model using rolling 12 months of returns, i.e., month t-12 to month t-1. In addition, we control for a set of common fund characteristics, including the natural log of fund TNA, annual expense ratio, log fund age, turnover, and percentage fund flow. These variables are measured as of end of month t-1. In addition, to control for the effect of market frictions and the effect of fund activeness, we include SIZESCORE, ILLIQSCORE, and ActiveShare, and their interaction terms with past fund alpha as additional explanatory variables. Again, these variables are constructed using data available at the end of month t-1. Also, as noted earlier, since our ActiveShare data are for the period of 1981-2012, the regressions involving this variable are for that particular sample period. To facilitate interpretation of the regression results, we cross-sectionally standardize key variables involved in the interaction terms (i.e., subtracting their cross-sectional means and then dividing them by the cross-sectional standard deviations); these standardized variables include past alpha, II, SIZESCORE, ILLIQSCORE, and ActiveShare.

The regression results are reported in Panel A of Table 11. The first regression, reported in Column (1), controls for a set of common fund characteristics but does not control for the effect of market frictions or fund activeness. The coefficient for the key variable of interest, the interaction term II*Past Alpha, is 0.0279, significantly positive. This suggests that information intensity has a significant impact on the relation between past performance and subsequent performance. In addition, the coefficient on II per se is insignificant. Note that the interaction term II*Past Alpha is close to zero for a typical fund whose alpha is close to zero. Thus, the insignificant coefficient on II means that for an average fund, II has no impact on subsequent performance, consistent with the results from the single-sort analysis reported in Table 4. Finally, the coefficient on past alpha per se is also insignificant. This suggests that information intensity soaks up all the performance persistence effect.

Regressions reported in Columns (2) to (4) control for the effects of SIZESCORE, ILLIQSCORE, and ActiveShare, respectively. Three of the four variables – SIZESCORE, ILLIQSCORE, and ActiveShare, do not have significant coefficients; nor are the coefficients on their interaction terms with past alpha. This suggests that fund investments in small and illuiqid stocks and fund ActiveShare do not directly impact performance or performance persistence.[15]

As shown in Table 9, return volatility of fund holdings STDEV and the fund activeness measure R2 have significant impact on performance persistence; further, they have quite different effects on the performance of funds with low and high past alphas. To properly control for their differential impact on fund performance, we perform a separate set of regressions in Panel B of Table 11. In this panel, we create five dummies for funds ranked in the five past-alpha quintiles, referred to as "past $\alpha 1$" to "past $\alpha 5$". We further create three sets of interaction terms involving the past-alpha dummies. These dummy variables are interacted with 1) the information intensity measure II, 2) the logistic transformation of R2 ("TR", following Amihud and Goyenko, 2013), and 3) the measure of fund holdings' return volatility, STDEV. Other control variables are similar those in Panel A of the same table. Again, key variables involved in the interaction terms, including past alpha, II, STDEV, and TR, are cross-sectionally standardized before used in the regressions.

The results in this panel show that the interaction between the top past-alpha dummy and II remains significant in all regression specifications, suggesting that the effect of information intensity in predicting fund performance among high past alpha funds is not explained away by the effects of R2 or volatility, or other fund characteristics controlled for. The interaction term between the bottom alpha dummy and STDEV is significantly negative while the interaction between the top alpha dummy and STDEV is insignificant, consistent with the notion that volatility of fund holdings mainly predicts performance among the low alpha

[15]Note that the dependent variable of the regressions is already the four-factor abnormal return. This might explain the insignificant coefficient of SIZESCORE. In addition, Cremers and Petajisto (2009) report that ActiveShare does not significantly predict the four-factor alpha of funds (their Table 8) but significantly predicts the benchmark-adjusted fund performance (their Table 4). The dependent variable of our regressions is the four-factor alpha. Thus the insignificant coefficient on ActiveShare we obtain here is consistent with their findings.

funds. The interaction term between the top alpha dummy with R2, however, does not consistently produce significant coefficients across various regression specifications.

We have performed additional regressions to ensure the robustness of inference. For brevity we discuss them here without tabulating the results. First, we perform regressions involving the logit transformed R2 (TR) for the subperiod studied by Amihud and Goyenko (2013) and with R2 censored at the top and bottom 1%. The coefficient for the interaction term between II and top alpha dummy remains significant, suggesting that during this subperiod the effect of II is not subsumed by that of R2. Second, we also control for an effect known as "reliance on public information". This effect is documented by Kacperczyk ad Seru (2007). They quantify funds' reliance on public information based on how closely fund portfolio weight changes tracks analyst recommendation changes. We follow their study to construct the measure RPI and perform regression analysis for the subperiod of time of 1994-2015 when analyst recommendation data necessary for constructing RPI are available. The results show that the effect of II is not subsumed by RPI.

4.4 Fund Performance around Corporate Events

In this section, we take a closer look at the specific types of information fund managers may uncover from high II stocks. Previous studies have shown that a variety of corporate events and news cause large price movements.[16] Unfortunately, tracking all the wide varieties of events is impossible. Instead, we focus on two types of corporate events – earnings announcements and M&A announcements. To gauge the impact of the events to stock returns, we compute the event window return as the cumulative stock return during the five-day window, from two days before the announcement date to two days after. We then compute the quarterly fund-level event-window performance as the weighted average event-

[16]For example, Jiang and Yao (2013) report that during the period from 1974 to 2009, about 10% of jumps take place during earnings announcement windows, and about 12% of earnings announcements trigger jumps. In an unpublished appendix, they identify all events associated with price jumps for stocks in the Dow Jones Industrial Average during the two year period from July 2003 to June 2005. These events include earnings announcements, management earnings forecasts, macroeconomic news, legal events, analyst forecast and recommendation changes, mergers and acquisitions, significant product failures, management turnover, news about sales, news about industry peers, stock repurchases, dividends, spinoffs, and union negotiations.

window returns during a quarter for stocks held by the fund, using the beginning-of-quarter portfolio weights. Given the association between these two types of events and stock price jumps, the event-window performance at least in part reflects the effectiveness of funds in turning rewarding information production opportunities into actual information production.

Table 12 reports the event-window performance of funds double-sorted by past alpha and II. Panel A is for the event-window performance during the 4 quarters prior to fund ranking. Funds ranked in the bottom quintile of past alpha, regardless of their II rank, ramp up significant losses during the event windows. Among these funds, the event-window performance difference between the top and bottom II quintiles is insignificant. By contrast, funds ranked in the top past alpha quintile experience significant profits during the event windows. Among these funds, there is a significant difference in event-window performance between the top and bottom II quintiles. It seems that the event-window performance is an important source of performance difference during the fund ranking period.

Panel B of the table reports the event-window performance during the quarter after fund ranking. Across funds ranked in the bottom quintile of past alpha, the event-window performance tends to be insignificant and there is no significant difference between the top and bottom II quintiles. In contrast, among funds ranked in the top past alpha quintile, the event-driven performance is significantly positive for the top-II quintile, and there is a significant difference in event-window performance between the top and bottom II quintiles. Finally, in top II quintile, there is a significant event-window performance difference between the top and bottom past alpha quintiles, while the difference is insignificant within the bottom II quintile. These patterns are consistent with those based on the overall fund performance reported in Table 5, thus offering support to the notion that skills in information production make a big difference when investing in high information intensity stocks.

Between the two types of events, earnings announcements occur much more frequently and M&A announcements are sporadic. We have also estimated the event-window performance using the single type of event of earnings announcements. The results are largely similar.

4.5 Information Intensity and Fund Flow Sensitivity to Past Performance

Given the significant impact of information intensity in predicting fund performance, we ask whether fund investors are aware of this impact and allocate their fund investments accordingly. We examine fund investors' decisions via fund flows, and use Fama-MacBeth regressions to see how information intensity affects fund flow response to past performance. The dependent variable of the regressions is the percentage fund flow during the quarter after fund ranking.[17] The main explanatory variables of interest include past fund alpha (the four-factor alpha using rolling 12-month estimation), II, and the interaction term between past alpha and II. The common control variables are similar to those in Table 11 – the natural log of fund TNA, annual expense ratio, log fund age, turnover, and lagged fund flow. In addition, we include SIZESCORE, ILLIQSCORE, ActiveShare, and their interaction terms with past fund alpha as additional explanatory variables. Again, because volatility and R2 exhibit differential effect on fund performance across past alpha groups, we create a separate set of regressions involving past alpha quintile dummies and their interactions with STDEV and TR, the logistic transformation of R2. Similar to Table 11, key variables involved in the interaction terms, including past alpha, II, SIZESCORE, ILLIQSCORE, ActiveShare, STDEV, and TR, are cross-sectionally standardized before used in the regressions.

Panel A and B of Table 13 report the results. Across various regression settings, the coefficient for the main variable of interest, the interactions between II and past alpha in Panel A and the interactions between the top alpha dummy with II in Panel B, tend to be significantly positive. The results suggest that fund flows are extra sensitive to past performance when fund information intensity is high. Therefore, to a large extent, fund investors are aware of the role of information intensity in generating performance persistence, and guide their fund investment decisions accordingly. A qualification to this inference is that in the regression specification (4) and (5) reported in Panel A, when we control for

[17] We use quarterly fund flows instead of monthly flows, because in early sample years fund TNAs are available only at the quarterly frequency.

the effects of SIZESCORE and ILLIQSCORE jointly, or additionally jointly control for the effect of ActiveShare, the coefficient for the interaction between II and past alpha becomes insignificant.

5 Conclusions

We propose a measure on the information intensity of mutual fund investment strategies and examine the impact of information intensity on fund performance. Stocks with high information intensity attract active fund managers. On average, funds investing mostly in high information intensity stocks do not generate superior performance. But within these funds, skills in information production matter for performance. Skilled funds such as those with high past alphas are able to successfully generate information and deliver outperformance, while unskilled funds experience poor performance despite their investment in information-intense stocks. In contrast, there is no performance persistence among funds that invest mostly in low information intensity stocks. Further analysis shows that the effect of fund information intensity on performance persistence is different from the effect of the return volatility or illiquidity of fund stock holdings, and different from the effect of existing measures of fund activeness. Finally, information intensity increases fund flow sensitivity to past performance. These findings suggest that in the presence of significant information production cost, information intensity is an important dimension of the active investment decisions by fund managers and the fund selection decisions by investors.

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Table 1: Summary Statistics

This table provides summary statistics on the sample of mutual funds and their stock holdings each year from 1980 to 2014. We report the number of funds, the average number of stocks held per fund, the average total net assets, the average annual expense ratio, the average fund turnover ratio, the average and cross-sectional standard deviation of fund information intensity II.

Year	Number of Funds	Number of Holdings	TNA ($m)	Expense (%)	Turnover (%)	Average II (%)	Stdev of II (%)
1980	216	57	192	0.96	70	8.28	2.41
1981	228	60	177	0.96	67	8.70	2.61
1982	229	57	217	0.97	73	8.93	2.67
1983	253	66	272	0.97	74	8.68	2.56
1984	282	66	264	0.98	72	9.55	2.35
1985	310	66	336	0.99	77	8.41	1.91
1986	349	69	374	1.02	79	8.39	1.63
1987	403	71	354	1.11	93	8.61	1.40
1988	421	72	373	1.22	83	9.56	1.30
1989	468	74	438	1.28	83	9.55	1.47
1990	494	72	402	1.29	88	7.19	1.81
1991	578	78	529	1.24	89	7.83	1.43
1992	651	79	610	1.26	82	7.40	1.56
1993	805	86	684	1.25	83	7.93	1.37
1994	957	92	657	1.24	82	8.05	1.51
1995	1,083	94	861	1.25	88	8.25	1.55
1996	1,172	99	1,051	1.26	88	8.86	1.52
1997	1,344	98	1,249	1.25	89	8.04	1.91
1998	1,462	95	1,391	1.27	91	7.57	2.09
1999	1,593	96	1,633	1.29	100	7.49	2.36
2000	1,789	100	1,471	1.30	107	7.63	1.65
2001	1,885	103	1,238	1.34	103	8.17	1.46
2002	1,964	103	947	1.37	99	7.49	1.48
2003	1,983	109	1,244	1.40	89	9.51	1.81
2004	2,063	110	1,387	1.35	83	9.91	1.97
2005	2,092	110	1,507	1.30	85	10.96	2.48
2006	2,049	113	1,728	1.28	86	12.22	1.93
2007	2,173	122	1,778	1.22	94	10.82	1.89
2008	2,148	125	1,038	1.21	107	8.44	1.44
2009	2,155	134	1,349	1.23	93	8.85	1.36
2010	2,012	133	1,539	1.20	84	11.23	1.50
2011	1,928	126	1,522	1.17	79	9.14	1.56
2012	1,793	128	1,728	1.15	73	11.91	2.01
2013	1,673	128	2,344	1.12	66	11.69	2.00
2014	1,594	129	2,505	1.09	64	10.97	2.10

Table 2: Characteristics of Funds across Information Intensity Quintiles

This table reports the average fund characteristics across information intensity quintiles. In each quarter, we sort funds into quintile portfolios based on information intensity (II). Panel A reports the following fund characteristics: II, the weighted averages of JV, RV, return standard deviation (STDEV), two measures of fund activeness ActiveShare and R2, the number of stock holdings, and annual fund turnover. Panel B reports the following fund characteristics: fund TNA, expense ratio, age, and four scores that measure fund styles along the dimensions of market cap, book-to-market ratio, momentum, and illiquidity — SIZESCORE, BMSCORE, MOMSCORE, and ILLIQSCORE.

Panel A: Fund Activeness

II Rank	II (%)	JV (%)	RV (%)	STDEV (%)	ActiveShare	R2	# Holdings	Turnover (%)
1-Low	6.87	0.43	5.23	1.96	0.77	0.92	75	77
2	7.93	0.53	5.35	2.01	0.78	0.93	98	80
3	8.74	0.66	5.93	2.13	0.83	0.92	102	84
4	9.78	0.92	7.21	2.34	0.89	0.91	102	90
5-High	11.77	1.37	8.85	2.60	0.94	0.90	99	89
High-Low	4.90	0.94	3.62	0.63	0.17	-0.02	25	13
t stat	(22.51)	(9.16)	(8.02)	(9.17)	(13.33)	(-3.18)	(9.44)	(3.34)

Panel B: Fund Characteristics

II Rank	TNA ($m)	Fee (%)	Age (Yrs)	SIZESCORE	BMSCORE	MOMSCORE	ILLIQSCORE
1-Low	1,417	1.11	19.9	4.67	-5.288	0.176	-0.127
2	1,323	1.11	18.9	4.09	-5.378	0.165	-0.126
3	1,056	1.17	17.0	3.00	-5.269	0.176	-0.125
4	778	1.24	14.9	1.74	-5.317	0.213	-0.122
5-High	526	1.32	12.5	0.67	-5.537	0.229	-0.117
High-Low	-892	0.21	-7.4	-3.99	-0.249	0.053	0.010
t stat	(-4.96)	(13.29)	(-6.19)	(-13.88)	(-1.27)	(1.68)	(2.34)

Table 3: Persistence of Information Intensity

This table reports the persistence of fund information intensity II. In each quarter, we sort funds into quintile portfolios based on II, and calculate the average II for quintile portfolios during each of the subsequent five years. II is expressed in percentage points.

II rank	Year 1	Year 2	Year 3	Year 4	Year 5
1-Low	7.71	8.16	8.34	8.47	8.58
2	8.47	8.65	8.78	8.85	8.91
3	9.18	9.22	9.26	9.28	9.31
4	10.10	10.06	10.05	10.02	10.02
5-High	11.61	11.27	11.13	11.09	11.08

Table 4: Performance of Fund Portfolios Sorted by Past Alpha and by Information Intensity

This table reports the performance of sorted fund portfolios. In each month, we sort funds into equal-weighted quintile portfolios based on either past 12-month four-factor alpha (Panel A) or Information Intensity II (Panel B). We report the after-expense four-factor alpha of each portfolio, and the average standard deviation of the net returns across funds in each portfolio. The four-factor alpha and standard deviation are both reported in percentage points.

Panel A: Funds Sorted by Past Alpha

	1-Low	2	3	4	5-High	High-Low
Alpha (%)	-0.216***	-0.109***	-0.079***	-0.067**	0.056	0.272***
t stat	(-4.41)	(-3.29)	(-2.75)	(-2.23)	(1.17)	(4.21)
Return Dispersion (%)	2.45	1.97	1.91	2.01	2.51	0.06

Panel B: Funds Sorted by Information Intensity

	1-Low	2	3	4	5-High	High-Low
Alpha (%)	-0.118***	-0.110***	-0.086***	-0.064	-0.039	0.079
t stat	(-3.37)	(-4.15)	(-2.64)	(-1.59)	(-0.74)	(1.28)
Return Dispersion (%)	1.96	1.84	2.07	2.29	2.41	0.46

Table 5: Performance of Fund Portfolios Double-Sorted by Past Alpha and Information Intensity

This table reports performance of fund portfolios formed on monthly independent double-sorts by past alpha and information intensity II. Past alpha are estimated from the Carhart four-factor model using rolling 12-month after-expense fund returns. The performance measures include after-expense net return (Panel A), after-expense four factor alpha (Panel B), and the Characteristic Selectivity (Panel C), all reported in percentage points.

Panel A: Net Return

	II					
Past Alpha	1-Low	2	3	4	5-High	High-Low
1-Low	0.805***	0.829***	0.808***	0.788***	0.830***	0.025
	(3.72)	(3.80)	(3.61)	(3.28)	(3.25)	(0.23)
2	0.851***	0.854***	0.890***	0.955***	0.927***	0.075
	(4.05)	(4.11)	(4.18)	(4.20)	(3.84)	(0.73)
3	0.865***	0.855***	0.908***	0.995***	1.024***	0.159
	(4.14)	(4.17)	(4.27)	(4.42)	(4.35)	(1.60)
4	0.869***	0.878***	0.932***	0.967***	1.095***	0.226**
	(4.16)	(4.24)	(4.29)	(4.32)	(4.63)	(2.15)
5-High	0.874***	0.946***	1.011***	1.179***	1.248***	0.374***
	(3.78)	(4.16)	(4.38)	(4.74)	(5.00)	(3.30)
High-Low	0.069	0.118	0.202**	0.391***	0.417***	0.348***
	(0.89)	(1.59)	(2.50)	(4.44)	(5.50)	(3.68)

Panel B: Four-factor Alpha

	II					
Past Alpha	1-Low	2	3	4	5-High	High-Low
1-Low	-0.155***	-0.143***	-0.161***	-0.243***	-0.250***	-0.095
	(-2.71)	(-3.06)	(-2.84)	(-3.94)	(-3.49)	(-1.09)
2	-0.110***	-0.125***	-0.101**	-0.085*	-0.139**	-0.029
	(-3.09)	(-3.98)	(-2.48)	(-1.72)	(-2.24)	(-0.41)
3	-0.112***	-0.112***	-0.089**	-0.049	-0.031	0.081
	(-3.66)	(-3.77)	(-2.36)	(-1.04)	(-0.53)	(1.26)
4	-0.098***	-0.113***	-0.090**	-0.062	0.032	0.129**
	(-2.63)	(-3.49)	(-2.30)	(-1.32)	(0.60)	(2.06)
5-High	-0.115	-0.071	-0.038	0.119**	0.198***	0.313***
	(-1.62)	(-1.26)	(-0.76)	(2.03)	(3.33)	(3.70)
High-Low	0.040	0.073	0.123*	0.362***	0.448***	0.408***
	(0.51)	(1.06)	(1.65)	(4.38)	(6.01)	(4.23)

Panel C: Characteristic Selectivity

	II					
Past Alpha	1-Low	2	3	4	5-High	High-Low
1-Low	-0.075	-0.056	-0.062	-0.082*	-0.039	0.035
	(-1.29)	(-1.16)	(-1.35)	(-1.65)	(-0.74)	(0.50)
2	-0.037	-0.014	-0.004	0.028	0.004	0.041
	(-0.77)	(-0.35)	(-0.10)	(0.68)	(0.08)	(0.65)
3	-0.022	-0.023	-0.007	0.042	0.025	0.047
	(-0.47)	(-0.56)	(-0.17)	(1.14)	(0.63)	(0.80)
4	-0.022	-0.011	0.022	0.017	0.055	0.077
	(-0.48)	(-0.28)	(0.60)	(0.45)	(1.37)	(1.33)
5-High	-0.048	0.019	0.023	0.118***	0.148***	0.196***
	(-0.81)	(0.45)	(0.58)	(2.59)	(3.14)	(2.88)
High-Low	0.027	0.075	0.086*	0.200***	0.187***	0.160**
	(0.44)	(1.52)	(1.70)	(3.88)	(3.85)	(2.40)

Table 6: Performance of Fund Portfolios Double-Sorted by Alternative Fund Skill Proxies and Information Intensity

This table reports performance of fund portfolios formed on monthly independent double-sorts by alternative fund skill proxies and information intensity II. The reported performance is the after-expense four factor alpha, in percentage points. The alternative fund skill proxies are Similarity and Return Gap. In Panel A, funds are double-sorted by Similarity and II. In Panel B, fund are double-sorted by Return Gap and II.

Panel A: Funds double-sorted by Similarity and II

	II					
Similarity	1-Low	2	3	4	5-High	High-Low
1-Low	-0.058	-0.126*	-0.091	-0.195**	-0.216**	-0.158
	(-0.75)	(-1.69)	(-1.22)	(-2.45)	(-2.54)	(-1.58)
2	-0.072	-0.128***	-0.068	-0.093	-0.096	-0.024
	(-1.62)	(-3.24)	(-1.37)	(-1.45)	(-1.17)	(-0.28)
3	-0.122***	-0.106***	-0.140***	-0.095*	0.003	0.126
	(-3.28)	(-3.69)	(-3.61)	(-1.70)	(0.04)	(1.35)
4	-0.111*	-0.123**	-0.109**	-0.050	-0.008	0.103
	(-1.76)	(-2.51)	(-2.56)	(-0.99)	(-0.13)	(1.07)
5-High	-0.124	-0.063	-0.015	0.083	0.124**	0.248**
	(-1.21)	(-0.74)	(-0.19)	(1.19)	(1.98)	(2.54)
High-Low	-0.066	0.063	0.077	0.279**	0.340***	0.406***
	(-0.50)	(0.48)	(0.61)	(2.36)	(3.26)	(3.44)

Panel B: Funds double-sorted by Return Gap and II

	II					
Gap	1-Low	2	3	4	5-High	High-Low
1-Low	-0.104*	-0.127***	-0.088*	-0.043	-0.086	0.018
	(-1.89)	(-2.65)	(-1.69)	(-0.78)	(-1.40)	(0.24)
2	-0.106***	-0.074**	-0.064*	-0.083	-0.057	0.049
	(-2.68)	(-2.51)	(-1.66)	(-1.64)	(-0.94)	(0.69)
3	-0.088***	-0.071**	-0.085**	-0.075	-0.013	0.075
	(-2.59)	(-2.25)	(-2.10)	(-1.60)	(-0.20)	(1.07)
4	-0.107***	-0.135***	-0.126***	-0.069	-0.077	0.030
	(-2.85)	(-3.84)	(-2.96)	(-1.40)	(-1.23)	(0.43)
5-High	-0.140**	-0.132***	-0.103**	-0.071	0.036	0.176**
	(-2.30)	(-2.82)	(-2.26)	(-1.34)	(0.59)	(2.16)
High-Low	-0.036	-0.006	-0.015	-0.028	0.122**	0.158**
	(-0.54)	(-0.10)	(-0.24)	(-0.44)	(1.96)	(2.05)

Table 7: The Effect of Lagged Information Intensity Measures on Performance Persistence

This table reports the performance of fund portfolios using lagged fund II. Each month, we double-sort funds independently by past 12-month four-factor fund alpha and lagged information intensity measures into 5 by 5 (25) groups. In Panels A to D, the information intensity measure II is lagged by one to four quarters respectively. We form an equal-weighted fund portfolio within each group and report its next-month after-expense four-factor alpha, in percentage points.

	II lagged by one quarter						II lagged by two quarters					
Past Alpha	1-Low	2	3	4	5-High	High-Low	1-Low	2	3	4	5-High	High-Low
1-Low	-0.151***	-0.157***	-0.145**	-0.259***	-0.244***	-0.093	-0.186***	-0.161***	-0.211***	-0.183***	-0.271***	-0.084
	(-2.65)	(-3.43)	(-2.51)	(-4.14)	(-3.46)	(-1.09)	(-3.41)	(-3.09)	(-3.65)	(-3.11)	(-3.83)	(-1.02)
2	-0.122***	-0.122***	-0.078*	-0.109**	-0.086	0.037	-0.108***	-0.091***	-0.128***	-0.076	-0.078	0.031
	(-3.48)	(-3.78)	(-1.83)	(-2.18)	(-1.42)	(0.54)	(-3.19)	(-2.78)	(-2.93)	(-1.55)	(-1.30)	(0.47)
3	-0.115***	-0.125***	-0.099***	-0.086*	0.020	0.134**	-0.119***	-0.106***	-0.133***	-0.073	0.048	0.167***
	(-3.59)	(-4.05)	(-2.80)	(-1.82)	(0.35)	(2.13)	(-3.60)	(-3.46)	(-3.63)	(-1.55)	(0.84)	(2.61)
4	-0.117***	-0.135***	-0.075*	-0.056	0.023	0.141**	-0.118***	-0.118***	-0.090**	-0.040	0.027	0.145**
	(-3.35)	(-4.12)	(-1.83)	(-1.24)	(0.46)	(2.32)	(-3.28)	(-3.45)	(-2.33)	(-0.92)	(0.53)	(2.40)
5-High	-0.116*	-0.087*	-0.045	0.091	0.201***	0.317***	-0.088	-0.117**	-0.007	0.074	0.163***	0.250***
	(-1.65)	(-1.65)	(-0.91)	(1.62)	(3.34)	(3.81)	(-1.32)	(-2.15)	(-0.15)	(1.35)	(2.71)	(3.12)
High-Low	0.035	0.070	0.100	0.350***	0.445***	0.410***	0.099	0.045	0.203***	0.256***	0.433***	0.335***
	(0.45)	(1.00)	(1.36)	(4.37)	(6.02)	(4.40)	(1.32)	(0.61)	(2.80)	(3.48)	(5.68)	(3.60)

	II lagged by three quarters						II lagged by four quarters					
Past Alpha	1-Low	2	3	4	5-High	High-Low	1-Low	2	3	4	5-High	High-Low
1-Low	-0.145**	-0.196***	-0.181***	-0.224***	-0.250***	-0.105	-0.137**	-0.166***	-0.194***	-0.203***	-0.244***	-0.107
	(-2.41)	(-4.11)	(-3.08)	(-3.85)	(-3.54)	(-1.27)	(-2.39)	(-3.33)	(-3.43)	(-3.52)	(-3.52)	(-1.37)
2	-0.103***	-0.112***	-0.063	-0.082*	-0.104*	-0.001	-0.109***	-0.106***	-0.069*	-0.073	-0.080	0.029
	(-3.21)	(-3.32)	(-1.47)	(-1.71)	(-1.76)	(-0.02)	(-3.24)	(-2.96)	(-1.66)	(-1.53)	(-1.28)	(0.43)
3	-0.113***	-0.106***	-0.122***	-0.035	-0.011	0.102*	-0.139***	-0.074**	-0.077**	-0.082*	0.008	0.147**
	(-3.48)	(-3.64)	(-3.18)	(-0.77)	(-0.20)	(1.66)	(-4.45)	(-2.35)	(-2.14)	(-1.80)	(0.16)	(2.43)
4	-0.118***	-0.108***	-0.083**	-0.051	0.006	0.124**	-0.127***	-0.097***	-0.070*	-0.047	0.004	0.131**
	(-3.55)	(-3.28)	(-2.19)	(-1.17)	(0.12)	(2.13)	(-3.71)	(-3.28)	(-1.72)	(-1.07)	(0.08)	(2.21)
5-High	-0.130*	-0.040	0.011	0.058	0.164***	0.294***	-0.113*	-0.095*	-0.002	0.072	0.138**	0.251***
	(-1.90)	(-0.78)	(0.22)	(1.04)	(2.78)	(3.65)	(-1.70)	(-1.91)	(-0.03)	(1.31)	(2.31)	(3.21)
High-Low	0.015	0.156**	0.192**	0.281***	0.414***	0.399***	0.024	0.071	0.192**	0.275***	0.382***	0.358***
	(0.18)	(2.46)	(2.49)	(3.83)	(5.38)	(3.97)	(0.29)	(1.08)	(2.53)	(3.85)	(5.06)	(3.71)

Table 8: Subperiod Performance of Fund Portfolios Double-Sorted by Past Alpha and Information Intensity

This table reports the after-expense four-factor alpha (in percentage points) for each of the 5 by 5 portfolios formed in independent double-sorts by past alpha and information intensity II. Past alpha is estimated from the four-factor model using past 12 months of after-expense fund returns. Panel A is for the subperiod of 1980-1996 and Panel B is for the subperiod of 1997-2014.

Panel A: 1980-1996

	II					
Past Alpha	1-Low	2	3	4	5-High	High-Low
1-Low	-0.097	-0.083	-0.062	-0.165**	-0.221***	-0.124
	(-1.19)	(-1.15)	(-0.71)	(-2.04)	(-2.76)	(-1.18)
2	-0.079	-0.087*	-0.075	-0.019	-0.164**	-0.085
	(-1.50)	(-1.87)	(-1.48)	(-0.31)	(-2.21)	(-0.93)
3	-0.055	-0.100**	-0.081	0.011	0.106	0.161**
	(-1.24)	(-2.26)	(-1.62)	(0.18)	(1.47)	(2.10)
4	-0.081	-0.116**	-0.070	0.013	0.153**	0.233***
	(-1.48)	(-2.19)	(-1.21)	(0.19)	(2.50)	(2.87)
5-High	-0.155*	-0.028	-0.056	0.199**	0.311***	0.466***
	(-1.70)	(-0.35)	(-0.77)	(2.53)	(3.71)	(4.12)
High-Low	-0.058	0.056	0.006	0.363***	0.532***	0.591***
	(-0.50)	(0.54)	(0.05)	(3.32)	(4.52)	(3.89)

Panel B: 1997-2014

	II					
Past Alpha	1-Low	2	3	4	5-High	High-Low
1-Low	-0.226***	-0.202***	-0.202***	-0.224***	-0.163	0.062
	(-2.93)	(-3.75)	(-3.01)	(-2.63)	(-1.56)	(0.50)
2	-0.134***	-0.154***	-0.101*	-0.096	-0.050	0.083
	(-2.95)	(-4.11)	(-1.78)	(-1.38)	(-0.55)	(0.80)
3	-0.161***	-0.108***	-0.050	-0.044	-0.033	0.129
	(-4.00)	(-3.09)	(-1.00)	(-0.67)	(-0.40)	(1.38)
4	-0.111**	-0.084**	-0.058	-0.039	-0.010	0.101
	(-2.29)	(-2.29)	(-1.23)	(-0.65)	(-0.12)	(1.10)
5-High	-0.117	-0.072	0.036	0.104	0.189**	0.306**
	(-1.12)	(-0.92)	(0.55)	(1.20)	(2.28)	(2.56)
High-Low	0.108	0.130	0.239***	0.328***	0.352***	0.244*
	(1.02)	(1.43)	(2.60)	(2.71)	(3.77)	(1.96)

Table 9: Performance of Fund Portfolios Under Alternative Double-Sorts

This table reports the performance of fund portfolios under alternative independent double sorts. The performance measure is the after-expense four factor alpha, in percentage points. In Panel A, funds are double-sorted by past alpha and STDEV. In Panel B, funds are double-sorted by past alpha and R2. In Panel C, funds are also double-sorted by past alpha and R2, where R2 are censored at the top and bottom 1% and the sample period is from 1990 to 2010. In Panel D, funds are double-sorted by past alpha and SKEW. Past alpha is estimated using past 12 month's data under the Carhart four-factor model. STDEV is the weighted average return volatility of stocks held by a fund. R2 is the regression R-square of the Carhart four-factor model using past 24 months of returns. SKEW is the weighted average return skewness of stocks held by a fund.

Panel A: Funds double-sorted by past alpha and STDEV

	STDEV					
Past Alpha	1-Low	2	3	4	5-High	High-Low
1-Low	-0.072	-0.090**	-0.167***	-0.236***	-0.390***	-0.315***
	(-1.21)	(-2.05)	(-3.80)	(-4.72)	(-5.52)	(-3.38)
2	-0.065*	-0.073**	-0.096**	-0.188***	-0.231***	-0.166**
	(-1.68)	(-2.30)	(-2.54)	(-4.19)	(-3.47)	(-2.10)
3	-0.029	-0.111***	-0.082**	-0.096**	-0.130*	-0.101
	(-0.79)	(-3.73)	(-2.33)	(-2.11)	(-1.83)	(-1.21)
4	-0.012	-0.047	-0.053	-0.055	-0.121*	-0.109
	(-0.28)	(-1.36)	(-1.41)	(-1.21)	(-1.76)	(-1.32)
5-High	0.016	0.041	0.051	0.114**	0.062	0.044
	(0.29)	(0.81)	(1.00)	(2.06)	(0.79)	(0.45)
High-Low	0.085	0.131**	0.218***	0.349***	0.452***	0.365***
	(1.21)	(2.35)	(3.91)	(5.80)	(6.07)	(3.93)

Panel B: Funds double-sorted by past alpha and R2

	R2					
Past Alpha	1-Low	2	3	4	5-High	High-Low
1-Low	-0.261***	-0.204***	-0.225***	-0.192***	-0.185***	0.077
	(-3.56)	(-3.17)	(-3.97)	(-3.82)	(-4.31)	(1.08)
2	-0.066	-0.114**	-0.090**	-0.136***	-0.137***	-0.071
	(-1.18)	(-2.34)	(-2.28)	(-3.81)	(-4.69)	(-1.26)
3	-0.061	-0.029	-0.077**	-0.085***	-0.119***	-0.058
	(-1.11)	(-0.61)	(-2.07)	(-2.76)	(-4.29)	(-1.08)
4	0.009	-0.033	-0.044	-0.094***	-0.095***	-0.104*
	(0.16)	(-0.73)	(-1.17)	(-2.61)	(-3.01)	(-1.82)
5-High	0.125	0.096	0.012	-0.049	-0.047	-0.172**
	(1.60)	(1.50)	(0.24)	(-1.04)	(-1.03)	(-2.03)
High-Low	0.386***	0.300***	0.237***	0.142**	0.138***	-0.249***
	(3.82)	(3.41)	(3.37)	(2.28)	(2.68)	(-2.59)

Panel C: Funds double-sorted by past alpha and censored R2 (1990-2010)

	R2					
Past Alpha	1-Low	2	3	4	5-High	High-Low
1-Low	-0.252**	-0.228**	-0.249***	-0.234***	-0.243***	0.009
	(-2.56)	(-2.56)	(-3.35)	(-3.39)	(-4.57)	(0.09)
2	0.029	-0.101	-0.072	-0.162***	-0.151***	-0.180**
	(0.39)	(-1.52)	(-1.31)	(-3.26)	(-4.17)	(-2.43)
3	0.041	-0.054	-0.077	-0.082**	-0.141***	-0.182***
	(0.61)	(-0.88)	(-1.61)	(-2.05)	(-4.18)	(-2.66)
4	0.077	0.001	-0.013	-0.100**	-0.110***	-0.187**
	(1.08)	(0.02)	(-0.25)	(-2.13)	(-2.87)	(-2.47)
5-High	0.275**	0.157*	0.008	-0.046	-0.074	-0.349***
	(2.57)	(1.69)	(0.11)	(-0.68)	(-1.16)	(-2.91)
High-Low	0.527***	0.385***	0.257***	0.188**	0.170***	-0.357***
	(4.00)	(3.08)	(2.59)	(2.20)	(2.62)	(-2.84)

Panel D: Funds double-sorted by past alpha and SKEW

	SKEW					
Past Alpha	1-Low	2	3	4	5-High	High-Low
1-Low	-0.160**	-0.218***	-0.197***	-0.161***	-0.345***	-0.185**
	(-2.46)	(-4.08)	(-3.69)	(-2.94)	(-5.12)	(-2.44)
2	-0.061	-0.066*	-0.130***	-0.154***	-0.126**	-0.065
	(-1.42)	(-1.89)	(-3.25)	(-3.59)	(-2.17)	(-1.05)
3	-0.005	-0.090***	-0.107***	-0.064	-0.100*	-0.096
	(-0.11)	(-2.90)	(-3.22)	(-1.54)	(-1.78)	(-1.41)
4	-0.015	-0.020	-0.103***	-0.072*	-0.074	-0.058
	(-0.34)	(-0.56)	(-2.99)	(-1.91)	(-1.41)	(-0.85)
5-High	0.161**	0.114*	0.050	0.005	0.073	-0.088
	(2.16)	(1.93)	(0.83)	(0.10)	(1.35)	(-1.10)
High-Low	0.321***	0.332***	0.248***	0.166**	0.419***	0.097
	(3.55)	(4.24)	(3.20)	(2.26)	(5.99)	(1.12)

Table 10: Controlling for Competing Effects With Triple-Sorted Fund Portfolios

This table reports the performance of fund portfolios resulting from a triple-sorting procedure that examines the effect of II on performance persistence while controlling for competing effects. Fund performance is measured by after-expense four-factor alpha, in percentage points. Each month, we first sort funds into quintiles first based on a fund characteristic representing a competing effect. Then, within each quintile we further independently sort funds into 25 (5 by 5) groups based on past alpha and II. Finally, we combine funds in the same quintiles of past-alpha and II but from different quintile ranks of the first sorting variable into one single equal-weighted portfolio. This procedure resulting in 25 fund portfolios with different past alpha and II but with relatively even distribution of the controlled fund characteristic (i.e., the first sorting variable). The controlled effects include SIZESCORE, ILLIQSCORE, R2, ActiveShare, and STDEV.

Panel A: Controlling for SIZESCORE

	II					
Past Alpha	1-Low	2	3	4	5-High	High-Low
1-Low	-0.213***	-0.230***	-0.161***	-0.134***	-0.215***	-0.002
	(-3.47)	(-4.80)	(-3.15)	(-2.62)	(-3.78)	(-0.03)
2	-0.201***	-0.134***	-0.093**	-0.101**	-0.091*	0.110*
	(-4.17)	(-3.30)	(-2.34)	(-2.31)	(-1.89)	(1.81)
3	-0.169***	-0.115***	-0.059	-0.069*	0.007	0.176***
	(-3.81)	(-2.84)	(-1.55)	(-1.72)	(0.16)	(3.05)
4	-0.088*	-0.134***	-0.058	-0.063*	0.043	0.132**
	(-1.90)	(-3.46)	(-1.58)	(-1.69)	(1.02)	(2.10)
5-High	-0.084	0.006	0.042	0.086*	0.158***	0.242***
	(-1.28)	(0.13)	(0.91)	(1.74)	(3.13)	(3.24)
High-Low	0.129*	0.236***	0.203***	0.220***	0.373***	0.244***
	(1.67)	(3.74)	(3.23)	(3.56)	(5.72)	(3.16)

Panel B: Controlling for ILLIQSCORE

	II					
Past Alpha	1-Low	2	3	4	5-High	High-Low
1-Low	-0.197***	-0.230***	-0.195***	-0.161***	-0.180***	0.017
	(-3.55)	(-4.51)	(-3.79)	(-2.83)	(-2.61)	(0.21)
2	-0.147***	-0.100***	-0.132***	-0.092**	-0.082	0.064
	(-3.59)	(-2.75)	(-3.22)	(-2.04)	(-1.43)	(0.93)
3	-0.120***	-0.101***	-0.118***	-0.042	-0.031	0.089
	(-3.33)	(-3.05)	(-3.28)	(-1.01)	(-0.59)	(1.44)
4	-0.110**	-0.076**	-0.057*	-0.062	-0.006	0.104
	(-2.54)	(-2.05)	(-1.70)	(-1.43)	(-0.11)	(1.49)
5-High	-0.079	-0.033	0.057	0.095*	0.163***	0.242***
	(-1.14)	(-0.64)	(1.22)	(1.93)	(2.71)	(2.80)
High-Low	0.118	0.198***	0.252***	0.256***	0.342***	0.225**
	(1.58)	(2.90)	(3.70)	(3.98)	(4.82)	(2.55)

Panel C: Controlling for ActiveShare

	II					
Past Alpha	1-Low	2	3	4	5-High	High-Low
1-Low	-0.231***	-0.187***	-0.165***	-0.219***	-0.196***	0.035
	(-3.78)	(-3.67)	(-3.32)	(-4.14)	(-3.17)	(0.45)
2	-0.161***	-0.111**	-0.064	-0.099**	-0.125**	0.036
	(-3.22)	(-2.46)	(-1.44)	(-2.04)	(-2.41)	(0.55)
3	-0.122***	-0.095**	-0.128***	-0.056	-0.009	0.113*
	(-2.76)	(-2.22)	(-3.18)	(-1.31)	(-0.18)	(1.80)
4	-0.103**	-0.094**	-0.051	-0.028	-0.005	0.098
	(-2.28)	(-2.19)	(-1.19)	(-0.70)	(-0.11)	(1.64)
5-High	-0.101	0.015	0.046	0.040	0.135**	0.235***
	(-1.46)	(0.28)	(1.00)	(0.83)	(2.53)	(2.99)
High-Low	0.130	0.201***	0.211***	0.259***	0.331***	0.200**
	(1.61)	(2.93)	(3.20)	(3.82)	(4.86)	(2.32)

Panel D: Controlling for R2

	II					
Past Alpha	1-Low	2	3	4	5-High	High-Low
1-Low	-0.188***	-0.117**	-0.167***	-0.259***	-0.277***	-0.089
	(-3.54)	(-2.43)	(-3.11)	(-4.12)	(-4.09)	(-1.12)
2	-0.109***	-0.115***	-0.101**	-0.056	-0.159***	-0.050
	(-2.91)	(-3.34)	(-2.51)	(-1.17)	(-2.60)	(-0.74)
3	-0.123***	-0.109***	-0.109***	-0.025	-0.010	0.113**
	(-3.84)	(-3.31)	(-2.74)	(-0.54)	(-0.20)	(2.05)
4	-0.094**	-0.106***	-0.044	-0.025	0.022	0.116**
	(-2.39)	(-3.29)	(-1.08)	(-0.52)	(0.44)	(1.97)
5-High	-0.091	-0.098*	-0.003	0.129**	0.120**	0.211***
	(-1.38)	(-1.83)	(-0.06)	(2.50)	(2.24)	(2.92)
High-Low	0.097	0.019	0.165**	0.388***	0.397***	0.299***
	(1.32)	(0.27)	(2.34)	(5.49)	(5.42)	(3.34)

Panel E: Controlling for STDEV

	II					
Past Alpha	1-Low	2	3	4	5-High	High-Low
1-Low	-0.226***	-0.220***	-0.188***	-0.187***	-0.222***	0.004
	(-4.51)	(-5.22)	(-4.45)	(-3.84)	(-3.93)	(0.06)
2	-0.191***	-0.131***	-0.112***	-0.091**	-0.101*	0.090
	(-4.53)	(-3.94)	(-3.29)	(-2.31)	(-1.85)	(1.46)
3	-0.107***	-0.107***	-0.079**	-0.095**	-0.014	0.093
	(-2.62)	(-3.05)	(-2.33)	(-2.36)	(-0.27)	(1.45)
4	-0.082*	-0.086**	-0.080**	-0.040	-0.005	0.077
	(-1.78)	(-2.35)	(-2.10)	(-0.95)	(-0.10)	(1.09)
5-High	-0.037	-0.040	0.060	0.062	0.124**	0.161**
	(-0.59)	(-0.76)	(1.26)	(1.22)	(2.40)	(2.17)
High-Low	0.189***	0.180***	0.248***	0.248***	0.346***	0.157**
	(2.65)	(3.01)	(4.60)	(4.59)	(7.44)	(2.03)

Table 11: Fama-MacBeth Multivariate Regressions

This table reports results of Fama-MacBeth regressions that analyze the impact of information intensity on performance persistence. The dependent variable is the fund four-factor abnormal return. In Panel A, the main explanatory variables include past alpha, II, and their interactions. The control variables include Log(TNA), expense ratio, Log(Age), fund turnover, lagged flow, two proxies for the effects of market frictions –SIZESCORE and ILLIQSCORE, the fund activeness measure ActiveShare, as well as the interaction terms of past alpha with SIZESCORE, ILLIQSCORE, and ActiveShare. In Panel B, the main explanatory variables include the five past-alpha dummies (past $\alpha 1$ to past $\alpha 5$) for funds in the five past-alpha quintiles, II, and the interactions of II with the five past-alpha dummies. The control variables include STDEV, TR, and their interactions with past alpha dummies, as well as Log(TNA), expense ratio, Log(Age), fund turnover, and lagged fund flow. Variables involved in the interaction terms, including past alpha, II, SIZESCORE, ILLIQSCORE, ActiveShare, STDEV, and TR, are cross-sectionally standardized before used in the regressions.

Panel A: Controlling for SIZESCORE, ILLIQSCORE, and ActiveShare

	[1] (1980-2014)	[2] (1980-2014)	[3] (1980-2014)	[4] (1981-2012)	[5] (1980-2014)	[6] (1981-2012)
Log(TNA)	-0.0184***	-0.0176***	-0.0182***	-0.0169**	-0.0175***	-0.0173***
	(-3.02)	(-2.93)	(-2.98)	(-2.54)	(-2.89)	(-2.66)
Fee	-0.1182***	-0.1194***	-0.1145***	-0.1123***	-0.1165***	-0.1085***
	(-5.40)	(-5.67)	(-5.36)	(-5.22)	(-5.60)	(-5.16)
Log(Age)	-0.0072	-0.0081	-0.0064	-0.0091	-0.0072	-0.0073
	(-0.99)	(-1.16)	(-0.89)	(-1.24)	(-1.04)	(-1.02)
Turnover	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(-0.62)	(-0.60)	(-0.63)	(-0.58)	(-0.56)	(-0.52)
Lagged Flow	-0.0017	-0.0021	-0.0017	-0.0027	-0.0019	-0.0028
	(-0.44)	(-0.55)	(-0.46)	(-0.69)	(-0.52)	(-0.72)
Past α	0.0990***	0.0922***	0.0981***	0.0928***	0.0916***	0.0930***
	(5.48)	(5.34)	(5.42)	(5.15)	(5.32)	(5.25)
II	0.0260**	0.0203	0.0244*	0.0245*	0.0202	0.0224
	(1.96)	(1.33)	(1.68)	(1.70)	(1.27)	(1.36)
II * Past α	0.0279***	0.0249***	0.0271***	0.0283***	0.0244**	0.0272***
	(3.18)	(2.65)	(2.90)	(2.87)	(2.49)	(2.64)
SIZESCORE		-0.0096			-0.0108	-0.0119
		(-0.51)			(-0.56)	(-0.60)
SIZESCORE * Past α		-0.0114			-0.0113	-0.0161
		(-1.15)			(-1.14)	(-1.18)
ILLIQSCORE			0.0024		-0.0018	-0.0076
			(0.24)		(-0.18)	(-0.73)
ILLIQSCORE * Past α			0.0036		0.0032	0.0038
			(0.43)		(0.38)	(0.43)
ActiveShare				0.0061		-0.0026
				(0.38)		(-0.23)
ActiveShare * Past α				0.0109		-0.0046
				(1.01)		(-0.34)
R-square	0.09	0.11	0.10	0.11	0.12	0.13

Panel B: Controlling for STDEV and TR

	[1] (1980-2014)	[2] (1980-2014)	[3] (1980-2014)	[4] (1980-2014)
log(TNA)	-0.0171***	-0.0149***	-0.0153***	-0.0142***
	(-2.80)	(-2.66)	(-2.62)	(-2.58)
Fee	-0.1194***	-0.1027***	-0.1296***	-0.1115***
	(-5.53)	(-5.27)	(-5.93)	(-5.75)
Age	-0.0080	-0.0129*	-0.0139**	-0.0170***
	(-1.11)	(-1.89)	(-2.11)	(-2.68)
Turnover	-0.0001	0.0000	-0.0001	0.0000
	(-0.95)	(-0.03)	(-0.88)	(0.02)
Flow	-0.0015	-0.0023	-0.0016	-0.0022
	(-0.39)	(-0.64)	(-0.41)	(-0.63)
Past $\alpha 1$	0.0634	0.0703	0.2051	0.4321**
	(1.00)	(1.12)	(1.17)	(2.21)
Past $\alpha 2$	0.1625***	0.1376**	0.4508***	0.5017***
	(2.62)	(2.26)	(3.10)	(2.96)
Past $\alpha 3$	0.1926***	0.1673***	0.1935	0.2673*
	(3.08)	(2.72)	(1.36)	(1.73)
Past $\alpha 4$	0.2232***	0.2000***	0.0875	0.1337
	(3.61)	(3.28)	(0.59)	(0.77)
Past $\alpha 5$	0.3185***	0.3012***	0.0988	0.0593
	(4.85)	(4.65)	(0.55)	(0.30)
II * Past $\alpha 1$	-0.0269	0.0255	-0.0089	0.0198
	(-1.34)	(1.11)	(-0.80)	(1.59)
II * Past $\alpha 2$	0.0027	0.0177	0.0010	0.0098
	(0.17)	(0.92)	(0.10)	(0.91)
II * Past $\alpha 3$	0.0264*	0.0436**	0.0120	0.0203**
	(1.71)	(2.49)	(1.38)	(2.07)
II * Past $\alpha 4$	0.0285*	0.0485***	0.0179**	0.0296***
	(1.92)	(2.69)	(2.00)	(2.83)
II * Past $\alpha 5$	0.0724***	0.0607***	0.0410***	0.0357***
	(3.66)	(2.63)	(3.69)	(2.78)
STDEV * Past $\alpha 1$		-0.0971***		-0.0025***
		(-3.12)		(-3.86)
STDEV * Past $\alpha 2$		-0.0411		-0.0010*
		(-1.34)		(-1.65)
STDEV * Past $\alpha 3$		-0.0482		-0.0009
		(-1.60)		(-1.43)
STDEV * Past $\alpha 4$		-0.0502		-0.0012*
		(-1.61)		(-1.83)
STDEV * Past $\alpha 5$		-0.0103		0.0000
		(-0.31)		(-0.06)
TR * Past $\alpha 1$			-0.0055	0.0038
			(-0.14)	(0.10)
TR * Past $\alpha 2$			-0.0901***	-0.0759**
			(-2.60)	(-2.22)
TR * Past $\alpha 3$			-0.0233	-0.0201
			(-0.71)	(-0.63)
TR * Past $\alpha 4$			0.0056	0.0235
			(0.17)	(0.74)
TR * Past $\alpha 5$			-0.0435	-0.0293
			(-1.00)	(-0.71)
R-squared	0.15	0.19	0.18	0.22

Table 12: Event Window Performance of Funds Double-Sorted by Past Alpha and Information Intensity

This table reports the event-window performance of fund portfolios double-sorted by past alpha and II. In each quarter, funds are sorted into 25 (5 by 5) equal-weighted portfolios independently by past alpha and II. Fund event-window performance is the weighted average event-window returns during a given quarter over stocks held by a fund. The event-window return of a stock is the stock return during a 5-day window (two days before to two days after) around two types of corporate events: earnings announcements and M&A announcements. Panel A reports the event-window performance during the four quarters prior to fund ranking. Panel B reports the event-window performance during the quarter after fund ranking.

Panel A: Event-window performance during prior four quarters

	Information Intensity					
Past *Alpha*	1-Low	2	3	4	5-High	High-Low
1-Low	-0.074***	-0.067***	-0.035	-0.033	-0.100***	-0.026
	(-2.62)	(-2.71)	(-1.38)	(-1.21)	(-3.44)	(-0.72)
2	-0.031	-0.018	-0.008	0.055**	0.016	0.046
	(-1.41)	(-0.93)	(-0.38)	(2.24)	(0.58)	(1.45)
3	0.004	0.005	0.062***	0.088***	0.106***	0.102***
	(0.19)	(0.33)	(3.09)	(4.51)	(3.71)	(3.11)
4	0.038**	0.061***	0.085***	0.111***	0.182***	0.144***
	(2.00)	(3.27)	(4.33)	(4.59)	(6.53)	(4.44)
5-High	0.077**	0.146***	0.200***	0.233***	0.251***	0.174***
	(2.48)	(5.39)	(6.78)	(7.47)	(7.53)	(4.29)
High-Low	0.151***	0.213***	0.234***	0.266***	0.351***	0.200***
	(4.06)	(6.18)	(6.56)	(6.86)	(10.35)	(4.33)

Panel B: Event-window performance during subsequent quarter

	Information Intensity					
Past *Alpha*	1-Low	2	3	4	5-High	High-Low
1-Low	0.005	0.052**	0.052**	0.074***	0.044	0.040
	(0.17)	(2.35)	(2.19)	(2.97)	(1.49)	(0.97)
2	-0.021	0.003	0.053***	0.069**	0.069**	0.090**
	(-1.03)	(0.13)	(2.61)	(2.56)	(2.18)	(2.47)
3	0.021	0.010	0.040**	0.098***	0.128***	0.107***
	(0.91)	(0.51)	(2.16)	(4.06)	(4.90)	(3.08)
4	0.006	0.001	0.034	0.098***	0.109***	0.103***
	(0.28)	(0.06)	(1.50)	(4.15)	(3.65)	(3.02)
5-High	0.002	0.030	0.083***	0.140***	0.133***	0.131***
	(0.08)	(1.01)	(3.02)	(4.65)	(4.50)	(3.44)
High-Low	-0.002	-0.022	0.031	0.067**	0.089***	0.091*
	(-0.05)	(-0.66)	(0.98)	(1.99)	(3.07)	(1.76)

Table 13: Fund Flow Response

This table reports the results of Fama-MacBeth regressions that analyze the effect of information intensity on flow-performance sensitivity. The dependent variable is the quarterly fund flow expressed in percentage points. In Panel A, the main explanatory variables include past fund alpha and II, and their interaction term. The control variables include Log(TNA), expense ratio, Log(Age), fund turnover, lagged flow, two proxies for the effects of market frictions –SIZESCORE and ILLIQSCORE, the fund activeness measure ActiveShare, as well as the interaction terms of past alpha with SIZESCORE, ILLIQSCORE, and ActiveShare. In Panel B, the main explanatory variables include the five past-alpha dummies (past $\alpha 1$ to past $\alpha 5$) for funds in the five past-alpha quintiles, II, and the interactions of II with the five past-alpha dummies. The control variables include STDEV, TR, and their interactions with past alpha dummies, as well as Log(TNA), expense ratio, Log(Age), fund turnover, and lagged fund flow. Variables involved in the interaction terms, including past alpha, II, SIZESCORE, ILLIQSCORE, ActiveShare, STDEV, and TR, are cross-sectionally standardized before used in the regressions.

Panel A: Controlling for SIZESCORE, ILLIQSCORE, and ActiveShare

	[1] (1980-2014)	[2] (1980-2014)	[3] (1980-2014)	[4] (1981-2012)	[5] (1980-2014)	[6] (1981-2012)
Log(TNA)	-0.1734***	-0.1819***	-0.1733***	-0.1689***	-0.1800***	-0.2039***
	(-3.35)	(-3.54)	(-3.39)	(-3.01)	(-3.54)	(-3.53)
Fee	-0.0028	-0.0384	-0.0095	0.0249	-0.0369	0.0053
	(-0.02)	(-0.21)	(-0.05)	(0.13)	(-0.20)	(0.03)
Log(Age)	-1.2253***	-1.1837***	-1.2164***	-1.2406***	-1.1841***	-1.2156***
	(-14.13)	(-13.69)	(-14.46)	(-13.59)	(-14.02)	(-13.69)
Turnover	0.0036**	0.0030**	0.0033**	0.0038**	0.0030**	0.0034**
	(2.39)	(2.10)	(2.27)	(2.45)	(2.07)	(2.19)
Lagged Flow	0.2109***	0.2087***	0.2096***	0.2163***	0.2078***	0.2139***
	(11.92)	(11.79)	(11.80)	(11.61)	(11.72)	(11.44)
Past α	1.6943***	1.7364***	1.7062***	1.7958***	1.7467***	1.8329***
	(14.26)	(15.04)	(14.68)	(14.01)	(15.08)	(13.93)
II	0.1878*	0.0449	0.0141	0.1838*	-0.0716	-0.0170
	(1.77)	(0.46)	(0.14)	(1.73)	(-0.74)	(-0.17)
II * Past α	0.1624**	0.1493*	0.1580*	0.1884**	0.1508	0.1773
	(2.29)	(1.69)	(1.84)	(2.19)	(1.52)	(1.61)
SIZESCORE		-0.2528***			-0.2113**	-0.3251***
		(-2.59)			(-2.18)	(-2.78)
SIZESCORE * Past α		0.0247			0.0429	-0.0680
		(0.26)			(0.44)	(-0.48)
ILLIQSCORE			0.3417***		0.2929***	0.3108***
			(3.96)		(3.36)	(3.42)
ILLIQSCORE * Past α			0.0464		0.0538	0.0507
			(0.61)		(0.68)	(0.59)
ActiveShare				0.0683		-0.1917*
				(0.72)		(-1.78)
ActiveShare * Past α				-0.1029		-0.1809
				(-1.08)		(-1.33)
R-square	0.14	0.15	0.15	0.15	0.15	0.16

Panel B: Controlling for STDEV and TR

	[1] (1980-2014)	[2] (1980-2014)	[3] (1980-2014)	[4] (1980-2014)
log(TNA)	-0.1646***	-0.1877***	-0.1043**	-0.1214**
	(-3.27)	(-3.86)	(-2.16)	(-2.55)
Fee	-0.0904	-0.1368	-0.0938	-0.1092
	(-0.51)	(-0.81)	(-0.52)	(-0.62)
Age	-1.2271***	-1.2634***	-1.0408***	-1.0638***
	(-13.69)	(-14.22)	(-12.30)	(-12.64)
Turnover	0.0033**	0.0036**	0.0036**	0.0038**
	(2.18)	(2.45)	(2.34)	(2.56)
Flow	0.2140***	0.2108***	0.2222***	0.2179***
	(11.93)	(11.70)	(11.55)	(11.27)
Past $\alpha 1$	5.5607***	5.9021***	4.2903***	4.5126***
	(8.41)	(8.84)	(6.92)	(7.20)
Past $\alpha 2$	6.7840***	7.0644***	5.4405***	5.6198***
	(10.53)	(10.92)	(9.13)	(9.36)
Past $\alpha 3$	7.3436***	7.6675***	6.1004***	6.3154***
	(11.47)	(11.76)	(10.02)	(10.25)
Past $\alpha 4$	8.1739***	8.4804***	6.7172***	6.9001***
	(12.30)	(12.66)	(10.75)	(10.90)
Past $\alpha 5$	10.3046***	10.4799***	8.7623***	8.8017***
	(15.22)	(15.28)	(13.95)	(13.94)
II * Past $\alpha 1$	-0.0095	0.0506	-0.0105	0.0629
	(-0.07)	(0.32)	(-0.09)	(0.44)
II * Past $\alpha 2$	-0.1396	-0.0855	-0.0323	0.0722
	(-0.98)	(-0.57)	(-0.27)	(0.54)
II * Past $\alpha 3$	0.0081	-0.0894	0.0244	-0.0392
	(0.06)	(-0.55)	(0.19)	(-0.24)
II * Past $\alpha 4$	0.0850	0.1796	0.1190	0.2421
	(0.63)	(1.13)	(0.93)	(1.60)
II * Past $\alpha 5$	0.6694***	0.6929**	0.7904***	0.7290***
	(2.88)	(2.43)	(3.29)	(2.59)
STDEV * Past $\alpha 1$		0.0029		-0.0125
		(0.02)		(-0.07)
STDEV * Past $\alpha 2$		-0.1704		-0.2337
		(-1.04)		(-1.54)
STDEV * Past $\alpha 3$		0.1126		0.0983
		(0.58)		(0.53)
STDEV * Past $\alpha 4$		-0.2616		-0.2985
		(-1.34)		(-1.56)
STDEV * Past $\alpha 5$		-0.4870		-0.3067
		(-1.58)		(-0.98)
TR * Past $\alpha 1$			-0.1593	-0.1737
			(-1.15)	(-1.27)
TR * Past $\alpha 2$			-0.0819	-0.0743
			(-0.58)	(-0.53)
TR * Past $\alpha 3$			-0.1497	-0.1248
			(-0.83)	(-0.69)
TR * Past $\alpha 4$			-0.0043	0.0575
			(-0.04)	(0.47)
TR * Past $\alpha 5$			-0.6054***	-0.5168***
			(-3.37)	(-3.05)
R-squared	0.17	0.18	0.18	0.20

The Influence of Learning and Bargaining on CEO-Chair Duality: Evidence from Firms that Pass the Baton

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Abstract

We use firms that combine the CEO and board chair positions conditioned on CEO performance, known as "passing-the-baton" (PTB), to examine learning in corporate governance. Focusing on PTB-firms, we propose and test a learning model in which firms use PTB to learn about CEO ability and retain talented CEOs. As predicted by the model and consistent with learning, unadjusted performance and idiosyncratic volatility decline following the combination. Compared to an appropriate counterfactual, idiosyncratic volatility declines but firm performance does not decline. Our results underscore the importance of learning in corporate governance and using the chair position to retain talented CEOs.

JEL classification: G30; G23

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The Influence of Learning and Bargaining on CEO-Chair Duality: Evidence from Firms that Pass the Baton

1. Introduction

Theoretical research (e.g. Hermalin and Weisbach 2014, 2017) stresses the importance of learning in understanding observed governance outcomes. Although recent empirical evidence emphasizes learning by investors (see, e.g., Pan, Wang, and Weisbach, 2015), there is little empirical work that focuses directly on how learning influences governance mechanisms. We use the practice of awarding the CEO the additional role of chair after a period of observation to examine learning in corporate governance. In this governance practice, called "passing the baton" (PTB) by Vancil (1987) and Brickley, Coles, and Jarrell (1997), the board learns about the ability and fit of the CEO before awarding the additional position of board chair. Failing to incorporate the role of learning in corporate governance paradigms can lead to an incomplete understanding of widely observed governance practices, such as combining the roles of CEO and board Chair, that seem to conflict with simple normative predictions from agency theory. Our research sheds light on the importance of learning in corporate governance and provides new evidence on the efficacy of combining the CEO and chair positions in some firms.

In the aftermath of the governance failures of the early 2000s and the financial crisis of 2008, governance activists and policy makers have increasingly called for separating the roles of CEO and chair of the board.[1] Despite the widespread opinions of governance activists and the normative implications of agency theory, empirical evidence on the influence of CEO-chair duality on firm performance is inconclusive.[2] Indeed, Brickley, Coles, and Jarrell (1997) conclude that the costs of separating the two roles are larger than the benefits for many firms. In support of this view, Krause, Semadeni, and Canella (2014) survey the literature and find that no consensus evidence emerges to suggest either a negative or positive influence.[3] The aggregate evidence lead Krause et al. to conclude that mandates that require

[1] They base their demands on the premise that combining the two roles exacerbates conflicts of interest between shareholders and the CEO since there is no arms-length monitoring of the CEO by an independent chair. In support of this viewpoint, agency theory suggests that boards, as proxy monitors for shareholders, should be independent from the management of the firm (Fama and Jensen, 1983a; 1983b).

[2] See Dey, Engel and Liu (2011), Grinstein and Valles (2008), Linck, Netter, and Yang (2008), Goyal and Park (2002), and Core, Holthausen, and Larcker (1999).

[3] In their summary of the results, 33.3% of the studies find no relation between firm performance and duality, 16.7% report an unambiguous negative relation, and 16.7% report an unambiguous positive relation. Other studies report that the influence of CEO-chair duality on firm performance is context specific. For instance, 19.4% of the performance studies reviewed by Krause,

separation of the two roles would be unwise, "… not because the issue of CEO duality is unimportant, because it is too important and too idiosyncratic for all the firms to adopt the same structure under the guise of best practices…. boards should be left free to adopt the structure they deem to be strategically beneficial for their firms."[4]

Our approach to duality is motivated by the conceptual framework of Hermalin and Weisbach (1998, 2003), which argues that observed board structures are endogenous equilibrium outcomes that represent constrained optimal responses to agency problems. We posit that the inconclusive and context-specific evidence in the literature arises from endogenous self-selection that complicates empirical identification strategies and the ability to recognize the correct counterfactual firms. Moreover, most analyses of CEO-chair duality rely primarily on predictions derived from basic agency theory and do not consider the importance to certain firms of using a governance structure that facilitates learning about the CEO. Hermalin and Weisbach (2014) argue that such a learning perspective provides insight into phenomena such as executive selection and turnover. We propose a learning model of CEO-chair duality and implement an identification strategy that addresses sample selection issues to determine proper counterfactual firms. Our model and identification is based on the group of firms that initially separate the roles of CEO and chair, and combine them only after a probationary period during which the board of directors observe the new CEO's actions and the firm's performance.

To sharpen our intuition and develop testable implications, we posit a simple model in which the PTB process serves as a way to learn about the ability of a CEO. After learning about the ability of the CEO, the board will award the additional position of board chair if the CEO demonstrates sufficient talent. The chair position enhances the CEO's bargaining power relative to the board, which is optimal in this case since it improves the retention of high-quality CEOs by mitigating concerns that the board will renege on compensation contracts. The intuition of the model helps us to formulate several predictions that we test in our empirical analysis. A key implication is that the post-award performance is expected to be lower than the strong performance prior to the CEO's appointment to chair. As we show, this is an artifact of the learning/selection process and the underperformance disappears when we use an appropriate

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et al. report a positive influence only under certain situations while 13.9% find a negative influence only for specific firm environments.

[4] A related meta-analysis of 31 studies by Dalton, Daily, Johnson, and Ellstrand (1998) concludes that the duality of the firm leadership structure does not affect firm performance.

counterfactual. Hence, our analysis explains why a research design that fails to control for selection issues can easily lead to opposite – and possibly biased – conclusions.

For our empirical analysis, we use an extensive sample of over 18,000 firm-year observations over 1995-2010 to test predictions from our model and to investigate whether awarding the CEO the additional role of board chair is consistent with shareholder wealth maximization. An initial examination of the data reveals that many firms, at least over our 16-year sample period, never combine both roles or always combine both roles. These two groups of dichotomous firms have strikingly different firm characteristics, indicative of selection issues that would make it difficult to attribute causality in cross-sectional regressions. Our primary focus is on the third group -- the PTB firms -- that initially separate the roles of CEO and chair and combine them only after a probationary period during which the board of directors observe the new CEO's actions and the firm's performance. In addition to the learning hypothesis that underlies our model, we consider alternative factors that could drive PTB and promotion decisions. For instance, boards could provide an incentive benefit prior to appointment by using promotion to the chair position as a reward for strong performance. Alternatively, a coopted, compromised board may hasten the promotion to chair and allow the CEO to further consolidate power and perquisites. Overall, we find that the PTB process is largely consistent with optimal learning and retention of high quality CEOs. We find no evidence to support the premise that combining the roles systematically results in poor performance.

As the first step in our empirical analysis, we examine differences between firms that always combine both roles, pass the baton, or always separate the roles. Of particular note, we find that PTB firms are more likely to be present in industries that are less homogenous than firms that always combine or never combine the two roles. In less homogenous industries, CEO performance is difficult to benchmark to industry peers (Parrino (1997)), which is consistent with the notion of there being a greater benefit to use PTB to learn about CEO ability in these industries. The difficulty in benchmarking also likely leads to contracts that are more incomplete, which imposes greater risk on the CEO. We also use a hazard model to analyze the determinants of awarding both titles as opposed to keeping them separate. Supporting the premise that firms award both titles after a probationary period in which the CEO proves her ability, we find that CEOs that exhibit superior industry-adjusted performance receive the chair title more quickly. However, we also find that good industry performance hastens the award of both titles. This result suggests that firms combine the two roles to retain CEOs when industry conditions create better outside

employment opportunities, in line with the model's retention rationale for awarding the chair.[5] Ceteris paribus, older firms take longer to award the title of Chair, while firms with multiple segments combine both titles more quickly. The latter result suggests that more complex organizations may be better served by combining the roles of the CEO and the chair, which is consistent with the conclusions of other studies (Faleye (2007), Dey, Engel, and Liu (2011), and Palmon and Wald (2002)).

Our model suggests that, ceteris paribus, talented CEOs in a weaker bargaining position relative to the board will tend to be promoted to chair more quickly. CEOs that are more vulnerable to future actions by the board would be more likely to pursue outside opportunities. This prediction is supported by evidence that when the board is not coopted – the promotion to chair occurs more quickly. This finding fails to support an alternative explanation that agency considerations and influence are central to the CEO being appointed chair.

To study the consequences of combining the two roles on firm performance, we estimate CEO-firm pair fixed effect regressions in which the effect of the decision to combine the roles is captured by dummy variables for the year of the combination and the subsequent years. Our results indicate positive abnormal returns prior to the award. The Bayesian learning/selection process in our model implies that post-appointment performance will appear worse than the strong performance that preceded the chair award. Indeed, a naïve analysis of the post-chair appointment performance, one that fails to control for selection issues and mean reversion in performance data, indicates a significant drop in firm performance relative to the pre-chair period. However, to properly specify a test to discern whether the drop in performance can be attributed to the promotion or to conditions under which promotions tend to occur, we need to benchmark the post-promotion performance appropriately. Since the pre-chair appointment period is characterized by strong performance, we use propensity score matching to construct a matched sample of firms where the matching criteria includes similar pre-appointment performance and firm attributes that predict a high propensity for using a PTB succession strategy. The matched sample is drawn from the set of firms that always or never award the chair to the CEO. We find that relative to the matched sample, there is no evidence of post-appointment underperformance in stock-price returns or in accounting

[5] This interpretation is in the spirit of Oyer (2004), who argues that firms optimally pay CEOs for good luck to retain CEOs when industry performance is good and competitors have the resources to hire away talented CEOs.

returns. Moreover, supporting the learning hypothesis, we observe a significant decline in idiosyncratic stock volatility in both the unmatched and matched data. Overall, these results are consistent with predictions of our model and with appointment to chair being made optimally.

We turn next to the board's decision of when (and whether) to award the title of chair to the CEO and what this implies in terms of the learning hypothesis relative to alternative factors – incentives and agency -- that could impact the promotion process. If a main purpose of the PTB policy is to learn about managerial quality and retain talented CEOs, good performance in the initial years may be sufficient to persuade the board of the CEO's quality. An incentive rationale for PTB would not generally imply an early promotion: since a promotion would tend to weaken incentives after the award, it could be sub-optimal to award the chair relatively early. Similarly, if the promotion exacerbates agency problems and CEO entrenchment, an early promotion might have worse implications for firm value. For our test, we separate our sample into two groups. The first (second) group consists of CEOs that are awarded (are not awarded) their additional title within four years of becoming the CEO, which is the median in our sample. Our results for these two groups are similar to those for the full sample: we document no underperformance in returns or accounting returns relative to a sample of firms matched on pre-chair performance and other firm attributes Thus, our analysis of early and late promotions supports the notion that CEO incentives do not decline following the combination of roles, nor does there appear to be a worsening of agency frictions.

The stock market's response to the CEO being appointed chair provides additional evidence that is consistent with the learning hypothesis. If the PTB process is intended to provide ex-ante incentives or indicates greater CEO entrenchment and agency problems, we would expect a negative reaction to the chair appointment. Similarly, if the pre-appointment process is perceived by the market as a lucky outcome rather than ability, we would expect a muted or even negative reaction to the appointment. On the other hand, if the promotion is regarded as the board's vote of confidence on CEO ability, we expect a positive response. We find that the market responds positively (CAR =1.31%) to early promotions, which suggests that early promotions reveal directors' private information about the quality of the CEO to the market. On the other hand, the market response to late promotions is statistically insignificant from zero. The lack of a response to late promotions suggests there is little surprise at the announcement since the market (like the board) has observed the CEO's performance over a relatively long period.

The CEO's total compensation and the sensitivity of compensation to stock-price performance increase significantly following the award of the additional title. Our model suggests that this could be the intended outcome in terms of bargaining power and compensation, if the objective is to retain a high quality CEO and to mitigate potential agency problems. Similar to the performance results, we observe no change in annual compensation or the sensitivity of compensation to stock-price performance relative to the matched counterfactual. However, both the unmatched and match-adjusted sensitivity of the CEO's total portfolio to stock-price performance continues to increase after combination of both roles. Further analysis also reveals that the change in annual compensation is not sensitive to whether the boards have been coopted by the CEO (see Coles, Daniel, and Naveen, 2014), which suggests the increase in compensation is more likely to derive from the board having learned about the CEO's ability and bargaining rather than managerial power over the board. In fact, the total sensitivity to performance of the CEO's portfolio actually increases marginally more when the board is coopted than when it is not. The finding that portfolio incentives continue to increase post-appointment suggests that the CEO-Chairs continue to hold the firm's stock or stock options as opposed to cashing out.

Our study builds on Brickley, Coles, and Jarrell (1997), who argue that separation has both potential costs and potential benefits, by introducing learning as a primary motivation for the PTB process. Brickley, et al. conclude that the costs of separation are larger than benefits for most large firms. Additionally, they argue that if the CEO is not awarded both titles, she would be less motivated to work hard, and that firms that perform well reward the CEO with the additional title. Using a sample of 661 large publicly traded U.S. firms in 1988, they find that firms with separate CEO and board chairs do not perform any better than the firms that have these roles combined. Their event study evidence suggests that market response is insignificant when the firms combine or split the two roles. The authors suggest that their results are best characterized by the "passing the baton" (PTB) process proposed by Vancil (1987), in which the new CEO serves a probationary period under a separate chair who is generally the prior CEO. If the new CEO clears this hurdle, then she earns the additional title of board chair and the old chair resigns. Also consistent with the PTB argument, Fahlenbrach, Minton, and Pan (2011) find that firms with the old CEO on the board monitor the new CEO more intensely and achieve better performance. Palmon and Wald (2002), however, document that the market reaction to combining or splitting the roles

of CEO and chair is negative for small firms, positive for large firms, and unrelated to proxies for PTB progression.

The results of our analysis also relate to Dahya, McConnell, and Travlos (2002), who study the implications of the Cadbury Committee report on the *Code of Best Practices* on British firms. One of the important features of the *Code* was its recommendation that the position of the board chair and CEO be held by different individuals.[6] They report that the negative relationship between CEO turnover and performance became stronger following the issuance of the *Code.* They also report that the sensitivity of turnover to performance was concentrated among the firms that adopted the *Code*. However, Dahya and McConnell (2007) find that performance improvements related to adoption of the *Code* result from additions of independent directors to the board; they find no influence of separating the roles of CEO and chair on firm performance. More recently, Yang and Zhao (2014) report that firms with combined titles of CEO and chair are valued 6% higher than firms with separate titles. We note that these studies all classify firms as either separate or combined. Thus, our research complements these studies by examining PTB firms, which have periods of separation and combination, as a distinct group

Overall, our research provides three main contributions. First, our analysis offers evidence on the importance of learning in governance structures by proposing and testing the predictions of a learning model of CEO-chair duality. Second, we implement an identification strategy that addresses sample selection issues to determine proper counterfactual firms. Third, our research design and findings help to reconcile the conflicting evidence in the literature about the merit of CEO-chair duality. From a policy perspective our findings indicate that the CEO-chair combination is not necessarily against the interests of shareholders and that a single governance structure is likely not appropriate for all firms. More broadly, our results support the conceptual arguments in Hermalin and Weisbach (1998, 2003) that observed that persistent board structures are likely to be equilibrium outcomes, and the results emphasize the role of learning in shaping these equilibrium outcomes. Thus, our evidence suggests that we should exercise caution in the rush to separate the role of board chair from that of the CEO. Forcing separation by fiat may push many firms away from their optimal equilibrium structures.

[6] Unlike in the U.S., the U.K. Corporate Governance Code sets out a clearer role for the board chair. It has also been noted in the press and the academic literature that the chair plays a more visible role among U.K. firms.

2. A Simple Model of Learning and Duality

2.1 The model

We propose a simple learning model of the decision to award the board chair position to corporate CEOs. We show that it may be optimal to award the chair contingent on the performance of the CEO. Among the implications of the model, post-award performance is expected to be lower than the strong performance prior to appointment. The CEO's compensation and promotion decisions are made by the firm's board of directors acting in the interest of the firm's shareholders. We argue that an important reason to award the chair position might be to increase the CEO's bargaining power relative to the board: This could mitigate CEO concerns about reneging by the board, given the inherently incomplete nature of compensation contracts (e.g., Hart and Moore, 1990. However, the award, which increases the CEO's bargaining power, is also likely to increase CEO compensation. We also attempt to characterize conditions in which firms are more likely to adopt PTB strategies and discuss tests to distinguish between learning and alternative factors that could affect the appointment process.

We consider a two-period set-up in which a new CEO is hired on date t=0. The first output is produced on date t=1 and a second output is delivered on date t=2. All agents are risk-neutral and there is no discounting between time periods. Corporate insiders, i.e., the board and the CEO, are symmetrically informed and update their beliefs about the CEO's ability, denoted by α, upon observing the firm's output.[7] We will allow for the possibility that other agents in the market may have noisier updates about managerial ability than the firm's insiders since they receive a relatively noisier signal about the firm's performance.

The firm's output on date t is denoted by $y_{t,}$ such that:

$$y_t = \alpha + \epsilon_t, \tag{1}$$

Equation (1) indicates that the output is equal to the manager's ability α plus random noise ϵ_t. Manager's ability is not directly observed. However, agents have a common prior on the manager's ability at the time

[7] We follow Harris and Holmstrom (1982), Murphy (1986) and other papers in assuming that learning about managerial ability occurs in a setting with symmetric information i.e., the CEO learns of his ability along with other agents.

of hiring $(t = 0)$, and will update their beliefs based on firm performance. The common prior on manager's ability is a normal distribution $\alpha \sim N\ (\alpha_0, \sigma_0^2)$, where α_0, σ_0^2 represent the mean and variance of manager's ability as of $t = 0$. The noise term is assumed to be drawn from a normal distribution with zero mean and variance σ_ϵ^2 i.e., $\epsilon_t \sim N\ (0, \sigma_\epsilon^2)$.

The timing of events is as follows. After being hired, the manager delivers his first output y_1 at *t=1*. From standard results, if the manager produces an output y_1 the posterior distribution $N(\alpha_1, \sigma_1^2)$ from the perspective of the board and CEO will be such that:

$$\alpha_1 = w_1\,(\alpha_0) + (1 - w_1)y_1, \tag{2}$$

where $w_1 = \frac{\sigma_\epsilon^2}{\sigma_0^2 + \sigma_\epsilon^2}$. The conditional variance is given by: $\sigma_1^2 = \left(\frac{1}{\sigma_0^2} + \frac{1}{\sigma_\epsilon^2}\right)^{-1}$.

The process of learning may not be identical across agents. In particular, we allow for the possibility that there are differences in the way learning occurs across firm insiders and outside investors. For instance, the board may have more precise information regarding the CEO's performance than outside investors. To model this we assume that outside market participants receive a somewhat noisier signal of the firm's performance than the board. The signal received by outsiders can then expressed as:

$$y_t^a = \alpha + \epsilon_t + \mu_t, \text{ with } \ \mu_t \sim N\left(0, \sigma_\mu^2\right).$$

In this case, outsiders' posterior on the CEO's ability is similar to equation (2), except with σ_ϵ^2 replaced by $(\sigma_\epsilon^2 + \sigma_\mu^2)$, which captures the notion that outsiders may have a noisier assessment of managerial ability, relative to insiders.

There may be other differences as well, such as in the priors regarding managerial ability and in the process by which learning occurs. For instance, the board could have sharper priors and be better able to discern the success and effort of an internally sourced CEO, relative to that of an external hire. This may reasonably be interpreted as the output of an internal CEO having a lower σ_ϵ^2, implying more rapid learning about CEO ability.

There are four possible outcomes contingent on the outcome y_1: (i) a sufficiently poor performance could lead to the CEO being replaced by the board; (ii) the CEO could leave the current firm for outside opportunities; (iii) CEO could continue with the firm without being awarded the chair and,

finally, (iv) he could continue with the firm and be awarded the chair. To discuss outcomes, we first characterize the compensation process. We assume that when it is difficult to write sufficiently complete contracts, the CEO's compensation is determined as the outcome of a Nash bargaining game between the CEO and a board that acts in the interests of shareholders (e.g., Hart and Moore (1990)). When the CEO is initially hired, his bargaining power is denoted by β_0, where $1 > \beta_0 \geq 0$. The initial bargaining power may reflect, for instance, the nature of CEO's connections with the board e.g., if he is an inside appointment or if the board is coopted.

We assume that the CEOs receive their compensation at some stage after the period begins but before the realization of the output.[8] Wage contracts are inherently incomplete and the compensation that the CEO receives is subject to renegotiation on these dates (see e.g., Hart and Moore, 1990). Hence, the compensation that the CEO receives is not constrained by prior wage agreements.

In the above setting, the CEO's compensation will determined by his bargaining power, his reservation wage and the value he is expected to generate. To conserve on notation, we normalize the CEO's reservation wage to 0. Further, we assume that if a CEO is fired on an intermediate date, the output produced in the period will be zero, consistent with a replacement CEO having expected ability 0. Under these assumptions, the outside options of both the CEO and board are equal to zero. Hence, the surplus the CEO produces in the first period is α_0, relative to the zero value of outside options. As a result of bargaining, the CEO receives a fraction β_0 of the surplus and his period-1 wage is: $W_1 = \beta_0\alpha_0$. In the second period, if the CEO's bargaining power remains at β_0 (and he remains with the firm), his expected compensation will be $W_2 = \beta_0\alpha_1$. The CEO's bargaining power is not fixed however and can be enhanced by promotion to chair. The benefit to the firm is that by yielding more power to the CEO is that it can dissuade a well-performing CEO from (costly) exploring of outside opportunities prior to the second period – since the CEO is more reassured about future treatment by the board. Note that the board has an incentive to give the CEO greater bargaining power since contracts are incomplete, and the board cannot credibly commit to a compensation contract.

[8] This is for simplicity but is without loss of generality since the CEOs are risk-neutral and incentives do not affect the output.

Although not important for analyzing the promotion decision, we can easily characterize the conditions under which the firm chooses to dismiss the CEO. Under the assumption that it is virtually costless to find a new CEO and dismiss the current CEO,[9] the decision will depend on the posterior assessment of the CEO's ability $\alpha_1$and the expected ability of the replacement CEO. If the prior on a replacement CEO is $\alpha_R \sim N(0, \sigma_R^2)$, the current CEO will be dismissed after the first period if: $\alpha_1 < 0$.

More interesting for our purposes is the decision to increase the likelihood of retaining a talented CEO by promoting him to chair. We model the retention decision as follows: After market participants have observed y_1, the CEO may choose to explore outside opportunities. In particular, we assume that with probability $f(\alpha_1)$ the CEO can locate another firm that is seeking a CEO and where his perceived ability is valued more than at his current firm. The probability $f(\alpha_1)$ is increasing in α_1, since a strong performance makes the CEO more attractive to other firms. We take $f(0) = 0$ and $f(\alpha_1) \to 1$ as $\alpha_1 \to \infty$. His search comes at a personal cost of k.

If the CEO does find such an external position, we assume that his current firm competes with the new firm in trying to retain/attract the CEO. We take the outcome of bidding between the firms to be resemble an English auction. Hence, the CEO switches to the new firm (since the CEO is assumed to be more valuable in the new firm) and his compensation is driven up to the highest value his current firm is willing to pay.[10] We take this to be the entire value (α_1) that the CEO could have brought to his current firm.

On the other hand, if the CEO fails to find an alternative position, we assume he is retained at his current firm. To capture the notion that the CEO has a limited time to decide whether to remain with the firm or leave, we assume that he can engage in such a search only once prior to the start of the second period. If his search fails, the firm has no incentive to offer him more than what he would receive with his current bargaining power. Hence, if the search fails, the CEO can expect to receive $\beta_0\alpha_1$.[11] Given his

[9] Dismissal and search costs can be introduced easily but would contribute little to the discussion.

[10] We are implicitly assuming that the current firm has some way to commit to paying α_1. If the most that the current firm can commit to paying is $M_1 < \alpha_1$, then this could limit the most that the CEO obtains in a bidding contest between the current and new firm.

[11] We have simplified the exposition by assuming that an outside firm bids for the CEO only if the value he is expected to produce is greater than α_1. Outside firms that expect the CEO to produce less than α_1 (even if it's more than $\beta_0\alpha_1$) don't engage in bidding for the CEO, possibly because they expect to lose for certain and face some incremental costs relative to

personal search cost of k, his expected compensation from searching can be expressed as: $f(\alpha_1)\alpha_1 + (1 - f(\alpha_1))\beta_0\alpha_1 - k$. This represents a gain of $f(\alpha_1)\alpha_1(1 - \beta_0) - k$ over his expected compensation $\beta_0\alpha_1$ in the absence of a search. Hence, the CEO will search as long as:

$$f(\alpha_1)\alpha_1(1 - \beta_0) - k \geq 0 \tag{3}$$

Let us denote by α_1^* the value of α_1 such that equation (3) is just satisfied as an equality. In other words, for $\alpha_1 > \alpha_1^*$, the CEO is expected to engage in a search for outside opportunities, unless he is offered an alternative arrangement at his current firm. By our assumption about the ability of replacement CEOs (i.e., $\alpha_R \sim N(0, \sigma_R^2)$), it is in the interest of the current firm to retain the CEO as long as it can offer him compensation that is less than the surplus $\alpha_1$he is expected to produce. We have assumed that contracts are always subject to renegotiation, so that unless there is a change in the CEO's bargaining power, he expects to receive $\beta_0\alpha_1$. Hence, if the CEO's perceived ability after the first period is $\alpha_1 \geq \alpha^*$, he will search unless there is some means of committing to compensate him at least as much as he expects to receive from searching. Our contention is that appointing the CEO to chair serves as a way to commit to a better subsequent treatment by the board and can, therefore, be used to retain the CEO. We are assuming here that it is optimal for the firm to commit to the higher compensation to retain the CEO. Further, as noted, if it were possible to write credible contracts, it would not be necessary to promote the CEO to chair. A credible contract would be possible if the compensation were, for instance, tied to performance measures that could be verified.

The notion that yielding greater power to the CEO can be beneficial and reduce CEO concerns has been made elsewhere.[12] We denote the bargaining power after promotion to be $\beta_1 > \beta_0$.[13] As a result of bargaining power β_1, the expected compensation to the CEO in the next period is $\beta_1\ \alpha_1$.

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their alternative candidate. Hence, the CEO's compensation at his current firm remains unaffected unless the external firm has a value for the CEO that exceeds α_1

[12] See, e.g., Hermalin and Weisbach (1998), Almazon and Suarez (2003), Adams and Ferreira (2007), and Williamson (2008).

[13] The bargaining level β is not necessarily unique to duality and may be determined by a host of factors such as the ease of replacing the CEO, the committees to which the CEO is appointed, the number of insiders and the relationship of board members to the CEO among other considerations.

Hence, if the CEO is promoted to chair (conditional on not searching) he will accept the chair and not search as long as:

$$\beta_1\, \alpha_1 \geq f(\alpha_1)\delta\alpha_1 + \big(1 - f(\alpha_1)\big)\beta_0\alpha_1 - k. \tag{4}$$

For our analysis, we assume that equation (4) is satisfied and that the promotion to chair is effective in inducing the CEO with $\alpha_1 > \alpha_1^*$ from engaging in costly search. Next, we discuss some of the testable implications of our model.

2.2 Model Implications and alternative hypotheses:

1. Firm complexity and industry homogeneity:

Our first prediction draws on two underlying assumptions about PTB firms. The first assumption is that firms adopting PTB strategies will tend to be firms in which CEO ability is not easily discerned. Thus, significant learning may occur over time. The second assumption is that PTB firms operate in environments that make it difficult to write effectively complete and credible compensation contracts.

It follows from the first assumption that PTB firms can be expected to be somewhat more complex than other firms. The literature suggests that firm complexity is associated with characteristics such as: a larger board and firm size, a higher percentage of inside directors, higher financial leverage, and greater R&D intensity. In our tests we examine whether PTB firms have attributes usually associated with firm complexity.

Second, we expect PTB firms to be more prevalent in environments in which it difficult to write and enforce effective incentive contracts based on common accounting and stock performance measures. In particular, we would expect PTB firms to be less common in homogenous industries (Parrino (1997), since CEO performance is easier to benchmark to industry peers in such industries. Further, we expect that CEOs that have a weaker relationship with the board will be more concerned about acquiring power relative to the rest of the board. Hence, if the CEO faces a more independent board that is not coopted, we expect that CEO to be promoted more rapidly. Finally, when the board has greater information about CEO ability e.g., when the CEO is an internal appointment, we would expect promotions to occur over a shorter horizon (see the discussion following equation (2)). We can, therefore, state:

Prediction-1: Under the learning Hypothesis:

- *Firms that are more complex and less transparent and that belong to less homogenous industries are more likely to follow a PTB strategy in appointing CEOs to chair positions.*
- *Firms that follow a PTB strategy will be more rapidly promote CEOs to chair positions when the board is more independent and not coopted or when the CEO is internally sourced.*

. We consider two alternative hypotheses for firms to follow PTB strategies. Our first alternative hypothesis is that the possibility of being promoted to chair could provide the CEO with strong promotion incentives. The promotion-incentive hypothesis would be consistent with more complex and less transparent firms adopting PTB, since incentive contracting might be difficult in such firms. Later, we develop other predictions that will allow us to test between the learning-retention hypothesis against the promotion-incentive hypothesis.

Our second alternative hypothesis is that CEO entrenchment and agency problems could be primarily responsible for promotion to chair. Some aspects of Prediction 1 allow us to distinguish between the learning-retention and the agency hypothesis. In particular, if agency problems drive the promotion to chair, we would expect CEOs to be more rapidly promoted in firms with boards that are coopted, contrary to Prediction 1. Hence, if CEOs in firms with coopted boards are less likely to be promoted more rapidly or if the time to promotion is unrelated to board cooption, then the evidence would not be consistent with the agency explanation.

2. Post-promotion performance:

Our model suggests that if learning about managerial quality is an important factor underlying the PTB strategy, then promotion to board chair is likely to be preceded by strong firm performance. As we show below, our model also suggests that the post-promotion performance will tend to be lower than the CEO's performance in the periods leading up to the promotion. However, this reflects the conditions under which learning leads to promotions rather than an indication of duality affecting firm performance. We can state:

<u>Prediction 2:</u> *In the period prior to the CEO being appointed chair, the firm's performance is expected to be strong (y_t will exceed a^*). The performance (y_t) is expected to be greater than the average subsequent performance exhibited by the firm. Hence, the average performance post-chair promotion will tend to decline.*

Proof: The above implication follows from the updating equation (2). Suppose that the manager's expected ability at $t-1$ is a_{t-1}. We expect $a_{t-1} < a^*$, otherwise the CEO would already be chair. Now, if the CEO is appointed chair following date t performance, it must be because $a_t \geq a^*$ and $y_t > a^*$ since:

$$a_t = w_t\, a_{t-1} + (1 - w_t) y_t \geq a^* \Rightarrow y_t > a^*$$

Since $a_t \geq a_{t-1}$, the updating equation above implies $y_t > a_t$. Hence, the average subsequent performance (since a_t represents expected ability and expected subsequent performance) will tend to be below y_t. ■

Prediction 2 indicates that constructing the appropriate counterfactual is critical to assessing the value implications of CEO duality. In a setting with learning about managerial ability, a finding that firm performance drops subsequent to chair promotion does not imply that duality has negative value consequences. In our empirical analysis, we test for the performance effects of duality by carefully matching the post-promotion performance of PTB firms to a control group of non-PTB firms (i.e., always or never have duality) and that exhibit a performance similar to the pre-appointment performance of PTB firms. The control sample is one in which there is no promotion to chair, but the implications in terms of CEO future performance are likely to be similar.

Prediction 2 provides us with a way to test between the learning-retention hypothesis and alternative hypotheses. Unlike the learning hypothesis, if ex-ante promotion incentives are strong, we would expect to observe a drop in firm performance (given loss of the promotion incentive), relative to an appropriate matched sample of non-PTB firms. Further, given the anticipated decline in performance, it is not obvious that it would be optimal for CEOs to be promoted following a strong performance or

promoted relatively early in their tenures. Similarly, if the promotion was hastened by agency considerations and worsened CEO entrenchment, we would expect there to be a drop in firm performance.

3. Change in CEO compensation after promotion and firm-specific risk:

We next turn to the anticipated change in CEO compensation and incentives following promotion to chair. As we have argued, a change in compensation could be the intended result of optimally promoting the CEO to chair. Promoting the CEO to chair in our model has the desired effect of giving the CEO additional bargaining power and inducing the CEO to forgo the search for alternative opportunities. Our learning model does not have clear predictions with regard to a change in incentive compensation, since there is no decline in CEO incentives resulting from the promotion.

Under the alternative hypothesis of promotion-incentives, we would expect there to be an increase in CEO compensation incentives following promotion to chair. Such an increase in compensation incentives could help to offset the loss in promotion-incentives following the CEO's elevation to chair. If there is found to be no increase (or even a decrease) in incentive pay, this would support the learning-retention hypothesis over the promotion-incentive hypothesis.

If agency issues are an important factor in CEO promotion, however, we might expect to find compensation increases to be larger in firms in which boards are more dependent and coopted (i.e., boards for which a larger percentage of directors have less tenure than the CEO). A finding that there is no relation (or negative relation) between compensation change and more dependent and coopted boards, would suggest that agency issues are not central to the compensation change. In particular, lack of correlation between board cooption and compensation would be consistent with our learning-retention hypothesis.

Our learning hypothesis also provides predictions with regard to changes in firm-specific stock volatility over time such as, for instance, in the period before and after the CEO's promotion to chair since the decision to combine both roles conveys the information that the board has learned to outside investors. As investors gain more information about the CEO's ability, the market reaction to firm's performance will become more subdued. To see this, note that when there is greater uncertainty about CEO ability, the market's reaction to firm performance will be stronger because of what is also revealed about CEO ability – and, hence, the longer-term expected performance of the firm. This effect will be diminished as learning

proceeds and there is less uncertainty about managerial ability. These changes are expected to be reflected as a reduction in firm-specific over time. There is no clear prediction regarding the firm's systematic risk.

Our argument is similar to that in Pastor and Veronesi (2003) that also predicts that market learning about the CEO will be reflected in lower firm idiosyncratic risk. Recent evidence presented by Pan, Wang, and Weisbach (2015) supports this prediction. We note that the alternative promotion-incentive and agency hypotheses do not have clear predictions regarding changes in firm-specific volatility over time.

Prediction 3:

The learning hypothesis predicts:

(i) *An increase in CEO compensation following promotion.*

(ii) A reduction in firm-specific volatility following promotion.

4. Stock market reaction to announcement of CEO promotion:

If the objective of the PTB is to learn about managerial ability, then the chair appointment could communicate positive news about the board's evaluation of CEO ability. Our discussion (following equation (2)) allows for the possibility that board may have more precise information about CEO's ability, because they tend to receive sharper signals about the CEO's performance. As a result, we expect there to be an information gap between outside investors and the firm's insiders. Hence, we would expect a positive market reaction as investors updated their beliefs about the CEO's ability and likelihood of retention. At the same time, there may be little surprise or market reaction if the CEO has been in position for a relatively long period.

Alternative hypotheses do not predict a positive stock market reaction. The promotion-incentive hypothesis, for instance, would imply a drop in CEO incentives and a negative market reaction. Further, if there are concerns about an increase in agency costs the market reaction would be negative as well.

Prediction 4: Under the learning hypothesis -- *The stock market's reaction to the announcement of CEO appointment to chair will tend to be positive if it is relatively early in the CEOs tenure. We expect the market reaction to be more muted when it occurs later in the CEO's tenure.*

3. Sample and Data

We obtain an initial sample of all firms in the ExecuComp database from 1995 through 2010. We read proxy statements from 1995 through 2002 to obtain CEO/chair duality status, board characteristics, and CEO characteristics. These data come from the Corporate Library database after 2002. The initial sample comprises 2,960 firms and 22,283 firm years. For our analysis, we remove financial firms (SIC 6000 – 6799) and regulated utility firms (SIC 4910-4949), which results in a sample of 18,023 firm years, 2,092 firms and 3,972 CEO-firm pairs. We obtain financial data from Compustat and stock return data from CRSP.

In Table 1, we present descriptive statistics on the prevalence of CEO-chair duality. During our sample period of 1995-2010, there is a declining trend of dual CEO-chairs. In 1995, the percentage of CEOs having the additional title of chair was about 69%. That percentage has steadily declined over the sixteen-year period to 55%. Average firm age increased from 23.91 years to 27.02 years, while there was a small decline in average CEO tenure from 8.65 to 8.01 years over this period. In the second panel of the same table, we provide industry distributions. The substantial differences across industries, suggest that part of the trend in dual CEO-chairs could be due to changes in industry composition over time. Finally, the third panel shows that CEO tenure when the CEO-chair is separate is 4.66 years, substantially less than the 9.86 years for the full sample. The substantially lower CEO tenure when chair is separate comes from the fact that these firms tend to be younger and, in several cases that the CEO is in the pre-appointment phase of the PTB process.

Table 2 presents descriptive statistics for the firms in our sample. Industry-adjusted statistics are based on a firm's 3-digit historical SIC code. We winsorize all our data at the 1% level to limit the influence of outliers. Variable definitions are provided in the Appendix. The sample return data are skewed with an average (median) annual industry-adjusted stock return of 8.2% (0.34%). Firms in our sample have an average asset size of $5,363 million and an average board size of nine. For each industry, we construct an industry homogeneity measure using the method proposed by Parrino (1997). This proxy measures the correlation between common stock returns within two-digit SIC industries. We classify an industry as homogeneous if its homogeneity measure is above the sample median. Following Coles, Daniel, and Naveen (2014), we define a director as coopted if the CEO's tenure exceeds the director's

tenure, and a board as coopted if it consists of a majority of coopted directors. We use the percentile rank of a firm's foreign tax to total tax as a proxy for the extent of its foreign operations. The median number of business segments for an average firm in our sample is 2. The average tenure of a CEO in our sample is 7.96 years.

As the first step in our analysis, we compare firm characteristics by looking at the firm's history of combining the CEO and chair roles. We divide the sample into three groups: (i) firms that always combine the two roles, (ii) firms that always separate the two roles, and (iii) firms that follow a PTB strategy. To ensure clean comparisons, we remove 303 firms comprised of 2,994 firm years and 758 CEO-firm pairs that, over our sample period, combined or separated the two roles at different times, but did not follow PTB in awarding both roles after a period of observation. However, the results of our comparison are qualitatively unaffected if we assign these firms to any of the three categories. The comparative statistics are presented in Table 3.

For many firm attributes such as firm size (by assets and by sales), leverage, firm age, number of segments, the pass-the-baton firms (column 2) tend to fall between the always-combined firm (column 1) and the never-combined firms (column 3). These characterisitcs seem reasonable in light of the Coles, Daniel, and Naveen (2008) argument that firm attributes such as size and leverage reflect firm complexity and explain why these firms might choose particular governance structures such as board size. Hence, the pattern indicated in Table 3 appears largely consistent with the notion that some types of firms benefit substantially from CEO-chair duality and will always combine the CEO-chair roles. These firms tend to be more complex in terms of having a larger size, more segments, and greater leverage. On the other hand, there is an intermediate group of firms that appears to benefit from combining the positions, but for either learning or incentive motives finds it beneficial to rely on the PTB process. There is also a third group for which the costs of duality appear to outweigh the benefits.

There are some revealing attributes for the PTB firms that do not fall between the other two groups. In particular, PTB firms are much less likely to be in a homogeneous industry (consistent with Prediction 1-A) and are less likely to have a coopted board (inconsistent with an agency explanation). In a homogeneous industry, it is easier to benchmark CEOs against other CEOs in the industry. In a less homogeneous industry such benchmarking is more difficult, which creates greater concerns about giving

the CEO more power as chair without first obtaining more confidence in her ability. Hence, as discussed in developing our predictions, it seems reasonable to conjecture that the boards of firms in less homogenous industries would be more likely to want to use the PTB process to assess the ability of the CEO before awarding her the additional title of chair.

To effectively evaluate the CEO for promotion to chair likely requires a board in which directors have a diverse set of skills and appropriate incentives. Research suggests that larger boards possess a wider array of skills and are more appropriate for firms that have greater advising needs (Coles, Daniel, and Naveen (2008)) and that coopted boards are likely to be less independent and subject to influence by the CEO (Coles, Daniel, and Naveen (2014)). Thus, our comparative results are consistent with the premise that firms that follow PTB do so because it is optimal in their situation. Altogether, the comparison strongly indicates that firms that always combine the CEO and chair positions, firms that award the chair position via a pass-the-baton approach, or firms that always separate the two positions possess significantly different firm, board, and industry characteristics.

4. Determinants of Passing-the-Baton

To further examine the differences between firms with alternative leadership structures, we estimate multinomial logistic models. Table 4 presents the results of our analysis. We present the coefficient estimates from a multinomial logit model of the propensity to reward the CEO with both functions after a period of evaluation on the vector of performance, firm, CEO, and industry characteristics. To allow for a comparison of PTB firms against all other firms, we present estimates with both "always separate" and "always combined" as the base case. For each base case model, we present results with and without year dummy variables and industry dummy variables.

The results of the multivariate analysis largely confirm the univariate comparisons that suggest that PTB firms have characteristics that typically fall between those of firms that always combine both positions and firms that always separate both positions. However, for PTB firms, the coefficient on firm age is positive and statistically significant, and the coefficient on homogeneous industry is negative and significant for both base cases of "always separate" and "always combined."[14] Together, these findings

[14] Industry dummy variables will partially subsume the influence of the homogeneous industry dummy.

suggest that, as indicated by univariate comparisons, older firms in more heterogeneous industries are more likely to adopt the PTB strategy. The coefficient on the number of segments confirms the univariate evidence that more complex firms are likely to always combine both roles. More generally, the results are consistent with the argument that the choice of dual structure depends on the complexity and the scope of the organization (Fama and Jensen, 1983). Firms with more business segments are likely to be more complex than firms with fewer segments. CEOs of such organizations are likely to have firm-specific knowledge that makes it valuable for them to assume the additional role of chair of the board. The coefficients on CEO tenure also suggest that CEOs that always have both roles tend to amass longer tenures. Overall, these findings support Prediction 1, which states that firms that are more complex, less transparent, and that are in heterogeneous industries are likely to follow PTB.

Next we use a hazard model to estimate the propensity to combine the CEO and chair roles. We focus on PTB firms and exclude the firms that always separate or always combine the CEO-chair roles during the sample period. We add a dummy variable that indicates whether the CEO is an outsider in order to test our prediction that outsiders will receive both positions less quickly. Since longstanding insider CEOs tend to have long tenures that are mechanically related to their insider status, we create an orthogonal transformation of CEO tenure by regressing CEO tenure on the CEO outsider status. We then use the residuals from this regression as our control for CEO tenure. As expected, CEO tenure has a strong negative relation to CEO outsider status (the coefficient is -0.338, significant at the 0.001 level).

Table 5 presents the results of our hazard model using different proxies for firm performance. Model1 uses industry-adjusted stock returns and Model 2 uses industry median stock returns. Model 3 and Model 4 use industry-adjusted accounting returns (ROA) and industry median accounting returns, respectively. Model 5 combines industry-adjusted stock returns with industry-adjusted ROA, and Model 6 combines industry median stock returns with industry median ROA.

In support of the learning hypothesis (Prediction 2), the industry-adjusted performance of the CEO in the previous two years is a significant predictor of whether or not she receives the additional title of chair. The coefficients on industry-adjusted stock performance over the previous two years are jointly significant at the 1% level (Model 1) and the coefficients on industry-adjusted ROA are jointly significant at the 5% level (Model 3) Older firms are slower to reward CEOs with the additional title. Firms with

multiple segments are more likely to reward the CEO with the additional title of chair. Insider dominated boards are also more likely to reward the CEO with the additional title, which could suggest an agency problem or underscore the importance of firm-specific human capital. However, coopted boards are less likely to combine the two roles, which is inconsistent with the agency interpretation and consistent with our prediction that more independent boards will promote CEOs to chair earlier. Also consistent with our prediction, inside CEOs are more likely to be promoted earlier (Prediction 1-B). Firms with larger capital expenditures as a percentage of sales and higher leverage ratios are more likely to reward the CEO with the additional titles. These results support the argument that more complex organizations are often better served by combining the roles of the CEO and the chair.

To gain additional insight, we also examine the previous two-year's industry performance. The coefficients on the previous two-year industry median stock performance (Model 2) and the previous two-year industry median ROA (Model 4) are both jointly significant at the 1% level. One interpretation of these results is that both "luck" and "skill" influence the outcome. For instance, Oyer (2004) argues that firms optimally reward CEOs for luck for retention purposes when the industry performs well and competitors have additional resources to hire away a talented CEO. Alternatively, these results may indicate that the board learns about the ability of the CEO to operate effectively in the current industry environment. Recent evidence suggests that industry performance matters for CEO dismissal, which suggests that boards assess a CEO's ability to adapt to industry dynamics (Kaplan and Minton (2012), Eisfeldt and Kuhnen (2013), and Jenter and Kanaan (2015)). We note that the two explanations are not mutually exclusive.

When we include both industry-adjusted stock returns and industry-adjusted ROA in the same specification (Model 5), it appears that the stock-price performance dominates the accounting performance as a predictor of quick promotion to board chair. The coefficients on the lagged industry-adjusted stock returns are jointly significant at the 5% level, but the coefficients on the lagged industry-adjusted ROA are not jointly significant at standard significance levels. Similarly, Model 6 reveals that the lagged the industry median stock returns dominate the industry median ROA. The coefficients on the lagged industry median stock returns are jointly significant at the 1% level, but the coefficients on the lagged industry median ROA are not jointly significant at standard significance levels. Altogether, the results in Table 5

suggest that CEOs receive both titles more quickly following superior firm-specific performance and superior industry performance.

In untabulated results, we also estimate the hazard model on a sample that includes the firms that always separate or always combine the CEO-Chair roles during the sample period, allowing for a different baseline probability for each category. The results are qualitatively similar to those presented in Table 5. These findings suggest that our results are robust to alternative specifications of the hazard function. Overall, it appears that both performance relative to industry (Prediction 2) and industry performance play a role in the CEO's elevation to chair.

5. Consequences of Passing the Baton

5.1 Investor Reactions to Combination of CEO and Chair Roles

As the first step in our analysis of the consequences of combining the two roles, we examine the valuation impact of the announcement to award the title of board chair to the CEO. For the sample of firms for which we can identify the news releases associated with the award of the additional title, we examine the stock price reaction to the announcement. We follow the event study method of Patell (1976) based on the market model and use the value-weighted CRSP index as the proxy for the market.

We present the results of our event study analysis in Table 6. For the full sample, the cumulative abnormal returns for the three-day window of -1 to +1, is 0.35%, which is not statistically different from zero. However, the market response to sample firms that promote their CEOs within three years is 1.09% and is statistically significant at the 1% level. This result suggests that early promotions reveal directors' private information about the quality of the CEO to the market. This evidence is consistent with Prediction 4 of our model. The market response to late promotions is statistically insignificant from zero, which suggests the market has already assessed the quality of these longer-serving CEOs and anticipated any incentive effects of combining both roles.

We also segregate the sample based on (i) whether the board is coopted or not coopted (ii) whether the combination occurred before or after the implementation of Sarbanes Oxley and (iii) whether the CEO is an insider or outsider. Our analysis of coopted and non-coopted boards provides no support for the agency explanation. In fact, there is weak evidence of a positive market reaction when boards are coopted.

Whether the CEO is an insider or outsider or whether the combination occurs before or after the implementation of Sarbanes Oxley does not appear to influence the market reaction.

5.2 Univariate Comparison of Firm Performance and Policies Before and After Combining the Roles

The results presented in Table 3 through Table 5 strongly reveal that firms that choose different leadership structures are significantly different along many other dimensions. These differences suggest that we should carefully construct our research design to consider these sample selection issues and identify a counterfactual that allows us to draw causal inferences.

We draw our counterfactual firms from the set of firms that either always combine or separate the roles of CEO and chair, and use a two-step process to identify the matching firm as of the year prior to the combination of the two positions. First, we require that the matching firm be in the same decile of stock return (return on assets) as the treated firm in the year prior to combining the two positions to control for mean reversion in performance. An abnormally strong performance – as occurs prior to the chair award – would be expected to be followed by a reversion to the mean. Second, we estimate propensity scores for the likelihood of a firm choosing the PTB strategy based on the predictors in Table 4, and then use the nearest neighbor approach to identify a matched sample.

Table 7 presents a comparison of characteristics for PTB and matched firms. In stark contrast to the univariate comparisons in Table 3, the PTB and matched firms have very similar characteristics that are not statistically different. We do note that the means for the coopted board dummy variable is statistically different at the 0.09 level and the difference in the medians is marginally insignificant with a *p*-value of 0.11. The propensity to be in a homogenous industry is marginally insignificant with p-values of 0.12 and 0.13, respectively, for the mean and median. We present robustness tests along these dimensions in Table 10 and for a variety of financial policy variables in Table 11. The robustness tests confirm our primary results.

In Panel A of Table 8, we present univariate results for firm performance before and after receiving both CEO and chair positions. Without adjusting for the matched firms, results based on mean stock returns suggest a statistically significant performance decline from 20.03% to 14.66%. However, when we focus on the results based on match-adjusted stock returns, we do not observe a statistically significant

decline in performance. We also find similar results for accounting performance. For instance the mean accounting return declines from 14.30% to 13.72%, significant at the 10% level, but match-adjusted returns are not statistically different. Thus, the univariate performance comparisons suggest that the data are consistent with the learning hypothesis.

One could argue that there is an optimum time frame by which time the CEO is rewarded with the additional title. If the board delays the award of the title, the CEO could threaten to quit.[15] On the other hand awarding the additional title too soon could result in a mediocre performance subsequently. To test the implications of timing, we separate our sample into two groups. The first group consists of CEOs that receive the additional title of board chair in less than four years of becoming the CEO. The other group consists of CEOs that get the additional title in four years (sample median) or more. In untabulated univariate results, we find no material differences in the post-award firm performance following early or late combinations.

In Panel B of Table 8, we provide univariate results of firm financial policies before and after combining the CEO and the board positions. We present results for capital expenditures as a fraction of sales, R&D expense as a fraction of sales, financial leverage and the number of business segments. For policies, we follow a similar matching process as described above, but we required the PTB firm and the matched firm to be in the same decile by policy level. We focus our attention on match-adjusted results as discussed above. As a fraction of sales, the data suggest that match-adjusted capital spending increases and that match-adjusted R&D decreases. Moreover, firms tend to rely more on leverage to finance investment. Taken together, these results suggest that firms move into relatively safer investment following the combination of the two positions, consistent with the notion that CEOs take more risk to improve performance and receive both roles.

We directly examine evidence on stock-return volatility in Panel C of Table 8 by comparing total stock return risk, market risk, and firm-specific risk in the pre- and post-combination periods. We find that match-adjusted total risk declines significantly on both an unadjusted and match-adjusted basis. This decline is driven by a significant reduction in firm-specific risk -- CAPM market risk actually increases

[15] The CEO of HSBC, Michael Geoghegan, threatened to quit if he was not promoted to board chair (Sunday Times, 9/26/2010)

slightly, consistent with the use of greater leverage. This finding is consistent with the learning hypothesis but, from Prediction 3, this finding does not necessarily rule out the promotion-incentive alternative. Later, we will use fixed-effects specifications with matched benchmark firms to further examine these results.

5.3 Multivariate fixed-effects analysis of firm performance and policies

Ideally, we would like to compare the ex post financial performance of the firms that combine the two roles relative to otherwise identical firms that do not combine the two roles. We broadly follow the empirical strategy used by Pagano, Panetta, and Zingales (1998) to examine the decision by the firm to go public. We investigate the ex post consequences by estimating fixed effect regressions in which the effect of the decision to combine the two roles is captured by dummy variables for the year of the combination and the three subsequent years. By using firm fixed effects, each CEO-firm pair prior to the CEO receiving both roles serves as its own control for the period after the CEO assumes both roles. We also carry out the analysis using a match-adjusted CEO-firm pair. The analysis of unadjusted data provides a test of differences and the analysis of match-adjusted data provides a test of differences in differences. Specifically, we estimate the following specification for each performance or policy variable:

$$y_{it} = \beta_0 + \sum_{t=1}^{4} \beta_t Combined_t + \beta_5 Combined_{t>4} + u_i + d_t + \varepsilon_{it}$$

where u_i and d_t are CEO-firm pair and year fixed effects, respectively. Combined_t is an indicator variable that is 1 if period *t* is after the CEO became board chair and zero otherwise.

We present the first set of multivariate firm fixed-effect regression results in Table 9. Panel A provides the results on performance. When we do not control for a matched firm, the data reveal significant declines for both stock returns and ROA following the combination of the two roles. However, we find no evidence that awarding the additional role of board chair influences the match-adjusted stock returns or match-adjusted ROA in any year or cumulatively in the years following the promotion. Thus, the performance results are more consistent with the learning hypothesis than the incentive hypothesis.

Next, we examine firm policy variables in Panel B of Table 9. We again present results for unadjusted variables and for match-adjusted variables. Although unadjusted capital expenditures decline following the combination, we find no evidence of any influence in investment policy as measured by

match-adjusted capital expenditures or R&D. Firms appear to significantly increase their leverage after the award year, but there is no significant change for match-adjusted leverage. The data suggest the possibility of diversifying activities. Summing up the coefficients, firms add about 1.3 new business segments after combining the CEO-chair roles. There is, however, no significant increase in the number of business segments when we perform match-adjusted analysis.

We also use multivariate fixed-effects analysis to examine changes in total firm risk, CAPM systematic risk, and firm-specific risk. These results are presented in Panel C Table 9 and are similar to univariate results discussed earlier. The results indicate that after following the combination of the roles of CEO and chair, total risk and firm-specific risk declines significantly on both an unadjusted and match-adjusted basis. There is no significant change in systematic risk, so we conclude that the change in total risk derives from the reduction in firm-specific risk. Moreover, these results are consistent with the learning hypothesis as outlined in Prediction 3.

Table 10 presents robustness results of our performance analysis segmented by factors that could influence the decision to combine the two roles or the performance of the CEO following the combination of roles. First, we examine the influence of coopted boards, which was marginally statistically different at the mean (*p*-value of 0.09) between our PTB sample and our matched sample. For completeness, we examine both match-adjusted stock returns and match-adjusted return on assets. Then, we examine several other factors that could influence performance, namely, (i) CEO ownership (ii) industry homogeneity (iii) early or late combinations (iv) combinations before or after the implementation of the Sarbanes Oxley act.

We present the match-adjusted performance results for coopted and non-coopted boards in Panel A. The empirical estimates confirm our base results. We document no impact of combining the two positions on match-adjusted stock-return. The performance does not differ statistically between coopted and non-coopted boards (*p*-value of 0.89 for the entire post-combination period) Likewise, the post-combination accounting performance is not statistically different between coopted and non-coopted boards (*p*-value of 0.75 for the entire post-combination period). Thus, the data suggest that the match-adjusted performance results are robust to coopted board classification. More generally, the results for coopted boards offer no support for the alternative agency explanation of CEO-chair duality.

The results for performance and CEO ownership levels are presented in Panel B. Again, the robustness tests confirm our base results. We document no impact of combining the two positions on stock-return performance. Stock-return performance does not differ statistically between high CEO ownership and low CEO ownership (*p*-value of 0.66). Accounting performance also exhibits no significant differences by CEO ownership levels. For the entire post-combination period, accounting performance is not statistically different between low and high CEO ownership (*p*-value of 0.96). Thus, the empirical tests indicate that match-adjusted performance results are robust to CEO ownership.

Our conceptual arguments and empirical evidence presented thus far suggest that firms in more homogeneous industries are less likely to follow a passing-the-baton strategy. However, since we do observe that some firms in homogeneous industries employ PTB, and the differences between the PTB and matched firms are only marginally insignificant, it is appropriate to examine if industry homogeneity influences our results. Accordingly, we present firm performance results segregated by industry homogeneity in Panel C. The results are similar to our primary findings. Match-adjusted stock returns are not statistically different from zero for either category and are not statistically different across the two industry classifications (*p*-value of 0.83). For accounting performance, we observe no significant match-adjusted ROA regardless of industry category. The performance is not statistically different across the two categorizations (*p*-value of 0.49). Thus, even though firms in heterogeneous industries are more likely to follow a PTB process, our performance results are robust to presence in either type of industry.

It is conceivable that there could be an optimum time frame over which the CEO is given the additional title. If the board delays the award of the title, the CEO could be more likely to leave the firm for alternative employment. On the other hand, awarding the additional title too soon could result in a mediocre performance subsequently. To test early versus late promotions, we separate our sample into two groups. The first group consists of CEOs that get awarded their additional title within three years (the sample median) of becoming CEO. The other group consists of CEOs that get the additional title in four years or later. Our results on performance differentials are presented in Panel D of Table 10. We find no significant difference between the match-adjusted performance for the two groups based on either stock returns or ROA. Note, however, that since these are comparisons with firms matched in terms of past performance, the results do not imply that the firm would be better off delaying the promotion. Overall,

the data suggest that the change in post-award performance is no different for early recipients than for late recipients.

In Panel E, we present separate results based on CEO-chair combinations that occurred before or after the implementation of Sarbanes-Oxley. As is well recognized, the Sarbanes-Oxley (SOX) Act resulted in some significant changes in accounting practices, corporate governance rules and regulations. Moreover, SOX and the events surrounding the passage of SOX increased external scrutiny and focused more shareholder attention on corporate governance. Following the combination of the two roles, we find no statistically significant results for match-adjusted stock returns or for accounting returns in either the pre-Sox or post-Sox periods for the entire post-combination period. In addition, the performance is not significantly different from that in the post-SOX years (*p*-value of 0.92 for stock returns and 0.33 for accounting returns). Thus, our results appear to be robust to combinations that occur before or after the implementation of SOX.

A possible concern with the fixed effects method is that observable policy variables may not be fixed within firms over time. As an additional test, we estimate multivariate regressions to understand the impact of policy changes on stock returns following the combination of the two positions. These results are presented in Table 11. The first two columns present the results for match-adjusted stock returns and the second two columns provide the results for match-adjusted accounting returns. We find no evidence across the different specifications that the match-adjusted stock returns are influenced by the combination of the two roles. Capital expenditures, R&D, and leverage all appear to be negatively related to firm performance prior to combining the two roles, but these policies do not appear to have a differential effect on stock return performance after combining the two positions. We do find that there is a differential relation between the match-adjusted return on assets and R&D, leverage, and the number of business segments after the combination of the roles. To test if these differential relations impact our general conclusions, we estimate a joint test of significance for the sum of each post-combination dummy variable, respectively, and the coefficients on the post-combination policy variables multiplied by the respective means of the policy variables in the post-combination period. In each case, we fail to reject the null hypothesis that the linear combination of these effects is different from zero (*p*-values range from 0.20 to 0.97). Thus, our results are robust to any policy changes that occur in the post-combination period.

5.4 Multivariate fixed-effects analysis of CEO compensation and incentives

Subsequent to the award of the additional title, the CEO may be able to use her increase in power to boost her own pay or decouple her pay from performance. If so, we expect to see an increase in compensation levels or a decrease in compensation incentives. We use the fixed effects regression method in Pagano, Panetta, and Zingales (1998) to examine the actual and match-adjusted compensation levels and incentives provided to the CEO. As before, each PTB firm is matched to a firm that is (i) in the same decile by compensation component and (ii) the nearest neighbor based on propensity scores.

To estimate compensation levels and performance-based incentives, we use the adjustment techniques recommended by Coles, Daniel, and Naveen (2013) to account for changes in compensation reporting created by FAS 123R. The natural logarithm of TDC1 from the ExecuComp database serves as our measure of total compensation. TDC1 combines compensation from salary, cash bonuses, stock options, restricted stock, and long-term incentive plans to estimate the CEO's total compensation. Following Core and Guay (2002) and Coles et al (2006), we compute the compensation delta as the dollar change in the executive's annual compensation with respect to a 1% change in stock price. In a given year, an executive's compensation delta is the sum of the delta of new restricted stock grants and the delta of new option grants. The delta of restricted stock grants equals the number of restricted stock grants multiplied by the stock price times 0.01, and the delta of option grants is the number of option grants multiplied by the change in the Black-Scholes option value for a 1% change in stock price.

We estimate an executive's risk-taking incentives as the sensitivity of the executive's Black-Scholes value of new option grants with respect to a 0.01 change in stock volatility (vega). We do not estimate the vega of stock grants since Guay (1999) documents that the vega of stocks is insignificant compared to the vega of options. Because founding families tend to have large equity ownerships in their firms, family executives' total wealth will be more sensitive to changes in stock price and volatility than the wealth of executives in nonfamily firms. To capture executives' existing incentive from their portfolio holdings, we calculate the portfolio delta and portfolio vega based on the executives' existing equity holdings at the beginning of the year following the approximation method of Core and Guay (2002). To estimate the risk-free rate used in vega and delta computations, we use the ten-year treasury notes constant maturity series available from the Federal Reserve Bank's official website.

Table 12 presents the results of our compensation analysis. Although the total compensation (unadjusted) significantly increases in every one of the years following the award of the additional title, the match-adjusted total compensation shows no increase (Panel A). In Panels B, C, D, and E, we present the results for the annual compensation delta, the total portfolio delta, the annual compensation vega, and the total portfolio vega. As with total compensation, the unadjusted annual compensation delta and annual compensation vega increase each year following the combination of leadership roles, but the changes in the match-adjusted delta and vega are largely insignificant (Panels B and D). Of particular note, the total portfolio delta (vega) increases each year on both an unadjusted and an adjusted basis (Panel C and E). The sum of the coefficients in the post-combination period is significant at less than the 1% level for both unadjusted and adjusted incentive measures. This result indicates that CEOs that obtain both roles tend to retain stock options and shares rather than cash out, which significantly increases their incentive alignment with shareholders. The option and share retention may serve as a bonding mechanism on the part of the CEO, or it may result from explicit or implicit pressure from the board or external monitors. Nonetheless, the consistent increase in incentive alignment is likely to serves as a mechanism that alleviates the agency problems that could arise from the combination of the CEO and the board chair positions.

In Table 13, we report the results for matched-firm compensation results for early and late CEO-Chair combinations. The results in panel A indicate that increases in total match-adjusted compensation accrue primarily to CEOs that receive both titles earlier, and these CEOs tend to also receive higher total compensation gains than do CEOs that receive both titles later (*p*-value of 0.02). This result supports the bargaining/retention framework since the decision to combine both roles early reveals the board's private information about the quality of the CEO and its willingness to increase compensation to retain the CEO. For CEOs that receive both positions later, the learning component and retention imperative are weaker. However, as shown in Panels B & D, there is no influence on annual incentive awards as measured by delta or vega. Total portfolio incentives, both delta and vega increase for both early and late combinations, and the increases are not statistically different (Panels C and E). Thus, the compensation results for early and late combinations tend to support the learning hypothesis and offer no support for the alternative agency explanation.

In Tables 14 and 15, we present the results for subsamples based on the coopted nature of the board and the pre- and post-SOX periods. Comparison of matched-firm compensation results for coopted and non-coopted boards suggests that there are no substantial differences in compensation, compensation delta, compensation vega, portfolio delta and portfolio vega between the two groups. Although CEOs with non-coopted boards and CEOs with coopted boards both tend to maintain stock and option portfolios that increase their alignment with shareholders, the portfolio delta actually increases more on the margin for CEOs with coopted boards (*p*-value of 0.08 for the difference). When we divide our sample into two sub groups – pre- and post- Sarbanes-Oxley, we find total compensation increases significantly following the combination for the post-Sox group (Table 15). The results might be explained in part by the increased accountability of the CEOs demanded by the regulation. Moreover, increases in portfolio delta are marginally greater for the post-SOX group (*p*-value of 0.08). However, contrary to the agency-model predictions, the notion that a CEO used increased power to boost her own pay is not supported by the data. Overall, we conclude that our evidence supports the premise that CEOs get additional title of chair based on the learning of their ability by the corporate board.

6. Conclusion

The combination of CEO and the chair positions conditioned on the performance of the CEO provides an opportunity to examine the role of learning in governance. In recent years, there has been growing regulatory and investor pressure to split the titles of CEO and board chair. In fact, there is a significant trend towards separation of the two titles. However, the empirical evidence in the literature is inconclusive on the impact of separating these roles. We argue that the inconclusive evidence arises from endogenous self-selection, including the board's need to learn about the CEO, which complicates empirical identification strategies and the ability to recognize the correct counterfactual firms.

To shed new light on the practice of some firms to combine the roles of CEO and chair after a period of time in which the board observes the actions and performance of the CEO, we propose a learning model of CEO-chair duality and implement an identification strategy to address sample selection issues. Our model and identification is based on "passing the baton" (PTB) firms that award the chair position after a probationary period during which the board of directors learns about the ability of the CEO. In the model, the board optimally awards the additional position of board chair if the CEO demonstrates

sufficient talent. The increase in CEO power improves the retention of high-quality CEOs by mitigating concerns about the board reneging on compensation contracts. The model delivers several implications that we test in our empirical analysis.

Using a sample of over 18,000 firm-year observations for the period 1995-2010, we explore the determinants and consequences of the combining the two roles. Firms that always combine the two roles, always separate the roles, or award the additional title following a period of evaluation exhibit significantly different firm characteristics, which suggest self-selection. We find that PTB firms are more likely to be from industries that are less homogenous. This is consistent with the learning rationale underlying PTB strategies, since CEO performance is harder to benchmark and where reneging on contracts may be of greater concern to CEOs. We also find that firms with more business segments are more likely to combine the two roles. These findings suggest that more complex organizations are better served by combining the roles of the CEO and the chair.

Overall, CEOs that receive the additional title of board chair outperform their industry benchmark before receiving both titles. In firms that combine the roles after observing the CEO's performance under a separate board chair, the combination is positively related to both firm and industry performance in the two years prior to the combination. As predicted by our model, a naïve analysis of the post-chair appointment performance, one that fails to control for selection issues and mean reversion in performance data, indicates a significant drop in firm performance relative to the pre-chair period. However, in a matched sample of firms where the matching criteria includes the pre-appointment performance and firm attributes that predict a high propensity for using a PTB succession strategy, we find that there is no post-appointment underperformance in stock returns or in accounting returns. These results suggest that the pass-the-baton succession process appears to be an equilibrium mechanism in which some firms optimally use the PTB structure to learn about the CEO and then award the additional title of board chair to increase the odds of retaining talented CEOs. Moreover, we document a statistically significant decline in both unmatched and match-adjusted idiosyncratic stock-return volatility, which is consistent with the learning model. Thus, the evidence is broadly consistent with the learning hypothesis that the additional title is awarded by the board after evaluating the ability of the CEO.

Our model suggests that, ceteris paribus, talented CEOs in a weaker bargaining position relative to the board will tend to be promoted to chair more quickly. The reason is that more vulnerable CEOs are more likely to pursue outside opportunities. Supportive of the prediction, we find that when the board is more independent and not coopted– the promotion to chair occurs more quickly. These findings are also counter to the notion that agency considerations and influence are central to the CEO being appointed chair. We also show that stockholders react positively to combinations that occur early in the CEO's tenure, which suggests that early promotions reveal directors' private information about the quality of the CEO to the market. This is inconsistent with alternative explanations such as an incentive rationale for PTB or agency problem, since both of these alternatives would suggest a negative market reaction to such promotions.

We do not interpret our results to indicate that there are no unique agency problems associated with combining the CEO and the chair position. However, the data do not suggest that PTB combinations result from agency problems. Furthermore, the incentives of CEOs that receive both positions become more closely aligned with the incentives of shareholders through personal wealth that is increasingly sensitive to share-price performance, which seems to be an equilibrium mechanism to mitigate potential agency problems that might arise from combining the two roles. When one considers the benefits of learning to many firms and the need to retain talented CEOs, we conclude that the process of combining the two roles after a period of observation is likely advantageous for these firms.

A major implication of our analysis for researchers is that one should consider learning mechanisms and retention objectives when evaluating various board structures. Structures that are seemingly incompatible with effective monitoring in a simple agency model may in fact be optimal when one considers the impact of learning on retention. For governance activists and policy makers, the implications of our analysis are straightforward: the results call into question the prevailing wisdom that suggests that shareholders will always be better served by separating the two roles. Thus, those who seek to reform governance should be cautious in proposing to unambiguously separate the roles of CEO and board chair. Forcing separation by fiat is likely not an ideal policy. Overall our evidence suggests that having one type of executive and board leadership structure is not optimal for all firms.

Appendix: Definitions and Data Source for Variables

Variable	Source	Definition
Combined CEO/Chair Positions	Proxy Statements, Corporate Library	CEO also chairs the board
Annual Stock Return	Compustat	$(PRCCF_t - PRCCF_{t-1} + DVPSX\_F)/PRCCF_{t-1}$
Annual Return on Assets	Compustat	(Operating Income before Depreciation and Amortization)/(Book Value of Total Assets); OIBDP/AT
Assets	Compustat	AT
Sales	Compustat	REVT
Firm Age	CRSP	First listing date on CRSP
Homogeneous Industry (0/1)	Calculated from CRSP data	Takes the value 1 if the Industry Homogeneity Measure (Parrino, 1997) is above the industry median
Board Size	Proxy Statements, Corporate Library	Number of directors on the board
Percentage Insider Directors	Proxy Statements, Corporate Library	Percentage of directors who work for the firm, are retired from the firm, or have an immediate family member who works or retired from the firm
Coopted Board (0/1)	Proxy Statements, Corporate Library	Takes the value 1 if the percentage of coopted directors is above the sample median. A director is coopted if the CEO has been in place longer than the director (Coles, Daniel, and Naveen, 2014)
% Foreign Tax (Percentile Rank)	Compustat	The percentile rank of Foreign Tax/Total Tax
Number of Business Segments	Compustat	The number of reported business segments
Capital Expenditures/Sales	Compustat	CAPX/REVT
R&D/Sales	Compustat	RDIP/REVT
Leverage Ratio	Compustat	Total Debt/Total Assets (DLTT+DLC)/(AT)
CEO Ownership (%)	Proxy Statements, ExecuComp	(Shares owned by the CEO)/)*100%
CEO Tenure	Proxy Statements, ExecuComp	Number of Years the CEO has been CEO
CEO Age	Proxy Statements, ExecuComp	Age of the CEO
Insider CEO (0/1)	Proxy Statements	Takes the value of 1 if the CEO is promoted from within the firm
Total Compensation	Execucomp	The sum of salary, bonus, other annual compensation, total value of restricted stock granted, total value of options granted, long-term incentive payouts, and all other total compensation (TDC1)
Compensation Delta	Calculated from Execucomp data	The dollar change in current CEO compensation for a 1% change in stock price following Coles, Daniel, and Naveen (2013)
Portfolio Delta	Calculated from Execucomp data	The dollar change in the CEO's portfolio holdings for a 1% change in stock price following Coles, Daniel, and Naveen (2013)
Compensation Vega	Calculated from Execucomp data	The dollar change in the CEO's Black-Scholes value of new option grants with respect to a 0.01 change in stock volatility following Coles, Daniel, and Naveen (2013)
Portfolio Vega	Calculated from Execucomp data	The dollar change in the CEO's Black-Scholes value of option portfolio with respect to a 0.01 change in stock volatility following Coles, Daniel, and Naveen (2013)

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Table 1. Combined CEO/Chair Roles, CEO Tenure, and Firm Age over Time and by Industry

This table presents summary statistics on the percentage of firms with CEOs who also of Chair the Board of directors, mean CEO tenure, and mean firm age. The sample excludes financial firms (SIC 6000 – 6799) and regulated utility firms (SIC 4910-4949). We provide statistics over time from 1995 to 2010 and across industry at the SIC code single-digit level.

Year	Observations	Percentage of Combined CEO-Chairs	CEO Tenure	Firm Age
1995	993	68.68	8.65	23.91
1996	1,075	68.84	8.48	22.62
1997	1,148	69.77	8.48	22.62
1998	1,175	68.60	8.48	22.25
1999	1,179	67.77	8.40	22.39
2000	1,111	69.04	8.14	22.44
2001	1,092	66.21	7.74	23.10
2002	1,101	66.76	7.71	23.90
2003	1,160	68.79	7.56	23.89
2004	1,177	66.61	7.94	24.33
2005	1,181	63.08	7.74	24.90
2006	1,102	60.25	7.57	24.90
2007	1,240	57.18	7.69	25.27
2008	1,160	58.53	7.77	26.10
2009	1,098	56.38	7.83	27.11
2010	1,031	55.00	8.27	27.02
All Years	18,023	64.46	8.01	24.21
Industry (Single-digit SIC)	**Observations**	**Percentage of Combined CEO-Chairs**	**CEO Tenure**	**Firm Age**
Agriculture, Forestry, and Fishing (0)	59	81.36	10.81	59.58
Mining and Construction (1)	1,200	65.25	8.45	23.17
Manufacturing (2)	3,697	71.11	7.51	30.71
Manufacturing (3)	6,288	63.93	7.82	25.64
Transportations and Public Utilities (4)	1,129	63.86	9.37	21.98
Wholesale and Retail Trade (5)	2,568	63.20	8.31	22.36
Services (7)	2,306	55.98	7.63	16.33
Health Services (8)	720	63.75	9.32	13.09
Other (9)	56	78.57	8.79	49.16
CEO-Chair Status		**Observations**	**CEO Tenure**	**Firm Age**
Combined CEO/Chair		11,618	9.86	26.26
Separate		6,405	4.66	20.50

Table 2. Summary Statistics

This table presents summary statistics for 18,023 firm years, 2,092 firms, and 3,972 CEO-firm pairs over 1995 - 2010. The sample excludes financial firms (SIC 6000 – 6799) and regulated utility firms (SIC 4910-4949). Industry adjustments are based on a firm's 3-digit historical SIC code. We classify an industry as homogeneous if its homogeneity measure (Parrino, 1997) is above the sample median. We use the sample percentile rank of a firm's foreign tax to total tax as a proxy for the extent of foreign operations. Leverage is the book value of total debt divided by the book value of total assets. All variables are winsorized at the 1% and 99% levels.

	Mean	Median	Minimum	Maximum	Standard Deviation
Combined CEO/Chair (0/1)	0.645	1	0	1	0.479
Passing the Baton Strategy (0/1)	0.440	0	0	1	0.496
Annual Ind.-adjusted Stock Return	0.082	0.003	-0.772	1.877	0.436
Annual Stock Return	0.173	0.103	-0.761	2.357	0.524
Annual Ind.-adjusted ROA	0.0218	0.012	-0.210	0.259	0.078
Annual ROA	0.148	0.143	-0.116	0.414	0.088
Assets ($ millions)	5,363.1	1,210.5	84.7	151,193	14,922.9
Sales ($ millions)	4,617.6	1,222.3	57.5	67.8	10,064.2
Firm Age	24.197	18	3	81	18.744
Homogeneous Industry (0/1)	0.438	0	0	1	0.496
Board Size	9.091	9	5	17	2.412
Percentage Insider Directors	0.220	0.182	0.067	0.600	0.123
Coopted Board (0/1)	0.285	0	0	1	0.451
% Foreign Tax (Percentile Rank)	63.237	58.913	43.799	100	18.988
Number of Business Segments	2.669	2	1	8	1.833
Capital Expenditures/Sales	0.076	0.041	0	0.733955	0.115
R&D Expense/Sales	0.043	0.004	0	0.402431	0.078
Leverage Ratio	0.213	0.201	0	0.751625	0.174
CEO Ownership (%)	2.443	0.334	0	33.63	5.773
CEO Tenure	7.960	5	0	37	7.868
CEO Age	55.468	55	39	76	7.344
Insider CEO (0/1)	0.830	1	0	1	0.375

Table 3. Comparison of Firm Characteristics by History of Combining the CEO and Chair Roles

This table presents firm, industry, and CEO characteristics for 15,029 firm years, 1.789 firms, and 3,214 CEO-firm pairs over 1995 - 2010. We segregate the sample by the firm's history of combining the roles of CEO and board chair over our sample period or allowing the CEO to receive both roles after a period of observation. Industry adjustments are based on a firm's 3-digit historical SIC code. The sample excludes financial firms (SIC 6000 – 6799) and regulated utility firms (SIC 4910-4949).We classify an industry as homogeneous if its homogeneity measure (Parrino, 1997) is above the sample median. We use the sample percentile rank of a firm's foreign tax to total tax as a proxy for the extent of foreign operations. Leverage is the book value of total debt divided by the book value of total assets. All variables are winsorized at the 1% and 99% levels.

	(1) Roles Always Combined	(2) CEO Earns Both Roles	(3) Roles Always Separate	*t*-statistics for Differences (1) – (2)	(1) – (3)	(2) – (3)
Combined CEO/Chair (0/1)	1	0.599	0	72.90***	NA	NA
Tobin's Q	1.959	2.011	2.12	2.36**	4.46***	3.11***
Annual Ind.-adjusted Stock Return	0.072	0.079	0.094	0.96	1.82*	1.28
Annual Stock Return	0.170	0.167	0.181	0.35	0.77	1.02
Annual Ind.-adjusted ROA	0.022	0.023	0.019	0.70	1.34	1.79*
Annual ROA	0.150	0.149	0.144	1.14	2.37**	1.75*
Assets ($ millions)	7,243.0	5.379.3	2,720.4	6.12***	12.58***	9.26***
Sales ($ millions)	5,7636.5	4,907.0	2,323.9	4.38***	14.49***	12.27***
Firm Age	27.098	26.131	16.066	2.61***	28.13***	31.04***
Homogeneous Industry (0/1)	0.476	0.396	0.491	9.01***	1.10	7.44***
Board Size	9.134	9.275	8.481	3.21***	10.88***	14.22***
Percentage Insider Directors	0.215	0.216	0.227	0.07	3.69***	3.81***
Coopted Board (0/1)	0.371	0.247	0.267	14.91***	8.59***	1.70*
% Foreign Tax (Percentile Rank)	63.268	63.637	60.152	1.09	6.27***	7.43***
Number of Business Segments	2.811	2.641	2.508	5.10***	6.34***	2.97***
Capital Expenditures/Sales	0.079	0.072	0.086	3.47***	2.08***	4.41***
R&D Expense/Sales	0.032	0.044	0.057	10.39***	10.50***	5.24***
Leverage Ratio	0.225	0.212	0.188	4.26***	7.78***	5.33***
CEO Ownership (%)	3.954	1.838	1.151	18.05***	23.38***	8.32***
CEO Tenure	10.662	6.709	5.602	27.51***	30.20***	7.86***
CEO Age	56.887	55.341	52.430	12.21***	24.26***	16.83***
Observations	5,194	7,929	1,906			

Table 4. Multinomial Logistic Analysis of Combining CEO and Board Chair Roles after a Probationary Period

This table presents coefficient estimates from a multinomial logistic model of the propensity to combine the functions of the CEO and board chair for a sample of 15,029 firm years, 1.789 firms, and 3,214 CEO-firm pairs over 1995 - 2010. The dependent variable is 0 if a firm always separates the roles of CEO and board chair, 1 if a firm follows a practice of awarding CEOs both titles after a period of serving as only CEO, and 2 if the firm always combines the two roles. Variables are defined in the Appendix and are winsorized at the 1% and 99% levels. *p*-values for significance, in parentheses, are based on robust standard errors clustered by CEO-firm pair. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Base Case: Always Separate				Base Case: Always Combined			
	Passing the Baton	Always Combined	Passing the Baton	Always Combined	Passing the Baton	Always Separate	Passing the Baton	Always Separate
Tobin's Q	0.018	0.039	-0.006	0.006	-0.022	-0.039	-0.012	-0.006
	(0.65)	(0.37)	(0.88)	(0.89)	(0.54)	(0.37)	(0.74)	(0.89)
Ln(Assets)	0.352***	0.474***	0.399***	0.533***	-0.123***	-0.474***	-0.134***	-0.533***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Ln(Firm Age)	0.595***	0.468***	0.626***	0.492***	0.127*	-0.468***	0.134*	-0.492***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.10)	(0.00)	(0.09)	(0.00)
Homogeneous Industry (0/1)	-0.397***	-0.212	-0.190	0.068	-0.185*	0.212	-0.258**	-0.068
	(0.00)	(0.13)	(0.30)	(0.73)	(0.08)	(0.13)	(0.05)	(0.73)
Ln(board Size)	-0.155	-0.632**	-0.282	-0.932***	0.477**	0.632**	0.650***	0.932***
	(0.58)	(0.04)	(0.34)	(0.00)	(0.03)	(0.04)	(0.00)	(0.00)
Inside Directors (%)	0.028	-1.007*	-0.989*	-2.277***	1.035***	1.007*	1.288***	2.277***
	(0.95)	(0.06)	(0.06)	(0.00)	(0.01)	(0.06)	(0.00)	(0.00)
Coopted Board (0/1)	-0.322***	-0.267**	-0.091	0.171	-0.054	0.267**	-0.261***	-0.171
	(0.00)	(0.02)	(0.47)	(0.22)	(0.47)	(0.02)	(0.01)	(0.22)
% Foreign Tax (Percentile Rank)	0.005*	0.008**	0.006*	0.009**	-0.003	-0.008**	-0.003	-0.009**
	(0.08)	(0.02)	(0.09)	(0.02)	(0.25)	(0.02)	(0.23)	(0.02)
Number of Business. Segments	-0.152***	-0.108***	-0.190***	-0.141***	-0.044*	0.108***	-0.048*	0.141***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.08)	(0.01)	(0.08)	(0.00)
Capital Expenditures/Sales	-0.669	-0.746	-1.197**	-1.082*	0.076	0.746	-0.115	1.082*
	(0.18)	(0.14)	(0.05)	(0.09)	(0.86)	(0.14)	(0.82)	(0.09)

Continued

Table 4. Continued

	Base Case: Always Separate				Base Case: Always Combined			
	Passing the Baton	Always Combined	Passing the Baton	Always Combined	Passing the Baton	Always Separate	Passing the Baton	Always Separate
R&D Expense/Sales	-0.601	-3.006***	-1.027	-3.439***	2.405***	3.006***	2.412***	3.439***
	(0.45)	(0.00)	(0.22)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Leverage Ratio	-0.115	0.319	-0.337	-0.075	-0.434	-0.319	-0.263	0.075
	(0.76)	(0.43)	(0.34)	(0.85)	(0.11)	(0.43)	(0.35)	(0.85)
CEO Ownership (%)	0.095***	0.132***	0.098***	0.136***	-0.037***	-0.132***	-0.038***	-0.136***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Ln(CEO Tenure)	0.027	0.602***	0.027	0.561***	-0.575***	-0.602***	-0.533***	-0.561***
	(0.72)	(0.00)	(0.72)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Ln(CEO Age)	2.134***	2.197***	1.905***	1.877***	-0.062	-2.197***	0.028	-1.877***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.88)	(0.00)	(0.95)	(0.00)
Constant	-10.672***	-12.253***	-11.262***	-10.161***	1.581	12.253***	-1.101	10.161***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.33)	(0.00)	(0.54)	(0.00)
Year Dummies (0/1)	No	No	Yes	Yes	No	No	Yes	Yes
Industry Dummies (0/1)	No	No	Yes	Yes	No	No	Yes	Yes
Pseudo R^2	0.0925		0..1107		0.0925		0.1107	

Table 5. Hazard Model for Propensity to Combine the CEO and Board Chair Functions

This table presents estimates of hazard ratios from a Cox proportional hazard model of the propensity to combine the CEO and board chair functions for 1,646 CEO-firm pairs and 688 firms that follow a passing-the-baton strategy. The sample comprises 7,929 firm years over 1995-2010. Firms that always separate or always combine the CEO-Chair roles during the sample period are excluded. The dependent variable equals 1 if the CEO receives both titles after a period of observation and zero if not. Variables are defined in the Appendix and are winsorized at the 1% and 99% levels. *p*-values, in parentheses, are based on robust standard errors clustered at the CEO-firm pair level. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Industry-adjusted Stock Return$_{-1}$ (β_1)	1.106**				1.085	
	(0.04)				(0.11)	
Industry-adjusted Stock Return$_{-2}$ (β_2)	1.184***				1.157***	
	(0.00)				(0.00)	
Industry Median Stock Return$_{-1}$ (β_3)		1.385***				1.347***
		(0.00)				(0.00)
Industry Median Stock Return$_{-2}$ (β_4)		2.517***				2.482***
		(0.00)				(0.00)
Industry-adjusted ROA$_{-1}$ (β_5)			2.839***		2.175**	
			(0.01)		(0.05)	
Industry-adjusted ROA$_{-2}$ (β_6)			0.721		0.814	
			(0.36)		(0.57)	
Industry Median ROA$_{-1}$ (β_7)				1.160		0.875
				(0.71)		(0.73)
Industry Median ROA$_{-2}$ (β_8)				2.275***		1.786*
				(0.01)		(0.08)
Ln(Assets)	0.980	0.982	0.975	0.982	0.975	0.983
	(0.52)	(0.57)	(0.43)	(0.57)	(0.44)	(0.58)
Ln(Firm Age)	0.882*	0.886*	0.878*	0.868**	0.886*	0.884*
	(0.07)	(0.08)	(0.06)	(0.04)	(0.08)	(0.07)
Homogeneous Industry (0/1)	0.924	0.912	0.930	0.918	0.932	0.911
	(0.34)	(0.26)	(0.38)	(0.30)	(0.40)	(0.26)
Ln(board Size)	1.488**	1.429**	1.472**	1.471**	1.476**	1.422**
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.05)
Inside Directors (%)	5.136***	5.225***	5.382***	5.416***	5.179***	5.234***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Coopted Board (0/1)	0.707***	0.676***	0.706***	0.699***	0.706***	0.678***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
% Foreign Tax (Percentile Rank)	0.998	0.999	0.998	0.998	0.998	0.999
	(0.32)	(0.67)	(0.42)	(0.40)	(0.40)	(0.69)
Number of Business. Segments	1.045**	1.035*	1.047**	1.045**	1.046**	1.036*
	(0.03)	(0.10)	(0.03)	(0.03)	(0.03)	(0.09)
Capital Expenditures/Sales	1.855**	1.618**	1.993***	1.950***	1.921***	1.592**
	(0.01)	(0.04)	(0.00)	(0.00)	(0.01)	(0.05)
R&D Expense/Sales	1.106	1.390	1.149	1.451	1.123	1.531
	(0.83)	(0.46)	(0.77)	(0.41)	(0.81)	(0.35)
Leverage Ratio	1.963***	1.898***	1.919***	1.919***	2.002***	1.925***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Continued

Table 5. Continued

	Model 1	Model 2	Model 4	Model 5	Model 6	Model 7
Outsider CEO (0/1)	0.733***	0.739***	0.738***	0.737***	0.739***	0.740***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
CEO Ownership (%)	0.992	0.992	0.992	0.991	0.992	0.992
	(0.36)	(0.33)	(0.37)	(0.27)	(0.38)	(0.33)
Residual Ln(CEO Tenure)	1.693***	1.739***	1.697***	1.718***	1.690***	1.740***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Ln(CEO(Age)	0.996	0.949	0.988	0.972	0.999	0.955
	(0.99)	(0.88)	(0.97)	(0.93)	(1.00)	(0.89)
Pseudo R^2	0.0126	0.0162	0.0125	0.0126	0.0127	0.0163
Joint ψ^2 for $\beta_1 = 0$ and $\beta_2 = 0$	12.71***				9.05**	
Joint ψ^2 for $\beta_3 = 0$ and $\beta_4 = 0$		173.3.6***				169.18***
Joint ψ^2 for $\beta_5 = 0$ and $\beta_6 = 0$			7.41**		3.92	
Joint ψ^2 for $\beta_7 = 0$ and $\beta_8 = 0$				10.43***		3.50

Table 6. Investor Reactions to the Announcement that a CEO Will Become Chair of the Board

This table presents event study results around the announcement that a CEO will be awarded the additional title of board chair. We use the event study method of Patell (1976) based on the market model and the value-weighted CRSP index. The sample excludes financial firms (SIC 6000 – 6799) and regulated utility firms (SIC 4910-4949,

	Obs.	CAR (t_{-1}-t_{+1})	Patell Z-score	Sign Rank Test
All Announcements	213	0.35%	0.96	0.47
Receive Tenure < 4 Years	119	1.09%	2.71***	2.27**
Receive Tenure ≥ 4 Years	94	-0.59%	-1.60	-1.27
Non-coopted Boards	152	-0.15%	-0.06	0.17
Coopted Boards	61	1.58%	1.89*	0.61
Before Sarbanes-Oxley Act	139	0.09%	0.18	-0.10
After Sarbanes-Oxley Act	74	0.82%	1.24	0.94
CEO is Insider	187	0.39%	1.30	0.86
CEO is Outsider	26	0.00%	-0.75	-0.95

Table 7. Comparison of Firm Characteristics after Propensity Score Matching

	Mean		Paired t-test	Median		Paired Sign Test
	PTB	Matched	p-value	PTB	Median	p-value
Stock Return (%)	19.71	2.09	0.70	11.64	11.86	0.90
Return on Assets (%)	15.02	15.08	0.91	14.59	13.87	0.15
Tobin's Q	2.07	2.15	0.27	1.62	1.57	0.46
Ln(Assets)	7.27	7.28	0.89	7.07	7.05	0.65
Ln(Firm Age)	2.96	2.98	0.62	3.00	3.00	0.48
Homogeneous Industry (0/1)	0.40	0.44	0.12	0.00	0.00	0.13
Ln(Board Size)	2.21	2.21	0.81	2.20	2.20	0.86
Percent Inside Directors (%)	23.90	23.75	0.82	21.83	21.43	0.77
Coopted Board (0/1)	0.16	0.19	0.09	0.00	0.00	0.11
% Foreign Tax (Percentile Rank)	62.75	63.20	0.69	58.72	58.18	1.00
Number of Business Segments	2.60	2.64	0.74	2.00	2.00	0.22
Capital Expenditures/Sales	0.08	0.08	0.35	0.04	0.40	0.83
R&D Expense/Sales	0.04	0.04	0.71	0.00	0.00	1.00
Leverage Ratio	0.22	0.23	0.50	0.22	0.22	0.87
CEO Ownership (%)	1.38	1.50	0.52	0.21	0.17	0.39
Ln(CEO Tenure)	1.29	1.30	0.70	1.39	1.10	1.00
Ln(CEO Age)	3.97	3.96	0.26	3.98	3.97	0.80

Table 8. Firm Performance and Policies Before and After Receiving Both CEO and Chair Positions

This table presents mean (median) firm stock and accounting performance before and after awarding the CEO the position of board chair. Variables are defined in The Appendix and are winsorized at the 1% and 99% levels. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

Panel A. Comparison of Firm Performance

	Obs.	Before Combining CEO and Chair	After Combining CEO and Chair	p-value for difference	Entire Period
Stock Returns	4,169	20.03%***	14.66%***	0.00***	16.91%***
	4,169	(12.10%)***	(9.62%)***	0.04**	(10.35%)***
Match-adjusted Stock Returns	4,169	1.09%	0.49%	0.68	0.74%
	4,169	(0.20%)	(0.57%)	0.97	(0.42%)
Return on Assets	4,169	14.30%***	13.72%***	0.09*	13.98%***
	4,169	(14.19%)***	(13.58%)***	0.01***	(13.95%)***
Match-adjusted Return on Assets	4,169	0.52 %	0.73%	0.62	0.65%***
	4,169	(1.05%)*	(0.66%)	0.67	(0.83%)***

Panel B. Comparison of Firm Policies

	Obs.	Before Combining CEO and Chair	After Combining CEO and Chair	p-value for difference	Entire Period
CAPEX/Sales	4,169	0.082***	0.078***	0.32	0.079***
	4,169	(0.043)	(0.037)	0.00***	(0.040)
Match-adjusted CAPEX/Sales	4,036	0.003	0.009***	0.13	0.007***
	4,036	(0.000)	(0.001)**	0.00***	(0.001)**
R&D/Sales	4,169	0.045***	0.043***	0.66	0.044***
	4,169	(0.000)***	(0.004)***	0.01**	(0.003)***
Match-adjusted R&D/Sales	4,060	0.002	-0.001	0.06*	0.000
	4,060	(0.000)	(0.000)***	0.00**	(0.000)
Leverage	4,169	0.207***	0.226***	0.00***	0.218***
	4,169	(0.199)***	(0.218)***	0.00***	(0.211)***
Match-adjusted Leverage	4,031	-0.013***	0.010***	0.00***	0.000
	4,031	(0.000)*	(0.000)	0.00***	(0.000)
Business Segments	4,169	2.400***	2.820***	0.00***	2.644***
	4,169	(2.000)***	(3.000)***	0.00***	(2.000)***
Match-adjusted Business Segments	4,029	-0.076**	-0.147***	0.15	-0.117***
	4,029	(0.000)***	(0.000)**	0.00***	(0.000)***

Panel C. Comparison of Firm Stock Risk

	Obs.	Before Combining CEO and Chair	After Combining CEO and Chair	p-value for difference	Entire Period
Total Risk	4,133	0.461***	0.423***	0.00***	0.439***
	4,133	(0.408)***	(0.375)***	0.00***	(0.388)***
Match-adjusted Total Risk	3,989	0.009**	-0.010***	0.00***	-0.002
	3,989	(0.004)***	(-0.001)	0.00***	(0.002)
CAPM Market Risk	4,133	0.990***	1.070***	0.00***	1.036***
	4,133	(0.868)***	(1.011)***	0.00***	(0.959)***
Match-adjusted CAPM Market Risk	4,027	0.003	-0.009	0.46	0.000
	4,027	(-0.000)	(0.001)	0.00***	(-0.004)
Firm-specific Risk	4,133	0.417***	0.361***	0.00***	0.384***
	4,133	0.369***	0.322***	0.00***	0.339***
Match-adjusted Firm-specific Risk	3,992	0.004	-0.015	0.00***	-0.007
	3,992	0.003	-0.006	0.00***	-0.007

Table 9. Effects of Combining the CEO and Board Chair Functions

This table presents our analysis of performance and policy variables after combining the CEO and the chair positions. Following the method in Pagano, Panetta, and Zingales (1998), we estimate the following specification for each dependent variable: $y_{it} = \beta_0 + \sum_{t=1}^{4} \beta_t Combined_t + \beta_5 Combined_{t>4} + u_i + d_t + \varepsilon_{it}$ where u_i and d_t are CEO-firm pair and year fixed effects, respectively. $Combined_t$ is 1 if period t is after the CEO became board chair and zero otherwise. The sample comprises 600 CEO-firm pairs. Variables are defined in The Appendix and are winsorized at the 1% and 99% levels. *p*-values, in parentheses, are based on robust standard errors clustered by CEO-firm pair. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Obs.	Year 1	Year 2	Year 3	Year 4	Year > 4	F-Test
Panel A. Performance Analysis							
Stock Return	4,169	-0.020	-0.088***	-0.047*	-0.105***	-0.120***	17.47***
		(0.39)	(0.00)	(0.07)	(0.00)	(0.00)	(0.00)
Match-Adjusted Stock Return	4,169	0.001	-0.018	-0.039	-0.062	-0.009	1.27
		(0.97)	(0.55)	(0.31)	(0.13)	(0.65)	(0.26)
ROA	4,169	-0.001	-0.001	-0.005	-0.007	-0.017***	4.23**
		(0.63)	(0.78)	(0.19)	(0.12)	(0.00)	(0.04)
Match-Adjusted ROA	4,169	0.005	0.008	-0.000	0.002	0.003	0.54
		(0.01)	(0.06)	(0.02)	(0.04)	(0.06)	(0.46)
Panel B. Policy Analysis							
Capex/Sales	4,169	-0.006***	-0.007***	-0.007**	-0.008**	-0.06	9.59***
		(0.00)	(0.01)	(0.03)	(0.02)	(0.11)	(0.00)
Match-Adjusted CAPEX/Sales	4,077	-0.004	-0.003	0.003	0.008	0.011*	0.87
		(0.25)	(0.45)	(0.48)	(0.20)	(0.09)	(0.35)
R&D/Sales	4,169	-0.002	-0.003	-0.001	-0.002	0.000	0.95
		(0.13)	(0.14)	(0.61)	(0.24)	(0.92)	(0.33)
Match-Adjusted R&D/Sales	4,060	-0.02	-0.02	-0.000	0.000	-0.001	0.27
		(0.16)	(0.30)	(0.99)	(0.96)	(0.88)	(0.60)
Leverage Ratio	4,169	0.006	0.019***	0.014**	0.012	0.015*	6.14**
		(0.12)	(0.00)	(0.04)	(0.15)	(0.09)	(0.01)
Match-Adjusted Leverage Ratio	4,031	-0.01	0.008	0.003	-0.006	0.007	0.10
		(0.84)	(0.28)	(0.77)	(0.59)	(0.56)	(0.76)
Business Segments	4,169	0.154***	0.189***	0.212***	0.273***	0.465***	25.98***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Match-Adjusted Business Segments	4,029	0.063	-0.031	-0.079	-0.010	-0.053	0.10
		(0.29)	(0.70)	(0.40)	(0.93)	(0.65)	(0.75)

Continued

Table 9. Continued

	Obs.	Year 1	Year 2	Year 3	Year 4	Year > 4	F-Test
Panel C. Firm Stock Risk Analysis							
Total Risk	4,133	-0.011**	-0.020***	-0.014*	-0.015*	-0.006	4.57**
		(0.03)	(0.00)	(0.06)	(0.09)	(0.59)	(0.03)
Match-adjusted Total Risk	3,989	-0.013**	-0.027***	-0.022**	-0.015	-0.013	7.10***
		(0.03)	(0.00)	(0.03)	(0.16)	(0.26)	(0.01)
CAPM Market Risk	4,133	0.021	0.028	0.026	0.005	0.064*	2.07
		(0.19)	(0.20)	(0.29)	(0.88)	(0.08)	(0.15)
Match-adjusted CAPM Market Risk	4,027	0.016	0.012	0.003	-0.043	0.024	0.01
		(0.76)	(0.67)	(0.92)	(0.26)	(0.53)	(0.91)
Firm-specific Risk	4,133	-0.019***	-0.030***	-0.029***	-0.034***	-0.034***	27.21***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Match-adjusted Firm-specific Risk	3,992	-0.013**	-0.020**	-0.024***	-0.017*	-0.025**	8.37***
		(0.05)	(0.01)	(0.01)	(0.09)	(0.02)	(0.00)

Table 10. Comparison of Change in Performance CEO-Chair Combinations: Robustness Tests

This table presents robustness tests for performance variables after combining the CEO and the chair positions. Following the method in Pagano, Panetta, and Zingales (1998), we estimate the following specification for each dependent variable: $y_{it} = \beta_0 + \sum_{t=1}^{4} \beta_t Combined_t + \beta_5 Combined_{t>4} + u_i + d_t + \varepsilon_{it}$ where u_i and d_t are CEO-firm pair and year fixed effects, respectively. $Combined_t$ is 1 if period t is after the CEO became board chair and zero otherwise. The sample comprises 600 CEO-firm pairs and 4,169 (4,116) observations for stock return (ROA). Variables are defined in The Appendix and are winsorized at the 1% and 99% levels. *p*-values, in parentheses, are based on robust standard errors clustered by CEO-firm pair. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Year 1	Year 2	Year 3	Year 4	Year > 4	F-Test
Panel A. Firm Performance by Non-Coopted (486 firms) and Coopted (114 firms) Boards at Combination						
Match-adjusted Stock Returns (Non-coopted)	-0.010	-0.004	-0.047	-0.029	-0.028	0.82
	(0.77)	(0.93)	(0.28)	(0.59)	(0.59)	(0.37)
Match-adjusted Stock Returns (Coopted)	0.051	-0.055	-0.025	-0.096*	-0.014	0.74
	(0.38)	(0.24)	(0.69)	(0.09)	(0.75)	(0.39)
p-value for Difference	0.35	0.38	0.77	0.35	0.80	0.89
Match-adjusted ROA (Non-coopted)	0.007	0.007	-0.007	-0.000	0.005	0.26
	(0.12)	(0.21)	(0.32)	(0.99)	(0.60)	(0.61)
Match-adjusted ROA (Coopted)	-0.003	0.012	0.009	0.004	0.002	0.44
	(0.75)	(0.20)	(0.32)	(0.76)	(0.84)	(0.50)
p-value for Difference	0.33	0.61	0.12	0.77	0.71	0.75
Panel B. Firm Performance for CEO Ownership Below Median (300 CEOs) and Above Median (300 CEOs)						
Match-adjusted Stock Returns (Below Median)	-0.018	-0.022	-0.054	-0.074	-0.041	0.44
	(0.71)	(0.59)	(0.31)	(0.18)	(0.38)	(0.51)
Match-adjusted Stock Returns (Above Median)	0.018	-0.017	-0.025	-0.052	0.002	1.95
	(0.65)	(0.71)	(0.63)	(0.37)	(0.96)	(0.16)
p-value for Difference	0.56	0.94	0.69	0.77	0.46	0.66
Match-adjusted ROA (Below Median)	0.006	0.012	-0.002	-0.001	0.004	0.30
	(0.34)	(0.14)	(0.84)	(0.91)	(0.73)	(0.58)
Match-adjusted ROA (Above Median)	0.004	0.005	0.002	0.005	0.001	0.28
	(0.44)	(0.49)	(0.81)	(0.66)	(0.90)	(0.60)
p-value for Difference	0.83	0.48	0.76	0.68	0.85	0.96
Panel C. Firm Performance by Homogeneous Industries (242 firms) and Heterogeneous Industries (358 firms)						
Match-adjusted Stock Returns (Homogeneous)	0.089	-0.031	-0.079	-0.114*	-0.032	0.98
	(0.07)	(0..49)	(0.19)	(0.08)	(0.56)	(0.32)
Match-adjusted Stock Returns (Heterogeneous)	-0.057	-0.010	-0.014	-0.032	-0.010	0.67
	(0.14)	(0.81)	(0.77)	(0.53)	(0.83)	(0.41)
p-value for Difference	0.02**	0.72	0.38	0.30	0.72	0.83
Match-adjusted ROA (Homogeneous)	0.010	0.009	-0.004	-0.001	-0.016	0.00
	(0.17)	(0.30)	(0.68)	(0.94)	(0.13)	(0. 97)
Match-adjusted ROA (Heterogeneous)	0.002	0.008	0.002	0.003	0.014	0.97
	(0.69)	(0.20)	(0.75)	(0.75)	(0.20)	(0.32)
p-value for Difference	0.37	0.91	0.59	0.78	0.03	0.49

continued

Table 10. Continued

	Year 1	Year 2	Year 3	Year 4	Year > 4	F-Test
Panel D. Firm Performance for Early (<4 years, 298 CEOs) and Late (≥ 4 years, 302 CEOs) Combinations						
Match-adjusted Stock Returns (Early)	0.042	-0.047	-0.028	-0.043	-0.043	1.20
	(0.35)	(0.27)	(0.55)	(0.39)	(0.36)	(0.42)
Match-adjusted Stock Returns (Late)	-0.037	0.014	-0.49	-0.085	0.011	0.61
	(0.37)	(0.75)	(0.40)	(0.18)	(0.83)	(0.38)
p-value for Difference	0.20	0.31	0.77	0.59	0.36	0.89
Match-adjusted ROA (Early)	0.015**	0.013	0.006	0.002	0.015	1.38
	(0.05)	(0.17)	(0.59)	(0.87)	(0.37)	(0.24)
Match-adjusted ROA (Late)	0.003	0.007	-0.002	0.002	-0.001	0.08
	(0.60)	(0.24)	(0.80)	(0.86)	(0.89)	(0.77)
p-value for Difference	0.16	0.58	0.54	0.96	0.37	0.38
Panel E. Firm Performance for Combinations Before (398 CEOs) and After (212 CEOs) Sarbanes Oxley						
Match-adjusted Stock Returns (Before SOX)	-0.016	-0.024	-0.057	-0.062	-0.039	0.45
	(0.71)	(0.56)	(0.20)	(0.21)	(0.39)	(0.50)
Match-adjusted Stock Returns (After SOX)	0.027	-0.021	-0.008	-0.091	0.074	1.65
	(0.50)	(0.71)	(0.91)	(0.22)	(0.38)	(0.20)
p-value for Difference	0.48	0.98	0.60	0.74	0.23	0.92
Match-adjusted ROA (Before SOX)	0.009	0.009	-0.012	-0.004	0.001	0.50
	(0.13)	(0.18)	(0.13)	(0.66)	(0.92)	(0.48)
Match-adjusted ROA (After SOX)	-0.002	0.003	0.027**	0.018	0.003	0.01
	(0.76)	(0.76)	(0.03)	(0.28)	(0.88)	(0.94)
p-value for Difference	0.30	0.65	0.02**	0.28	0.93	0.33

Table 11. Influence of Policy Changes on Firm Performance Following Combination of CEO and Chair Positions

This table present our analysis of the influence of policy changes on firm performance after combining the CEO and the chair positions. Following the method in Pagano, Panetta, and Zingales (1998), we estimate the following specification for each dependent variable: $y_{it} = \beta_0 + \sum_{t=1}^{4} \beta_t Combined_t + \beta_5 Combined_{t>4} + u_i + d_t + \varepsilon_{it}$ where u_i and d_t are CEO-firm pair and year fixed effects, respectively. $Combined_t$ is 1 if period t is after the CEO became board chair and zero otherwise. The sample comprises 600 CEO-firm pairs. Variables are defined in The Appendix and are winsorized at the 1% and 99% levels. *p*-values, in parentheses, are based on robust standard errors clustered at the CEO-firm pair level. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Match-Adjusted Stock Return	Match-Adjusted Stock Return	Match-Adjusted Return on Assets	Match-Adjusted Return on Assets
Year 1	-0.020		0.003	
	(0.71)		(0.75)	
Year2	-0.039		0.007	
	(0.49)		(0.46)	
Year3	-0.058		-0.001	
	(0.32)		(0.95)	
Year4	-0.087		0.000	
	(0.16)		(0.99)	
> Year5	-0.038		-0.003	
	(0.53)		(0.81)	
Capital Expenditures/Sales	-1.461***	-1.435***	-0.062	-0.064
	(0.00)	(0.00)	(0.20)	(0.18)
R&D/Sales	-1.088**	-1.043**	-0.663***	-0.667***
	(0.02)	(0.02)	(0.00)	(0.00)
Leverage	-0.319**	-0.294**	-0.148***	-0.150**
	(0.02)	(0.03)	(0.00)	(0.00)
Number of Business Segments	0.011	0.014	0.004	0.004
	(0.45)	(0.32)	(0.13)	(0.14)
CAPEX/Sales*Combined	0.101	0.069	-0.020	-0.017
	(0.60)	(0.70)	(0.59)	(0.64)
R&D/Sales*Combined	-0.227	-0.307	0.113	0.120**
	(0.42)	(0.24)	(0.10)	(0.05)
Leverage*Combined	0.097	0.054	0.033	0.037*
	(0.47)	(0.64)	(0.19)	(0.07)
No. Bus. Segments*Combined	-0.004	-0.009	-0.004*	-0.003*
	(0.76)	(0.38)	(0.07)	(0.07)
Constant	0.158**	0.132**	0.054***	0.056***
	(0.02)	(0.02)	(0.00)	(0.00)
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	4,169	4,169	4,116	4,116
R^2	0.023	0.022	0.084	0.083

Table 12. Comparison of Change in Compensation for CEO-Chair Combinations

This table present our analysis of CEO compensation after combining the COE and the chair positions. Following the method in Pagano, Panetta, and Zingales (1998), we estimate the following specification for each dependent variable: $y_{it} = \beta_0 + \sum_{t=1}^{4} \beta_t Combined_t + \beta_5 Combined_{t>4} + u_i + d_t + \varepsilon_{it}$ where u_i and d_t are CEO-firm pair and year fixed effects, respectively. $Combined_t$ is 1 if period t is after the CEO became board chair and zero otherwise. The sample comprises 600 CEO-firm pairs. Variables are defined in The Appendix and are winsorized at the 1% and 99% levels. *p*-values, in parentheses, are based on robust standard errors clustered at the CEO-firm pair level. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Obs.	Year 1	Year 2	Year 3	Year 4	Year > 4	F-Test
Panel A. Analysis of Ln(Total Compensation)							
Total Compensation	4,169	0.178***	0.224***	0.224***	0.324***	0.337***	62.46***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Match-Adjusted Total Comp.	4,068	0.020	-0.018	-0.013	0.041	0.011	0.04
		(0.62)	(0.72)	(0.82)	(0.49)	(0.88)	(0.84)
Panel B. Analysis of Ln(Compensation Delta)							
Compensation Delta	4,169	0.180***	0.153**	0.184***	0.285***	0.211**	12.29***
		(0.00)	(0.02)	(0.01)	(0.00)	(0.03)	(0.00)
Match-Adjusted Compensation Delta	4,082	0.702***	-0.239	0.376	0.509	0.208	0.24
		(0.00)	(0.29)	(0.21)	(0.15)	(0.53)	(0.62)
Panel C. Analysis of Ln(Total Portfolio Delta)							
Portfolio Delta	4,169	0.336***	0.424***	0.539***	0.557***	0.668***	156.27
		(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)
Match-Adjusted Portfolio Delta	4,082	0.208***	0.347***	0.510***	0.610***	0.667***	18.76***
		(0.09)	(0.58)	(0.95)	(0.24)	(0.68)	(0.00)
Panel D. Analysis of Ln(Compensation Vega)							
Compensation Vega	4,169	0.312***	0.434***	0.481***	0.659***	0.708***	111.79***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Match-Adjusted Compensation Vega	4,082	0.026	0.011	0.000	0.253*	-0.006	0.35
		(0.76)	(0.92)	(0.99)	(0.10)	(0.97)	(0.55)
Panel E. Analysis of Ln(Portfolio Vega)							
Portfolio Vega	4,169	0.180***	0.153**	0.184***	0.285***	0.211**	12.29***
		(0.00)	(0.02)	(0.01)	(0.00)	(0.03)	(0.00)
Match-Adjusted Portfolio Vega	4,036	0.210***	0.314***	0.402***	0.389***	0.565**	16.97***
		(0.00)	(0.00)	(0.01)	(0.00)	(0.02)	(0.00)

Table 13. Comparison of Matched-firm Compensation Results for Early and Late CEO-Chair Combinations

This table presents our analysis of CEO compensation for early and late CEO-chair combinations. Following the method in Pagano, Panetta, and Zingales (1998), we estimate the following specification for each dependent variable: $y_{it} = \beta_0 + \sum_{t=1}^{4} \beta_t Combined_t + \beta_5 Combined_{t>4} + u_i + d_t + \varepsilon_{it}$ where u_i and d_t are CEO-firm pair and year fixed effects, respectively. $Combined_t$ is 1 if period t is after the CEO became board chair and zero otherwise. The sample comprises 600 CEO-firm pairs. Variables are defined in The Appendix and are winsorized at the 1% and 99% levels. *p*-values, in parentheses, are based on robust standard errors clustered at the CEO-firm pair level. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Obs.	Year 1	Year 2	Year 3	Year 4	Year > 4	F-Test
Panel A. Analysis of Match-adjusted Ln(Total Compensation)							
Early Combination (298 CEOs)	1,740	0.065	0.052	0.119*	0.222***	0.156**	8.42***
		(0.26)	(0.42)	(0.08)	(0.00)	(0.01)	(0.00)
Late Combination (302 CEOs)	2,.328	0.036	-0.002	-0.044	-0.002	0.059	0.05
		(0.50)	(0.98)	(0.53)	(0.98)	(0.37)	(0.82)
p-value for Difference		0.70	0.53	0.08*	0.03**	0.21	0.02**
Panel B. Analysis of Match-adjusted Ln(Compensation Delta)							
Early Combination (298 CEOs)	1,743	0.107	0.019	0.129	0.313**	0.016	1.39
		(0.35)	(0.88)	(0.36)	(0.05)	(0.92)	(0.24)
Late Combination (302 CEOs)	2,339	0.190*	-0.107	-0.114	-0.033	-0.131	0.15
		(0.09)	(0.42)	(0.45)	(0.85)	(0.44)	(0.70)
p-value for Difference		0.60	0.48	0.22	0.12	0.48	0.22
Panel C. Analysis of Match-adjusted Ln(Portfolio Delta)							
Early Combination (298 CEOs)	1,760	0.185**	0.388***	0.470***	0.543***	0.403**	13.86***
		(0.02)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)
Late Combination (296 CEOs)	2,322	0.241***	0.313***	0.359**	0.312*	0.330*	7.60***
		(0.01)	(0.01)	(0.02)	(0.01)	(0.087)	(0.01)
p-value for Difference		0.64	0.64	0.56	0.28	0.76	0.56
Panel D. Analysis of Match-adjusted Ln(Compensation Vega)							
Early Combination (298 CEOs)	1,760	-0.007	0.085	0.154	0.449**	0.004	0.96
		(0.96)	(0.59)	(0.39)	(0.04)	(0.98)	(0.33)
Late Combination (296 CEOs)	2,322	0.079	-0.050	-0.162	0.023	-0.015	0.04
		(0.49)	(0.74)	(0.39)	(0.91)	(0.94)	(0.84)
p-value for Difference		0.63	0.53	0.21	0.13	0.94	0.36
Panel E. Analysis of Match-adjusted Ln(Portfolio Vega)							
Early Combination (298 CEOs)	1,713	0.234***	0.348***	0.587***	0.333**	0.330*	12.72***
		(0.00)	(0.00)	(0.01)	(0.01)	(0.07)	(0.00)
Late Combination (302 CEOs)	2,323	0.198***	0.183*	0.169*	0.390	0.289**	6.74***
		(0.01)	(0.06)	(0.06)	(0.15)	(0.02)	(0.01)
p-value for Difference		0.75	0.22	0.46	0.78	0.87	0.63

Table 14. Comparison of Matched-firm Compensation Results for Coopted and Non-coopted Boards

This table presents our analysis of CEO compensation after combining the CEO and chair positions for firms with coopted boards and with non-coopted boards. Following the method in Pagano, Panetta, and Zingales (1998), we estimate the following specification for each dependent variable: $y_{it} = \beta_0 + \sum_{t=1}^{4} \beta_t Combined_t + \beta_5 Combined_{t>4} + u_i + d_t + \varepsilon_{it}$ where u_i and d_t are CEO-firm pair and year fixed effects, respectively. $Combined_t$ is 1 if period t is after the CEO became board chair and zero otherwise. The sample comprises 600 CEO-firm pairs. Variables are defined in The Appendix and are winsorized at the 1% and 99% levels. *p*-values, in parentheses, are based on robust standard errors clustered at the CEO-firm pair level. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Obs.	Year 1	Year 2	Year 3	Year 4	Year > 4	F-Test
Panel A. Analysis of Match-adjusted Ln(Total Compensation)							
Non-coopted Board (506 CEOs)	3,261	0.00	-0.054	-0.036	0.041	0.026	0.01
		(0.99)	(0.31)	(0.55)	(0.51)	(0.72)	(0.91)
Coopted Board (94 CEOs)	807	0.105	0.184	0.128	0.066	-0.038	0.71
		(0.27)	(0.15)	(0.32)	(0.63)	(0.86)	(0.40)
p-value for Difference		0.32	0.08*	0.24	0.86	0.76	0.40
Panel B. Analysis of Match-adjusted Ln(Compensation Delta)							
Non-coopted Board (506 CEOs)	3,264	0.093	-0.041	-0.05	0.149	-0.020	0.10
		(0.29)	(0.67)	(0.66)	(0.26)	(0.88)	(0.75)
Coopted Board (94 CEOs)	818	0.361	-0.123	0.362	0.187	-0.209	0.38
		(0.08)	(0.64)	(0.14)	(0.55)	(0.49)	(0.54)
p-value for Difference		0.22	0.77	0.12	0.91	0.55	0.65
Panel C. Analysis of Match-adjusted Ln(Portfolio Delta)							
Non-coopted Board (503 CEOs)	3,283	0.132**	0.293***	0.341***	0.374***	0.355**	11.45***
		(0.04)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)
Coopted Board (91 CEOs)	799	0.520***	0.567**	0.792***	0.800**	0.561**	11.74***
		(0.00)	(0.01)	(0.00)	(0.00)	(0.05)	(0.00)
p-value for Difference		0.03**	0.25	0.09*	0.14	0.50	0.08*
Panel D. Analysis of Match-adjusted Ln(Compensation Vega)							
Non-coopted Board (503 CEOs)	3,283	-0.002	0.018	0.086	0.272*	0.029	0.64
		(0.98)	(0.88)	(0.53)	(0.09)	(0.87)	(0.42)
Coopted Board (91 CEOs)	799	0.223	0.019	-0.466	0.210	-0.204	0.04
		(0.27)	(0.95)	(0.21)	(0.59)	(0.57)	(0.85)
p-value for Difference		0.31	1.00	0.16	0.88	0.52	0.61
Panel E. Analysis of Match-adjusted Ln(Portfolio Vega)							
Non-coopted Board (506 CEOs)	3,223	0.205***	0.263***	0.211**	0.287***	0.322**	13.72***
		(0.00)	(0.00)	(0.02)	(0.01)	(0.02)	(0.0)
Coopted Board (94 CEOs)	813	0.217	0.248	0.311	0.750**	0.244	3.25*
		(0.11)	(0.14)	(0.12)	(0.03)	(0.53)	(0.07)
p-value for Difference		0.93	0.94	0.64	0.20	0.85	0.65

Table 15. Comparison of Matched-firm Compensation Results Before and After Sarbanes-Oxley

This table presents our analysis of CEO compensation after combining the CEO and the chair positions for combinations before implementation and after the implementation of Sarbanes Oxley. Following the method in Pagano, Panetta, and Zingales (1998), we estimate the following specification for each dependent variable: $y_{it} = \beta_0 + \sum_{t=1}^{4} \beta_t Combined_t + \beta_5 Combined_{t>4} + u_i + d_t + \varepsilon_{it}$ where u_i and d_t are CEO-firm pair and year fixed effects, respectively. $Combined_t$ is 1 if period t is after the CEO became board chair and zero otherwise. The sample comprises 600 CEO-firm pairs. Variables are defined in the Appendix, and are winsorized at the 1% and 99% levels. *p*-values, in parentheses, are based on robust standard errors clustered at the CEO-firm pair level. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Obs.	Year 1	Year 2	Year 3	Year 4	Year > 4	F-Test
Panel A. Analysis of Match-adjusted Ln(Total Compensation)							
Before Sarbanes-Oxley (397 CEOs)	2,803	-0.034	-0.074	-0.085	-0.041	-0.027	0.91
		(0.54)	(0.29)	(0.25)	(0.58)	(0.75)	(0.34)
After Sarbanes-Oxley (203 CEOs)	1,265	0.098	0.072	0.132	0.246***	0.127	3.15*
		(0.11)	(0.37)	(0.19)	(0.04)	(0.38)	(0.08)
p-value for Difference		0.13	0.19	0.11	0.05	0.35	0.07*
Panel B. Analysis of Match-adjusted Ln(Compensation Delta)							
Before Sarbanes-Oxley (397 CEOs)	2,800	0.071	0.024	-0.061	0.190	-0.021	0.02
		(0.51)	(0.85)	(0.66)	(0.24)	(0.89)	(0.90)
After Sarbanes-Oxley (203 CEOs)	1,282	0.272	-0.220	0.201	0.037	-0.210	0.16
		(0.18)	(0.96)	(0.97)	(0.28)	(0.77)	(0.69)
p-value for Difference		0.25	0.27	0.30	0.61	0.56	0.91
Panel C. Analysis of Ln(Portfolio Delta)							
Before Sarbanes-Oxley (395 CEOs)	2,891	0.098	0.258**	0.299**	0.247*	0.284*	5.23**
		(0.25)	(0.02)	(0.02)	(0.08)	(0.08)	(0.02)
After Sarbanes-Oxley (199 CEOs)	1,261	0.367***	0.470***	0.615***	0.921***	0.659**	13.01***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)
p-value for Difference		0.06**	0.30	0.21	0.04**	0.25	0.08*
Panel D. Analysis of Ln(Compensation Vega)							
Before Sarbanes-Oxley (395 CEOs)	2,821	-0.048	0.056	0.082	0.183	-0.039	0.15
		(0.67)	(0.68)	(0.61)	(0.30)	(0.84)	(0.70)
After Sarbanes-Oxley (199 CEOs)	1,261	0.161	-0.115	-0.239	0.441	0.146	0.15
		(0.29)	(0.60)	(0.38)	(0.19)	(0.70)	(0.70)
p-value for Difference		0.29	0.53	0.34	0.51	0.67	0.90
Panel E. Analysis of Ln(Portfolio Vega)							
Before Sarbanes-Oxley (397 CEOs)	2,759	0.172*	0.211*	0.198*	0.209	0.254*	5.44**
		(0.02)	(0.02)	(0.06)	(0.11)	(0.09)	(0.02)
After Sarbanes-Oxley (203 CEOs)	1,277	0.252**	0.335**	0.239	0.732***	0.511*	8.34***
		(0.01)	(0.04)	(0.21)	(0.00)	(0.09)	(0.00)
p-value for Difference		0.55	0.52	0.86	0.09*	0.47	0.28

PERSISTENT OPERATING LOSSES AND CORPORATE FINANCIAL POLICIES*

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Persistent Operating Losses and Corporate Financial Policies

Abstract

Among U.S. firms, operating losses have become substantially more prevalent, persistent, and greater in magnitude since 1970. Loss firms now comprise over 30% of the Compustat universe and such losses continue for a median of four years. We find that firms with negative operating cash flows account for more than half of the rise in average cash balances over the sample period, with average cash holdings increasing by 615% for negative cash flow firms vs. 95% for positive cash flow firms. Further, firms exhibiting operating losses now comprise the majority of equity issuers. These companies issue frequently, primarily through private placements, and use the funds raised in the issue to cover subsequent operating losses. We conclude that the immediate and expected ongoing liquidity needs of firms with persistent operating losses have substantially altered corporate financial policies.

1. Introduction

A growing body of research reports secular changes in the composition of publicly traded U.S. companies. As reported in Kahle and Stulz (2016), U.S. companies have evolved over the past several decades from being manufacturing entities to being more service and high-tech oriented. Coincident with this shift, U.S. companies spend less on capital expenditures and more on research and development (R&D) so that intangible capital now comprises more than 50% of net assets for the average company (Falato, Kadyrzhanova, and Sim (2013)). Cash flows have also become more volatile and Bates, Kahle, and Stulz (2009) tie this increase in volatility to secular increases in average corporate cash holdings.

In this study, we explore the evolution of profitability among U.S. firms and show that not only have cash flows become riskier; they are now much lower for a considerable subset of U.S firms. In the 1950's about 2% of public firms listed in Compustat reported operating losses (defined as negative cash flow from operations on the firm's Statement of Cash Flow). In contrast, the period since 1980 has been characterized by an explosion in the percentage of public firms with negative cash flow (CF), rising from 9% in 1979 to over 30% in several recent years. Moreover, similar patterns exist even if we measure operating cash flow before R&D expenditures have been deducted. Thus, these patterns are not simply a byproduct of rising R&D expenditures over time.

We further show that for most firms in recent years, operating losses are not a transitory phenomenon. Firms that lose money on operations this period are likely to lose money next period as well. For example, less than 14% of the firms that reported negative CF in 2014 subsequently reported positive CF in 2015, and the median 'run' of negative cash flow is four years. This persistence in operating losses is also a recent phenomenon; up until approximately 1990, firms

that reported an operating loss in one year had a greater than 50% chance of reporting positive operating earnings in the following year. Moreover, the magnitude of operating losses has grown substantially over time as well. In the 1970s, operating cash flow for firms in the bottom decile of operating cash flow exhibited losses equal to 11% of assets, on average. In the 2000s, these average losses for firms in the bottom decile have ballooned to 58% of assets.

Persistent operating losses create immediate and ongoing liquidity needs that must be met by existing internal resources or external finance (or both). We show that firms expecting such losses behave differently than firms with positive cash flow on several dimensions of corporate financial policy such as cash holdings, equity issuance frequency, and cash savings from issuance. Between 1970 and 2015, average cash holdings as a percentage of total assets increase by 91% for firms exhibiting positive cash flow. More strikingly, however, average cash holdings increase by 615% for firms with negative operating cash flow. Firms with negative cash flow account for more than half of the increase in average cash balances of U.S. firms reported in Bates, Kahle, and Stulz (2009).

Traditionally, the precautionary demand for cash has been framed within a context focused on the second moment of the distribution of cash flow. According to the precautionary savings theory of Keynes (1936), firms stockpile cash to protect themselves against adverse cash flow shocks because these shocks could lead to underinvestment. However, when the first moment of the cash flow distribution is negative, first moment considerations are likely to dominate second moment considerations. In such situations, the demand for cash stems more from the expected level of cash flow than from its volatility. Consistent with this view, we show that neither changes in cash flow volatility nor increases in R&D expenditures (two traditional proxies for the demand for precautionary cash) are sufficient to capture the additional amount of cash held by negative

cash flow firms. For example, among the subsample of firms that comprise the top two deciles of R&D spending, we find that the cash holdings of high cash flow firms have grown by 54% over our sample period, while cash holdings of low cash flow firms have grown by nearly 900%.

We infer from this evidence that among the growing number of firms that exhibit persistent operational deficits, cash stockpiling for these firms is less about guarding against the possibility of a shock to financing needs or costs, and more about the fact that cash flow is negative *right now* and is likely to remain that way. In other words, the stockpile is not solely a precaution against the possibility of underinvestment induced by unexpected financing needs. It is a deliberate plan to finance near term operational needs under an expectation of negative cash flows.

To explore the source of cash stockpiles in firms with negative operating flows, we analyze external financing activity and asset sales and find that the relative proportions of each have changed substantially over time. In the 1970's, high CF firms mostly issued equity and low CF firms relied predominantly on debt. By contrast, in the most recent period (2010–2015), low CF firms raise 15 times more equity capital than debt capital.

Consistent with Ritter and Welch's (2002) and Fama and French's (2004) evidence on new lists, we find that over the past four decades, negative cash flow firms represent an increasing proportion of firm-initiated equity issuances (IPOs, SEOs, and private placements).[1] In every year but one since 1989, the majority of firms issuing equity report negative operating cash flows (CF). In the last year of our sample, 2015, negative CF issuers outnumber positive CF issuers by a factor of 2 to 1. In addition, we find that equity issues of firms with negative operating cash flow are overwhelmingly private placements in recent years. Such private placements account for

[1] Firm-initiated equity issues are defined as stock issuances that exceed 3% of market equity. This definition captures the vast majority of IPOs, SEOs, and private placements while excluding most employee-initiated issuances such as ESPPs and the exercise of stock options (McKeon, 2015).

approximately 90% of the equity issues for negative cash flow firms in the last five years of our data. By contrast, the majority of equity issues for positive cash flow firms over the same period are seasoned equity offerings (SEOs).

Firm-initiated equity issues typically represent a substantial cash inflow to the firm and McLean (2011) argues that cash savings from equity issuance has been increasing over time. Additionally, Huang and Ritter (2016) find that immediate cash needs are an important determinant of equity issues and that firms save 65% of the proceeds from equity issues in cash at year-end, on average.

During our sample period, over 1/3 of firms initiating equity issues hold all of the proceeds as cash at year end. We illustrate the importance of operating losses by scaling each equity issuer's post-issue cash balances by the magnitude of the company's cash burn rate.[2] This scaled measure, commonly called "runway" within the venture capital industry, represents an estimate of how many months a firm with negative cash flows can continue to operate at the same rate without an infusion of external capital. Ceteris paribus, equity issuers could increase runway by increasing issuance size and stockpiling cash. However, we find that the median runway after issuance has stayed within the same range for decades, typically between 6 and 18 months, and, most notably, exhibits no time trend over the past two decades, a period during which average cash balances have exploded. In other words, cash savings from issuance have increased substantially, but burn rates have also risen concomitantly. The takeaway is that for equity issuers with negative cash flows, the increase in cash holdings is driven in large part by elevated operating needs in the sense

[2] We define monthly burn rate as –[Operating CF-Dividends-Capital Expenditures] divided by twelve. For example, a firm that reports negative CF of $100MM and capital expenditures of $20MM annually has a monthly burn rate of $10MM. Firms generating positive free cash flows do not have a burn rate.

that the number of months of operations covered by cash on hand has not changed substantially over time.

Ours is not the first study to document secular decreases in the profitability of U.S. firms. For example, Fama and French (2004) report that the profitability of newly listed firms has become increasingly left-skewed and that, as these firms are integrated into the economy, overall profitability becomes more left-skewed as well. Similarly, Kahle and Stulz (2016) document a decline in average profitability rates among U.S. firms. We extend this literature by showing that the secular trend in profitability is not just a 'new lists' effect, we document for the first time the increased persistence and magnitude of operating losses, and link these trends to secular changes in corporate financial policies.

Other prior studies have investigated financial policies in firms exhibiting losses. For example, DeAngelo, DeAngelo, and Skinner (1992) find that dividend decreases are strongly associated with the presence of losses, particularly if these losses are persistent. In contrast with the troubled firms studied in DeAngelo, DeAngelo, and Skinner (1992), we show that in recent years, firms with persistent operating losses are high-growth firms that are able to frequently raise equity capital.

Our study also contributes to three related strands of the literature. The first seeks to understand the magnitude of cash balances among U.S. firms and why average balances have grown so dramatically in recent years. Our findings complement and extend those from studies that ascribe a role for increased precautionary demands due to uncertainty in future financing needs, and for increased costs of repatriating foreign earnings in explaining high cash balances. We show that, in addition to these factors, an increased demand for operational cash to fund immediate, and expected ongoing liquidity needs is an important determinant of observed cash

balances. Our findings also provide a potential explanation for the finding in Pinkowitz, Stulz, and Williamson (2016) that differences in average cash balances between U.S. firms and their foreign counterparts are driven by a small set of U.S. firms with very high R&D expenditures. We show that high cash balances of high R&D firms are concentrated among those firms with persistent operating losses.

Second, our findings extend the literature on the motives for equity issuance. Kim and Weisbach (2008) report that additions to cash holdings are the primary use of equity issue proceeds in a large international sample of IPOs and SEOs. Moreover, McLean (2011) reports that the percentage of equity issue proceeds held as cash at the end of the year of issuance has increased substantially over time. These studies imply that cash stockpiling is an important motive for equity issuance. DeAngelo, DeAngelo, and Stulz (2010) report that most SEO issuers would have been unable to fund current operating plans in the absence of the equity issue. They thus attribute the issuance decision to the need to fund near-term investment. Our findings indicate that equity issuers in recent years are increasingly characterized by ongoing operating losses and, therefore, high cash burn rates. They not only have immediate funding needs, but also a need to stockpile cash to fund anticipated near-term future funding shortfalls. Nonetheless, this stockpile is of short duration, requiring the firms with persistent operating losses to issue equity far more frequently than has been documented in the prior SEO literature. The frequency of issuance is consistent with a staging of capital infusions of the type reported for newly public firms in Hertzel, Huson, and Parrino (2012).

Finally, our findings have implications for the empirical literature that models cash balances as a linear function of firm, country and institutional characteristics. These studies typically include contemporaneous cash flow among the set of variables that capture the firm's

sources and uses of funds and, therefore, its operating cash needs. Our findings imply that such models have become increasingly misspecified in recent years as the distribution of firms has shifted towards firms with persistent operating losses. Because these firms exhibit unusually high cash balances, existing models that ignore this nonlinearity systematically underestimate 'normal' cash holdings for firms with persistent negative cash flows.

The rest of the study progresses as follows: Section 2 documents the rise in operating loss firms. Section 3 reports results explaining how the rise in corporate cash holdings is related to operating losses. Section 4 reports results on the relation between operating loss firms and cash savings from equity issuance. Section 5 discusses implications of our findings, and Section 6 concludes.

2. Descriptive evidence on operating losses

The main sample consists of all U.S firms with total assets greater than $5 million (in 2015 dollars) between 1970 and 2015. The data are obtained from the Compustat database, Industrial Annual file. Historically regulated firms such as financial firms (SIC codes 6000–6999) and utilities (SIC codes 4900–4999) are excluded, as are firms missing data necessary for the calculation of cash ratios. Within this sample, we identify firm-initiated equity issues such as IPOs, SEOs, and private placements, using the method detailed in McKeon (2015), specifically, those issues in which proceeds from common stock issuance are greater than 3% of market equity.

We begin by documenting the prevalence of operating losses over time. We define an operating loss as a negative cash flow from operations as reported on the statement of cash flows. Prior to 1987, firms were not mandated to report cash flow from operations. When this figure is missing, we calculate an approximation as described in the Appendix. Figure 1 plots the

percentage of the sample that reports negative operating cash flows each year since 1960. The rise is striking. In the early part of the sample, negative operating cash flows are almost non-existent. Despite four recessions between 1960 and 1980 (as defined by the National Bureau of Economic Research (NBER)), the percentage of firms with negative cash flow only exceeds 10% three times. Since 1990, however, it has rarely been less than 25%.[3] In 2015, the final year in the sample, nearly 1/3 of the sample firms report negative operating cash flows.

One firm characteristic that has changed substantially over time is R&D expenditures (Brown et al., 2009). To investigate whether the rise in negative cash flow firms is driven primarily by high R&D expenditures, we measure OCFRD, which is operating cash flow with R&D added back. As it turns out, there is more to the story than R&D. The proportion of firms with negative OCFRD has also experienced a substantial rise over the same period and by 2015 nearly 1 in 4 firms reports negative operating cash flows *even before subtracting R&D expense*.

Figure 1 shows that negative cash flows are pervasive; however, a related question is whether negative cash flows are transitory. We find that it is increasingly the case that firms are experiencing persistent negative cash flows rather than negative cash flows that occur due to a temporary shock. Figure 2 illustrates a strong time trend in the persistence of negative cash flows. Panel A illustrates that in the 1970's and 80's most firms that experienced negative cash flows returned to positive cash flows in the following year. By contrast, less than ¼ of firms that reported negative cash flow in 2014 followed up with positive cash flow in 2015. Panel B reports the average number of years, including the current year, of consecutive negative cash flows. By construction, the lower bound of 1.0 represents a situation in which every firm reporting negative cash flow in a given year had positive cash flow in the prior year. Consistent with panel A, this

[3] Kahle and Stulz (2016) also report a decline in average profitability among U.S. firms, but do not investigate its persistence or its connection with corporate financial policies.

measure exhibits a strong time trend, peaking in the last year of the sample at nearly four years. This implies that the occurrence of negative cash flows is not likely to be surprising or unexpected for most firms in recent years. Rather, they are operating with the intention and expectation of extended cash flow deficits. A likely consequence of this expectation is that corporate policies for such firms, such as cash holdings, will be driven at least as much by a plan to manage expected operating deficits as by factors that induce excess holdings such as precaution against the possibility of a negative shock.

The final characteristic to note is that the magnitude of negative cash flow has grown substantially over time. Table 1, panel A reports average CF/assets for the ten deciles during four subperiods: 1970–1979, 1980–1989, 1990–1999, and 2000–2015. All deciles report lower cash flows over time, but within the lowest decile the change is most dramatic. In the 1970's the average firm in the lowest decile reported cash flow equal to -9% of assets. During the 2000–2015 subperiod, the average was -55% of assets. Put another way, firms in this decile burn an average of almost 5% of assets *per month* even before accounting for capital expenditures.

Taken together, Figures 1 and 2, and Table 1 highlight three stylized facts about the evolution of firms reporting negative cash flows: Negative cash flows are vastly more prevalent, more persistent, and the magnitude of average negative cash flows within the lowest decile has grown fivefold. Further, Figure 3 charts the distribution of cash flow for two subperiods at the beginning and end of the sample period and reveals that not only has a mass of firms appeared in the left tail in the most recent period, but the density in the center of the distribution has shifted left as well. These findings motivate the inquiry into implications of these transformative shifts in the distribution of cash flows for corporate policy.

In light of the drastic change in the distribution of cash flows, a related question is whether other characteristics of negative cash flow firms have changed. Table 2 reports summary statistics on a variety of firm level variables for firms with negative cash flows. Surprisingly, firm age, measured as number of years as a public firm in Compustat, has increased. The average age of negative cash flow firms in the 1970's is 6.5 years, rising to 11 years in the 2000's. Thus, the shift in the distribution of cash flow is not due simply to the characteristics of newly listed firms.[4] In terms of size, loss firms have become smaller over time at the median in term of total assets, but larger in terms of market capitalization. It follows that the market-to-book ratio is substantially higher in recent years, averaging 1.16 in the 1970's versus 2.70 in the 2000's. Leverage has fallen sharply, whether measured as book or market leverage, and R&D expenditures as a percentage of assets have increased substantially. Growth patterns have also changed. In the 70's, firms with negative cash flows exhibit signs of distress, with declining revenues and declining headcount, on average. In the 1990's and 2000's the opposite is true; negative cash flow firms are growing rapidly on average, both in terms of revenues and employee growth. Finally, payout policies have changed. In the 70's, negative cash flow firms maintained a dividend yield above 1% in the year of the loss. By the 2000's, this figure had declined to less than 0.2%. Overall, these statistics suggest that as negative cash flows have become more prevalent, persistent and larger, the characteristics of these firms have changed as well. In recent years, firms with negative cash flows are more commonly highly valued, growth firms.[5]

[4] Fama and French (2004) report that the profitability of newly listed firms has become increasingly left-skewed.

[5] The industry concentration of negative cash flow firms has also changed over time. In the 2000's, four industries (Drugs, Business Services, Chips, Medical Eq) account for over 50% of the observations of negative cash flow. By contrast, the top four industries in the 1970's (Wholesale, Retail, Business Services, Machinery) account for only 26% of the observations.

3. Operating losses and cash holdings

Numerous studies have documented and offered explanations for the rise of corporate cash holdings. Bates, Kahle, and Stulz (2009) measure the rise in cash holdings from 1980 to 2006 and attribute the increase to precautionary motives rather than agency explanations. Specifically, they point to changing firm characteristics including declines in working capital and capital expenditures, and increases in cash flow volatility and R&D. Younger firms exhibit these characteristics more strongly, and as they enter the economy, the optimal level of cash rises. In Table 2 of their study, they report that the rise in cash holdings for firms with negative earnings has been particularly large.

Table 3 reports that as the prevalence, persistence, and magnitude of negative operating cash flows has increased, cash holdings have grown dramatically. The most dramatic increase in cash balances occur within the lowest deciles of operating cash flow, and the point of divergence in the mid 1980's roughly corresponds with the beginning of the rapid growth of negative cash flow firms in Figure 1. In 1970, cash holdings across the cash flow continuum are similar, and even slightly lower for low cash flow firms. The lowest decile held 6.5% of assets in cash, while the highest 8 deciles held an average of 8.4% of assets in cash. During the final year of the sample, 2015, average cash holdings within the lowest decile has grown to over 63% of assets, an increase of 878% over 1970 levels. Cash holdings within the highest eight deciles has also grown, but much more modestly, increasing by 101% over the sample period. Overall, these figures are consistent with Bates et al. (2009), who document a tripling of cash ratios for negative net income firms over 1980–2006. The results in Table 3 indicate that the growth has not retreated in the years since 2006. The takeaway is that in order to understand the rise in average cash holdings generally,

more attention needs to be paid to the left side of the cash flow distribution where the rise is most evident.

Figure 4 plots the rise in cash holdings. The middle (grey) curve reports the average observed values for the entire sample and shows that average cash holdings have grown by 208% over the sample period. However, once the sample is split into positive cash flow firms (dotted curve) and negative cash flow firms (bottom black curve), it is clear that negative cash flow firms are responsible for the majority of the overall growth in cash holdings observed within the full sample. If negative cash flow firms are removed from the sample, the growth in cash holdings over 1970-2015 is less than half as large as the growth in cash holdings for the full sample (95% vs 208% increase). The growth in cash balances among negative cash flow firms is a striking 615%.

Three traditional explanations for holding excess cash include repatriation taxes, agency problems, and precautionary motives. While the uptick on the right end of the cash flow distribution could be caused by tax considerations, the massive rise on the left is within firms that are not likely to be subject to an offshore cash holdup due to repatriation taxes, because (i) they have negative earnings to offset the tax burden, and (ii) only 8.5% of our sample firms that report operating losses also report foreign income. Similarly, firms on the left side of the distribution are less prone to agency problems. In their study of the effect of agency problems on cash holdings, Nikolev and Whited (2014) cite three factors commonly associated with agency concerns: size, perquisite consumption, and limited managerial ownership. Negative cash flow firms are the least susceptible on all three counts. They are, on average, the smallest firms in the economy, they are subject to equity capital raising on a regular basis (as we later show), and are monitored more

closely than mature high cash flow firms. Finally, in unreported analysis we find that negative cash flow firms have the highest levels of managerial ownership.

Since tax motives and agency concerns are mitigated for firms with negative cash flows, we are left solely with precaution as an explanation for the 615% rise in cash holdings between 1970 and 2015. In recent years, there has been an increased focus on R&D expenditures in the literature. In addition to the Bates, Kahle, and Stulz (2009) study cited earlier, Falato and Sim (2015) use state-level changes in R&D tax credits to show that firms increase their cash-to-asset ratios when their home state increases R&D tax credits. Begenau and Palazzo (2016) link the rise in cross-sectional cash holdings with the propensity of newly public firms to hold more cash at entry, particularly those with high R&D intensity. Pinkowitz, Stulz, and Williamson (2016) find that differences in average cash balances between U.S. firms and their foreign counterparts are driven by a small set of U.S. firms with very high R&D expenditures,

High R&D intensity could impact cash holdings through two (not mutually exclusive) mechanisms. First, disrupting R&D programs is particularly costly (Brown and Peterson, 2011), so the firm may hold extra cash as a precaution. Second, however, many R&D intensive firms also report negative cash flow. R&D represents a cash expense that needs to be covered regardless of the fact that it is R&D, and resultant cash holdings intended to cover near term operations are more accurately described as a response to the first moment of cash flow rather than the second moment.

To determine whether the operating cash flow effect is simply an overlap with R&D intensive firms, we analyze R&D and cash flow jointly in Table 4. Panel A reports the joint distribution by decile for each measure. Not surprisingly, the largest mass is in the lowest cash flow decile and highest R&D decile, but it only represents 5.5% of the sample. Extending to the

three lowest deciles of Cash Flow and the three highest deciles of R&D only comprises 15.9% of the sample. Thus, although there is some overlap, it does not appear that the cash flow effect we study is simply a proxy for the R&D effect studied by others.

Panel B takes a step further to examine cash holdings at high R&D firms, defined as those within the top two deciles. The results indicate that growth in cash holdings for high R&D firms is heavily dependent on the firm's cash flow position. Specifically, for high R&D firms in cash flow deciles 3-10, where cash flow is typically positive, cash holdings have grown an average of 52%. In contrast, average cash holdings for high R&D firms in the lowest cash flow decile have grown 828%.

Figure 5 plots the relation between cash holdings and operating cash flow levels in each of four subperiods. Similar to Figure 4, the most striking increase is observed within firms at the low end of cash flow. However, Figure 5 reveals a more interesting observation, which is that the relation between cash holdings and cash flow has become increasingly nonlinear over time. Standard models of cash holdings, in which cash is specified as a linear function of cash flow (and other characteristics), obscure this effect. Misspecification due to incorrect functional form of the cash flow variable results in systematic prediction error. We discuss these implications in greater detail in Section 5.2.

While the relation between cash holdings and cash flow was roughly flat in the 1970's, each subsequent decade has increased in convexity. Thus, it is not the case that the increase in cash holdings in the time series is driven exclusively by the increasing prevalence and magnitude of negative earnings; the persistence is also important. For any given level of cash flow to the left of zero, the median firm in the 2000s holds more cash than does the median firm in the 1990s, which holds more than the median firm in the 1980s. What has changed over time is the duration

of the negative cash flows. A firm reporting negative cash flow in 1970 is expecting to revert to positive cash flows soon while a firm in the 2000s reporting the very same level of negative cash flow is more likely to be expecting that level to persist for an extended period.

We conclude this section by examining the association between cash holdings and cash flow realizations prior to, and subsequent to, the first year in which a firm reports negative cash flow. This analysis is motivated by the DeAngelo, DeAngelo and Skinner (1992) finding that dividend policies upon the realization of negative earnings respond to the future persistence of negative earnings. We hypothesize that cash policies are similarly responsive to the firm's expectation about the persistence of negative cash flows.

Table 5 reports median cash holdings for four subgroups based on the persistence of future negative cash flows and history of previous cash flows. The *Persistent* category consists of firms that are entering a run of negative cash flow that is at least three years in duration. The *Transitory* subgroup is made up of firms that return to positive cash flow the following year. *New Firms* are those that are less than three years old. *Fallen Angels* are firms that reported at least five years of positive cash flow before entering the negative cash flow sample. We find that firms entering a run of persistently negative cash flow realizations hold substantially more cash than firms experiencing a transitory negative cash flow shock. This is true not only for new firms, but also those that have previously reported a long stretch of positive cash flows. These results are consistent with the notion that the persistence of the negative cash flows matters for corporate policies and that firms act in a manner that suggests they have some foresight about the persistence of future cash flows.

4. Operating losses and external financing patterns

Our evidence indicates that firms with persistent operating losses build large cash balances to fund these losses. However, it is unclear how they amass such large cash holdings. Although firms with persistent losses exhibit large and ongoing liquidity needs, they are also likely to face large frictions in the market for external funds. The uncertainty as to the duration of losses, coupled with the possibility of information asymmetry raises the potential for agency problems if the firm raises a substantial amount of funds in the capital market. These concerns are common in the venture capital market and the literature identifies the staging of financing as one way to mitigate financing frictions in venture capital funded firms [see, for example, Gompers (1995)]. Hertzel, Huson, and Parrino (2012) extend this logic to newly public firms and find evidence consistent with staging in the timing and size of equity financing in IPO and initial follow-on equity offerings. Such staging, however, can also be costly in that it forces firms to incur additional issuance costs. In this section, we investigate the sources of external finance in our sample firms and analyze the extent to which financing patterns have evolved as firms have increasingly become characterized by persistent operating losses. In particular, we explore the extent to which the financing of firms are consistent with the staging of capital infusions.

4.1. Sources of external finance

In Table 6, we investigate three mechanisms that firms can utilize to generate cash: equity issues, debt issues, and the sale of fixed assets. We measure each of these sources, scaled by total assets, and compare the average values within each cash flow decile at the beginning of the sample and the end of the sample.

In the 1970's, low cash flow firms raised little equity relative to high cash flow firms. On average, a firm in the highest decile of cash flow raised over 10 times as much equity as a percentage of assets compared to a firm in the lowest cash flow decile. For debt, the story is different. Very low cash flow firms raised, on average, twice as much debt capital compared to equity and firms in all deciles other than the highest raised more debt than equity on average. The highest cash flow firms raise four times more equity capital than debt in the 1970's. Additionally, sale of fixed assets appears to be an important source of cash in the 70's for firms with very low cash flow. In the lowest decile of cash flow, sale of fixed assets is the largest source of cash, generating 33% more cash than debt issues and about 3 times as much cash as equity issues.

Almost the exact opposite is true in recent years. Over the past decade, low cash flow firms raise far more cash through equity than through either debt issues or the sale of fixed assets. Relative to assets, equity issues raise, on average, 14 times the proceeds of debt issues and 162 times the proceeds from the sale of fixed assets in the lowest decile of cash flow. Meanwhile, firms in the highest cash flow decile are now repurchasing both debt and equity, on average. These stylized facts have had a marked impact on capital structure for negative cash flow firms, consistent with the leverage summary statistics in Table 2.

4.2. Staging in debt financing through debt maturity structure

Although the staging of capital infusions is typically associated with the equity market, Hertzel, Huson, and Parrino (2012) note that the use of short maturities in debt financing can also be viewed as a form of staged financing. Companies with short maturity debt are forced to renegotiate with creditors to roll over existing debt claims, thereby offering creditors the ability to

adjust the terms of debt contracts based on perceptions of company performance and growth opportunities.

In Figure 6, we plot the median percentage of debt maturing in more than three years for our sample companies. Consistent with the findings in Custodio et al. (2013), we find that debt maturity significantly declines from the 1970's to 2008. When we split the sample into positive and negative cash flow firms, we find that the percentage of debt maturing in more than three years is always substantially less for negative cash flow firms than for positive cash flow firms. In fact, since 1997, the median negative cash flow firm has no debt maturing in more than three years. Interestingly, although median debt maturity has increased markedly for positive cash flow firms since 2008, the median percentage of debt maturing in greater than three years remains at 0% for negative cash flow firms. These findings are consistent with negative cash flow firms using short maturities to stage debt infusions. Moreover, our findings imply that a large portion (though not all) of the systematic decrease in debt maturity documented in Custodio et al. (2013) is associated with the increasing proportion of firms exhibiting negative cash flow.

4.3. Staging in equity financing

Figure 7 illustrates that over the same time period as the rise in cash holdings and overall prevalence of operating loss firms, the characteristics of equity issuers have changed, particularly with regards to cash flow. In the 1970's and 1980's, firms issuing equity are cash flow positive on average, but in every year since 1989, the average equity issuer is burning cash. These results are consistent with anecdotal evidence suggesting that it has become easier for negative cash flow

firms to raise equity capital in recent years and with the evidence in Fama and French (2004) showing that earnings become progressively left skewed through time for newly listed firms.[6]

To further analyze the relation between cash flow and equity issuance frequencies, we calculate the mean number of firm-initiated issuances per year for each cash flow decile based on quarterly data. Table 7 reports the results of this analysis. While Figure 7 suggests that a large portion of equity issuances are conducted by low cash flow firms, Table 7 demonstrates the inverse: a large portion of low cash flow firms are equity issuers. In fact, between 2010 and 2015 the lowest decile of cash flow recorded 0.89 firm-initiated issuances *per firm per year*.

In addition to variation in issue frequencies, positive and negative cash flow firms also differ in their choice of equity issuance mechanisms. Table 8 reports the proportion of firm-initiated equity issues that are issued to the public via an SEO versus issued through a private placement. Both positive and negative cash flow firms exhibit a positive trend in the use of private placements over time, but for negative cash flows firms this mechanism makes up the vast majority of equity issues. Over the last five years for which we have data (2009–2013), private placement comprise over 88% of all issues in every year for negative cash flow firms, rising as high as 93% in 2011. In addition, we find in untabulated results that of the few SEOs issued to the public, the majority are shelf offerings.

The combination of increased issuance frequency and increased rate of private placements among negative cash flow firms is consistent with the view that negative cash flow firms face substantial frictions in the equity issuance market. These frictions are potentially mitigated by a staging of capital infusions much like what is observed for private firms receiving venture capital

[6] For example, Jay Ritter notes that "In the early Eighties, the major underwriters insisted on three years of profitability. Then it was one year, then it was a quarter. By the time of the Internet bubble, they were not even requiring profitability in the foreseeable future." (*Rolling Stone*, April 5, 2010).

financing. Frequent equity issues are puzzling in the presence of large fixed issuance costs in the market for seasoned equity offerings. Our evidence suggests, however, that the staging of equity capital infusions is increasingly done through the private placement mechanism in which fixed issuance costs are much lower.

4.4. Equity issuance, cash savings, and runway

One of the primary features of precautionary cash savings from equity issuance is the stockpiling of issue proceeds for future use. Following McLean (2011), we measure cash minus issuance (CMI) as cash holdings at the end of the fiscal year minus total proceeds from equity issuances during the year, where we define equity issuance as all firm-initiated equity issues. When this variable carries a positive sign (CMI+), it indicates that the firm stockpiled all the equity proceeds from issues it initiated in a given year. In Figure 8, we plot the time series of CMI+ proportions for equity issuers. Interestingly, it does not display the strong time trend that characterizes average cash holdings. Over the sample period, the percentage of issuers that hold all the proceeds in cash typically varies between 30% and 50% with a mean of 39%. The 1970's and 2000's are in the higher segment of the range while the 1980's and 90's are in the lower portion of the range. Although several studies report that precautionary motives driven by the volatility of cash flows have risen greatly through the sample period, Figure 8 fails to detect a meaningful trend in cash stockpiling behavior from equity issuance. We therefore posit that it must be the case that there are additional factors influencing cash savings from equity issuance beyond these standard notions of precaution. One such factor is the first moment of the cash flow distribution, i.e., expected negative operating cash flows.

To investigate the size of the cash stockpile relative to the needs of the firm, we borrow a metric from the venture capital industry, where negative cash flows for portfolio firms are commonplace. Within venture-backed firms, a figure that often underlies decisions about cash holdings and equity issuance is the monthly "burn rate," which we define as operating cash flow minus dividends and capital expenditures, divided by 12. Table 9 reports the median burn rate as a percentage of total assets over time for equity issuers with negative cash flow. It is monotonically increasing, rising from about 8% in the 1970's to over 25% in the most recent period. In the 1970's, the median level of cash holdings for negative cash flow equity issuers was less than 5% of assets at year end. At 2015 burn rates, a stockpile of that size would be depleted before the ides of March.

Cash holdings divided by the monthly burn rate is often referred to as "runway," or in other words, how many months a company could sustain current operations without an infusion of external capital. Investors can limit runway by staging investment to mitigate overinvestment problems. Hertzel et al. (2012) find that public market staging is particularly strong for firms with high R&D and intangible assets. Additionally, they report that the median length of time before returning to the capital market is 12 months. We extend their findings by analyzing runway length over time to detect whether it has changed in ways similar to average cash holdings. Figure 9 plots the median runway at the time of issuance for negative earnings firms over the sample period, and shows that it has stayed within the same range for the last 30 years: between 6 and 18 months. Many other firm characteristics have changed, such as those associated with precautionary cash balances (e.g., R&D intensity and cash flow volatility), but these factors have not altered the median runway of equity issuers in meaningful ways. For negative cash flow firms, having about

a year's supply of cash is the norm. These firms aren't saving more relative to their needs; their operational needs have grown.

In a contemporaneous study, McLean and Palazzo (2016) analyze the timing and size of equity issues and report evidence that firms issue not only to cover short-term liquidity squeezes, but also to stockpile the proceeds as a precaution against adverse future market conditions. In light of their finding that precautionary considerations can influence issuance size, it seems likely that such considerations contribute to the time-series variation in the median runway we observe after issuance in Figure 8. Nonetheless, the fact that runway exhibits virtually no time trend over recent decades, while the average cash balances of issuers has exploded, points to operating needs, rather than precaution, as the first order factor influencing the time series of cash balances.

5. Other Implications and Discussion

In this section, we discuss other implications of the findings presented in this study, including (i) motivations for equity issuance, (ii) misspecification in models of cash holdings, and (iii) the cash flow sensitivity of cash.

5.1 Motivations for Equity Issuance

Our findings have implications for the literature on motivations for equity issuance. Kim and Weisbach (2008) show that cash holdings are the largest use of equity issuance proceeds for an international sample of over 30,000 IPOs and SEOs between 1990 and 2003. McLean (2011) extends this result by documenting that the percentage of equity issuance proceeds held as cash at the end of the year of issuance has increased over time. Specifically, he reports that in the 1970's firms retained an average of $0.23 in cash for each dollar of issuance, but that this figure rises to

$0.60 for the period 2000–2007. In a separate study, DeAngelo, DeAngelo and Stulz (2010) report that 62% of the SEO issuers in their sample would run out of cash by the end of the following year without the issuance. They attribute SEO decisions primarily to a "lifecycle theory that predicts young firms with high market-to-book (M/B) ratios and low operating cash flows sell stock to fund investment." Overall, our findings suggest that cash savings and lifecycle motives are not mutually exclusive.

For example, under the lifecycle explanation we should observe a disproportionate number of equity issuances at the low end of the cash flow spectrum, and this is exactly what we see in recent years. Table 10 reports the distribution of firm-initiated equity issues for the first ten years and the last ten years of the sample period to compare how the joint distribution of equity issues and cash flow has changed over time. In the first ten years of the sample, equity issuance frequency is skewed towards high cash flow firms. However, during the most recent period, from 2006–2015, equity issuances are dominated by negative CF firms: the lowest decile of CF accounts for 32% of all equity issues and the lowest two deciles comprise 52% of all equity issues. Consistent with the lifecycle theory, these two deciles have the youngest average age and high average M/B ratios.

These results imply that, for firms with positive burn rates, which make up the majority of equity issuers in recent years, it is possible to observe both a high savings rate in the year of issuance (as in McLean (2011)), as well as a full depletion of pre-issuance cash (as in DeAngelo, DeAngelo, and Stulz (2010)) during the following year. The issuances are topping up the stockpile on a regular basis, but the firms are burning through the stockpile rapidly. A portion of the stockpile is undoubtedly related to volatility-induced precaution, but the savings from issuance are also driven by near term operating needs.

5.2 Models of Cash Holdings

Nonlinearity in the association between cash holdings and cash flow implies that models of cash holdings that estimate such holdings as a linear function of cash flow are increasingly misspecified. One econometric option to deal with convexity is to add a squared term to the specification. However, it is primarily nonlinearity on the left side of the cash flow distribution that is the focus of this study. For this reason, we employ an indicator for negative values of cash flow, and an interaction term between this indicator and the value of cash flow/assets to capture the magnitude of the losses. These variables allow for inference of differential effects for negative and positive cash flow firms.

Table 11 reports results from OLS regressions of cash holdings on standard determinants used in the literature (equation 1) plus the new variables we describe above to capture the effects of negative cash flow on cash policy (equation 2). Specifically,

$$\frac{Cash}{Assets_{i,j,t}} = \alpha + \beta_1 \frac{CF}{Assets_{i,t}} + \beta_2 \ln(ME)_{i,t} + \beta_3 \overline{CF\ Vol}_{j,t} + \beta_4 I(R\&D\ Intense)_{i,t} + \beta_5 \frac{M}{B}_{i,t} + \beta_6 \frac{CapEx}{Assets_{i,t}} + \beta_7 \frac{Debt}{Assets_{i,t}} + \varepsilon_{i,t} \tag{1}$$

$$\frac{Cash}{Assets_{i,j,t}} = \alpha + \beta_1 \frac{CF}{Assets_{i,t}} + \beta_2 I(CF < 0)_{i,t} + \beta_3 \left[I(CF < 0) * \frac{CF}{Assets} \right]_{i,t} + \beta_4 \ln(ME)_{i,t} + \beta_5 \overline{CF\ Vol}_{j,t} + \beta_6 I(R\&D\ Intense)_{i,t} + \beta_7 \frac{M}{B}_{i,t} + \beta_8 \frac{CapEx}{Assets_{i,t}} + \beta_9 \frac{Debt}{Assets_{i,t}} + \varepsilon_{i,t} \tag{2}$$

Both specifications control for factors related to precaution. Specifically, *Size* to capture financing constraints, *Industry Cash Flow Volatility* to capture probability of a negative shock to cash flow, an indicator of *high R&D intensity* and *market-to-book* ratio, both of which are related to growth opportunities. To isolate the effect of precaution related to R&D from the cash flow effect of R&D, we control for the existence of an R&D intensive investment agenda, but not the level of R&D, which is an operating expense.

In column 1 of Table 11, *Cash Flow* carries a large negative coefficient, consistent with several prior studies, but challenging to interpret in light of the nonlinearity between cash flow and cash. Column 2 reveals the importance of including variables that capture operating needs. Both the negative earnings indicator and the interaction term are highly significant determinants of corporate cash holdings. Moreover, after controlling for operating losses, the coefficient on *Cash Flow* reverses and is highly significant in the opposite direction. One implication is that the model with the negative earnings variables should also improve model fit on the right side of the cash flow distribution, where large positive cash flows are otherwise penalized in predictions of cash holdings if cash flow is forced into a linear specification where it carries a negative coefficient.

A common variation of Equation (1) adds fixed effects to capture variation through time and/or across industries. Columns 3 and 4 add year fixed effects to the models and columns 5 and 6 add year and industry fixed effects. Neither fixed effects specification picks up the impact of negative cash flow firms. In both cases, the sign of the coefficient on *Cash Flow* in the linear specification is negative and significant, whereas the specification with indicators for negative cash flow flips the sign on the *Cash Flow* variable, implying that the relation between cash flow and cash holdings depends greatly on the sign of the cash flows.

In Figures 10A and 10B, we detail the effects of functional form misspecification on prediction error. Figure 10A compares average prediction error within each decile in the full sample panel regressions. The comparison is between the standard model and the model that captures nonlinearity by adding the negative indicator and interaction term as in (2). The improvement is most evident in the tails of the distribution, which is not surprising due to the convex relation. Overall, improvement is noted in seven of the ten deciles. These results are consistent with the finding in Table 11 that the linear specification does not do a good job of characterizing the relation between cash and cash flow.

Figure 10B compares three prediction models designed to account for time varying changes in cash holdings. The first is the standard model with year fixed effects added, the second adds both year and industry fixed effects. The third is the nonlinear model estimated in annual cross-sections for each year of the sample to allow the coefficients to vary through time, similar to the technique used in Harford et al. (2009) to predict leverage targets.

Both fixed effects models create larger prediction errors in most deciles, again particularly in the tails. In the case of year fixed effects, the annual cross sections perform better in eight of the 10 deciles, and when compared to the model with year and industry fixed effects the annual cross sections perform better in every decile. The reason is intuitive: the lion's share of the increase in cash holdings has occurred in the tails of cash flow, but year fixed effects impact the predicted value uniformly across the distribution. Overall, the results support the use of the indicator and interaction terms and suggest caution in estimating fixed effects models in which movement in the dependent variable is driven in part by an unspecified nonlinear component of one of the explanatory variables.

Finally, in Table 12, we use the augmented cash holdings model to provide a 'back of the envelope' estimate of the relative contribution of cash flow levels versus cash flow volatility to predicted cash holdings for negative cash flow firms. The first two columns report coefficients from estimating Equation (2) over five-year subperiods at the beginning (1970–1974) and end (2011–2015) of the sample period: The third and fourth columns report the subperiod median values of each variable for firms that report negative operating cash flow. The predicted contribution to cash holdings, reported in the final two columns, is the product of the coefficients and median observed values.

The effect of cash flow levels on predicted cash holdings is revealed by the cash flow variables. In this example, the level variables contribute over twice as much to the increase in predicted cash as the volatility variable. Thirty percent the increase in predicted cash/assets is attributable to cash flow levels, while 13% of the increase is attributable to cash flow volatility.

5.3.Cash Flow Sensitivity of Cash

Our findings speak primarily to cash *levels*, but a related facet of corporate policy is how cash *changes* with cash flow. Almeida, et al. (2004) measure the cash flow sensitivity of cash holdings using a sample of manufacturing firms over 1971–2000. They find that cash is sensitive to cash flow for financially constrained firms, but not for financially unconstrained firms. Such findings are consistent with constrained firms saving cash out of cash flow in high cash flow states and drawing down cash holdings when cash flow is negative.[7]

Our evidence implies, however, that in recent years, an increasing proportion of firms exhibit negative cash flows and *increase* their cash holdings by stockpiling a portion of the funds

[7] Also consistent with this view, Opler et al. (1999) find that operating losses are the primary explanation for large *decreases* in excess cash for their sample firm over the period 1971-1994.

raised through equity issues. Such behavior will attenuate the positive cash flow sensitivity of cash documented in earlier periods and failing to control for the different sensitivity of negative cash flow firms could have a material impact on measured cash-cash flow sensitivities.[8]

To investigate this possibility, Table 13 reports the results of tests in which we estimate the cash flow sensitivity of cash over the first ten years of our sample period (1970–1979) and the last ten years of the sample period (2006–2015). In columns (1) and (3), we constrain the cash flow sensitivity of cash to be the same for firms with positive and negative cash flow, while in Columns (2) and (4) we allow the sensitivity to differ. During the 1970–1979 subperiod, negative cash flow firms are less common. Not surprisingly, therefore, we find in Column (2) that allowing sensitivities to differ for negative earnings firms has only a modest impact on the estimated cash-cash flow sensitivities of positive cash flow firms. In other words, pooling positive and negative cash flow firms has little impact on inferences.

By contrast, Column 4 reveals that sensitivities for positive cash flow firms are substantially higher once cash flow sensitivities are allowed to differ for positive and negative cash flow firms in the 2006–2015 subperiod. The reason for this is clear. Negative cash flow firms account for an increased proportion of the sample and these firms do not exhibit the same positive sensitivity of cash-to-cash flow.

6. Conclusion

The population of U.S. firms is increasingly comprised of firms with persistent, large negative cash flows. Such characteristics create ongoing liquidity needs that are directly tied to current and near-term operations. Correspondingly, we find that cash balances have increased

[8] This possibility is recognized by Almeida et al. (2004) and they show that the sensitivity they document is robust to exclusion of negative cash flow firms.

much more substantially in recent decades for these firms than for the rest of the population. Perhaps most strikingly, we find that over the past four decades, average cash holdings have risen by over 615% for firms with negative cash flow, as compared with 95% for firms with positive cash flow. Our evidence thus supports the view that the recent growth in cash balances among U.S. firms is not solely a reflection of increased precautionary demands due to cash flow volatility, increased disincentives to repatriate foreign earnings, or increased agency problems. Rather, for an increasing proportion of firms, higher cash balances reflect near-term operational needs under an expectation of negative cash flows.

Additionally, we find that equity issuance activity is increasingly dominated by firms with negative cash flows. Although firms are saving a substantial proportion of equity issuance proceeds in cash, they are also burning cash at an unprecedented rate. As a result, there is virtually no time trend in estimates of cash runway over the last 25 years. Since 2000, firms with negative operating cash flows issue equity almost once every year and appear to mitigate the large fixed costs of SEOs by primarily raising equity through private placements. Such behavior is consistent with a supply-driven public market staging of finance of the type studied in Hertzel et al. (2012).

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Appendix A: Variable Descriptions

Cash Holdings	CHE/AT
EBITDA	EBITDA/AT
EBITDARD	[EBITDA+XRD]/AT. XRD is coded to 0 if missing.
Operating Cash Flow	OANCF. If missing, replaced by NI+DPC+TXDC+ESUBC+SPPIV+FOPO+FSRCO+WCAPC+APALCH+INVCH+RECCH
I(CF<0)	Indicator that takes a value of 1 when Cash Flow<0, and 0 otherwise
Cash Flow x I(CF<0)	Interaction that takes the value of Cash Flow when Cash Flow<0, and 0 otherwise
Size	Natural Log of AT
Industry CF Vol	Standard deviation of cash flows is measured for each firm over up to 10 years (minimum 3). Values are averaged based on Fama French 48 industries annually.
R&D	XRD. Coded to 0 if missing.
I(R&D Intense)	Indicator that takes a value of 1 when [XRD/AT]>0.02, and 0 otherwise
M/B	(AT+MKTVAL-SEQ)/AT. MKTVAL is replaced by CSHO*PRCC_C if missing.
Capital Expenditures	CAPX. Coded to 0 if missing.
Leverage (Book)	[DLTT+DLC]/AT
Leverage (Market)	[DLTT+DLC]/(AT-SEQ+MKVALT)
Revenue Growth	$[REV_t-REV_{t-1}]/REV_{t-1}$
Employee Growth	$[EMP_t-EMP_{t-1}]/EMP_{t-1}$
Dividend Yield	DVC/MKVALT
Firm-initiated Equity Issuance	SSTK when [SSTK/MKTVAL]>0.03
Net Equity Issuance	SSTK-PRSTK
Net Debt Issuance	$[DLTT+DLC]_t-[DLTT+DLC]_{t-1}$
Burn Rate	-[Operating Cash Flow-DVC-CAPX]. Divided by 12 for monthly burn rate.
Runway	CHE/Monthly Burn Rate

All variable mnemonics are from Compustat, Industrial Annual File
All ratios are winsorized at the 1st and 99th percentiles.

Table 1

Evolution of cash flow by decile

This table reports mean values of CF/assets for deciles formed annually. The full sample is 227,745 firm year observations over the period 1970-2015. Values are averaged over all firm year observations within the decile during the specified subperiod.

CF decile	1970-79	1980-89	1990-99	2000-15
1	(0.09)	(0.25)	(0.38)	(0.55)
2	0.04	(0.02)	(0.10)	(0.14)
3	0.08	0.04	(0.02)	(0.03)
4	0.10	0.08	0.02	0.02
5	0.12	0.11	0.04	0.05
6	0.14	0.13	0.07	0.07
7	0.16	0.16	0.09	0.10
8	0.19	0.20	0.12	0.12
9	0.23	0.25	0.16	0.16
10	0.35	0.43	0.24	0.25

Table 2

Summary statistics for negative cash flow firms

This table reports mean *(median)* values for firms with negative cash flow. All variables are defined in the appendix. The full sample is 227,745 firm year observations over the period 1970-2015.

	1970's	1980's	1990's	2000's
N	2,847	8,247	15,819	19,352
Firm Age	6.5	7.7	7.7	11.0
	6	*5*	*5*	*8*
Total Assets (2015$)	430	274	247	462
	109	*33*	*42*	*54*
Mkt Cap (2015$)	103	118	290	359
	32	*25*	*55*	*69*
M/B	1.16	1.86	2.73	2.70
	0.92	*1.23*	*1.73*	*1.70*
Book Leverage	0.386	0.348	0.248	0.224
	0.382	*0.328*	*0.180*	*0.095*
Mkt Leverage	0.387	0.273	0.170	0.139
	0.403	*0.246*	*0.093*	*0.047*
R&D/TA	0.015	0.041	0.092	0.146
	0.000	*0.000*	*0.007*	*0.061*
Revenue Growth	-1.7%	15.9%	35.1%	29.4%
	-3.8%	*-1.3%*	*10.4%*	*3.0%*
Employee Growth	-5.7%	0.7%	18.9%	7.7%
	-6.7%	*-4.6%*	*5.3%*	*0.0%*
Dividend Yield	1.07%	0.47%	0.20%	0.17%
	0.0%	*0.0%*	*0.0%*	*0.0%*

Table 3

Evolution of average cash holdings by cash flow decile

This table reports mean values of cash/assets for cash flow deciles formed annually. The full sample is 227,745 firm year observations over the period 1970-2015. Values are averaged over all firm year observations within each decile each year.

	Deciles		
	1	2	3-10
1970	0.065	0.062	0.084
1971	0.068	0.072	0.093
1972	0.070	0.067	0.093
1973	0.065	0.064	0.083
1974	0.054	0.061	0.075
1975	0.061	0.059	0.095
1976	0.061	0.065	0.100
1977	0.061	0.062	0.093
1978	0.056	0.055	0.089
1979	0.057	0.062	0.082
1980	0.061	0.059	0.099
1981	0.065	0.061	0.111
1982	0.081	0.077	0.114
1983	0.085	0.108	0.149
1984	0.138	0.124	0.116
1985	0.146	0.110	0.123
1986	0.148	0.155	0.135
1987	0.189	0.134	0.130
1988	0.174	0.101	0.122
1989	0.180	0.104	0.122
1990	0.211	0.110	0.116
1991	0.272	0.148	0.130
1992	0.322	0.156	0.134
1993	0.384	0.192	0.139
1994	0.343	0.155	0.129
1995	0.343	0.186	0.142
1996	0.415	0.278	0.151
1997	0.404	0.244	0.153
1998	0.385	0.236	0.140
1999	0.430	0.321	0.152
2000	0.420	0.345	0.161
2001	0.449	0.347	0.161
2002	0.446	0.337	0.165
2003	0.499	0.299	0.184
2004	0.517	0.327	0.194
2005	0.517	0.307	0.194
2006	0.522	0.323	0.191
2007	0.554	0.312	0.191
2008	0.499	0.272	0.174
2009	0.489	0.274	0.190
2010	0.551	0.254	0.191
2011	0.558	0.255	0.177
2012	0.546	0.270	0.172
2013	0.573	0.369	0.177
2014	0.610	0.436	0.175
2015	0.637	0.479	0.169
Growth: 1970 to 2015	878%	676%	101%

Table 4

Cash Flow and R&D

Panel A reports the joint distribution of cash flow and R&D deciles over the sample period. The full sample is 227,745 firm year observations over the period 1970-2015. Panel B reports average cash holdings by cash flow decile for the top two deciles of R&D.

Panel A: Joint Distribution of Cash Flow and R&D Deciles

		Lowest CF									Highest CF
		1	2	3	4	5	6	7	8	9	10
	1	0.5%	0.8%	1.1%	1.2%	1.3%	1.3%	1.1%	1.1%	0.9%	0.7%
	2	0.4%	0.8%	0.9%	1.1%	1.3%	1.3%	1.3%	1.2%	1.0%	0.7%
	3	0.5%	0.8%	0.9%	1.0%	1.1%	1.3%	1.3%	1.3%	1.1%	0.8%
R&D	4	0.6%	0.9%	1.0%	1.0%	1.0%	1.2%	1.2%	1.2%	1.0%	0.9%
Decile	5	0.7%	0.9%	1.0%	1.0%	0.9%	1.1%	1.1%	1.1%	1.1%	1.0%
	6	0.8%	1.1%	1.1%	0.9%	1.0%	1.0%	1.0%	1.0%	1.1%	1.1%
	7	1.0%	1.2%	1.0%	0.9%	0.9%	0.9%	1.0%	0.9%	1.1%	1.2%
	8	1.3%	1.5%	1.0%	0.8%	0.8%	0.8%	0.8%	0.9%	1.0%	1.1%
	9	2.6%	1.6%	0.9%	0.6%	0.6%	0.6%	0.6%	0.6%	0.8%	1.1%
	10	5.5%	1.0%	0.5%	0.3%	0.3%	0.3%	0.3%	0.4%	0.5%	0.8%

Panel B: Average Cash Holdings for High R&D Firms

		1970-1979	2006-2015	Growth
	1	0.06	0.59	828%
	2	0.07	0.29	344%
	3	0.07	0.18	164%
Cash Flow	4	0.07	0.13	88%
Decile	5	0.07	0.12	62%
	6	0.08	0.11	34%
	7	0.09	0.12	39%
	8	0.10	0.13	28%
	9	0.11	0.15	33%
	10	0.14	0.22	52%

Table 5

Cash Holdings in First Year of Negative Cash Flow

This table reports median values of cash/assets observed in the first year that the firm reports negative cash flow. The subgroups are formed for each decade based on the persistence of negative cash flows and cash flow history. The full sample is 227,745 firm year observations over the period 1970-2015. The Persistent category is made up of firms that are entering a run of negative cash flow that is at least three years in duration. The Transitory subgroup is made up of firms that return to positive cash flow the following year. New Firms are those that are less than three years old. Fallen Angels are firms that reported at least five years of positive cash flow before entering the negative cash flow sample.

	Persistent		Transitory	
	New Firms	Fallen Angels	New Firms	Fallen Angels
1970s	0.040	0.046	0.044	0.043
1980s	0.118	0.075	0.079	0.054
1990s	0.385	0.358	0.128	0.091
2000s	0.528	0.400	0.184	0.117

Table 6

Proceeds from the Sale of Debt, Equity and PPE

This table reports the average annual proceeds from equity issuance, debt issuance, and the sale of fixed assets, scaled by total assets, for firms in each cash flow decile. The full sample is 227,745 firm year observations over the period 1970-2015. The first ten years and last ten years of the sample are reported for comparison.

		1970-79			2006-15		
		Net Equity /Assets	Net Debt /Assets	Sale of PPE /Assets	Net Equity /Assets	Net Debt /Assets	Sale of PPE /Assets
	1	0.004	0.011	0.015	0.371	0.023	0.002
	2	0.001	0.024	0.011	0.137	0.023	0.003
	3	0.003	0.024	0.009	0.054	0.024	0.003
	4	0.002	0.023	0.009	0.025	0.027	0.003
Cash Flow	5	0.003	0.026	0.009	0.011	0.022	0.003
Decile	6	0.004	0.023	0.009	0.007	0.015	0.003
	7	0.006	0.020	0.009	0.000	0.011	0.003
	8	0.008	0.020	0.009	(0.005)	0.006	0.004
	9	0.012	0.023	0.009	(0.015)	0.001	0.004
	10	0.036	0.013	0.011	(0.026)	(0.014)	0.004

Table 7

Equity Issuance Frequency

This table reports the average number of firm-initiated equity issuances per firm per year, compiled from quarterly data. Quarterly issuance data is available over the period 1985-2015.

		1985-1989	1990-1999	2000-2009	2010-2015
	1	0.35	0.74	0.70	0.89
	2	0.25	0.48	0.38	0.54
	3	0.22	0.33	0.23	0.24
	4	0.20	0.27	0.18	0.15
Cash Flow	5	0.19	0.23	0.14	0.12
Decile	6	0.18	0.18	0.12	0.12
	7	0.16	0.15	0.10	0.08
	8	0.18	0.13	0.09	0.07
	9	0.23	0.12	0.08	0.06
	10	0.30	0.13	0.08	0.06

Table 8

Equity Issuance Mechanisms

This table reports the proportion of seasoned equity issuances that are public versus private placements. The full sample is 227,745 firm year observations over the period 1970-2015. Data on equity issuance mechanisms is available from 1995 to 2013.

	Negative CF		Positive CF	
Year	Public	Private	Public	Private
1995	77%	23%	95%	5%
1996	80%	20%	95%	5%
1997	60%	40%	94%	6%
1998	45%	55%	96%	4%
1999	40%	60%	91%	9%
2000	30%	70%	77%	23%
2001	21%	79%	67%	33%
2002	16%	84%	72%	28%
2003	19%	81%	64%	36%
2004	22%	78%	64%	36%
2005	22%	78%	60%	40%
2006	20%	80%	62%	38%
2007	19%	81%	57%	43%
2008	14%	86%	46%	54%
2009	12%	88%	67%	33%
2010	12%	88%	51%	49%
2011	7%	93%	58%	43%
2012	9%	91%	51%	49%
2013	12%	88%	71%	29%

Table 9

Annual Burn Rate for Equity Issuers

This table reports the percentage of assets depleted annually by equity issuers with positive burn rates. Burn rate is defined as [-Operating Cash Flow+dividends+capital expenditures]. The full sample is 227,745 firm year observations over the period 1970-2015.

Period	% burned
1971-75	8.2%
1976-80	7.7%
1981-85	13.1%
1986-90	12.5%
1991-95	13.5%
1996-2000	18.8%
2001-05	21.5%
2006-10	23.2%
2011-15	25.9%

Table 10

Distribution and Characteristics of Firm-initiated Equity Issues by Cash Flow decile

This table reports the distribution of equity issuers by cash flow decile over the period 1971-1980 and 2006-2015. Mean market-to-book asset ratios and mean firm age is reported for the period 2006-15.

			Lowest CF									Highest CF
Year		N	1	2	3	4	5	6	7	8	9	10
1971-1980	Eq Iss Distribution	3,428	9%	7%	8%	9%	9%	8%	9%	10%	11%	21%
	Cumulative		9%	16%	24%	32%	41%	49%	58%	68%	79%	100%
2006-2015	Eq Iss Distribution	6,864	32%	20%	11%	8%	6%	5%	5%	4%	4%	4%
	Cumulative		32%	52%	63%	72%	78%	83%	88%	92%	96%	100%
	Mean M/B		3.84	2.32	1.69	1.48	1.48	1.56	1.68	1.87	2.21	3.03
	Mean Age		11.5	14.4	17.4	21.1	22.6	23.7	24.2	24.0	22.8	18.8

Table 11

Determinants of cash holdings

This table reports results from OLS regressions of cash holdings (cash/assets) on various determinants. The full sample is 227,745 firm year observations over the period 1970-2015. Columns 1, 3, and 5 use a linear specification for cash flow while columns 2, 4, and 6 allow for non-linearity when earnings are negative by adding an indicator of negative earnings and an interaction that takes the value of CF/assets when it is negative and zero otherwise. Variables are defined in the appendix. Standard errors are clustered by firm and year. *, **, and *** indicate significance at the 10%, 5% and 1% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Cash Flow	-0.134 ***	0.117 ***	-0.131 ***	0.132 ***	-0.116 ***	0.122 ***
	(<0.001)	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*
I(CF<0)		0.040 ***		0.039 ***		0.036 ***
		(<0.001)		*(<0.001)*		*(<0.001)*
CF x I(CF<0)		-0.331 ***		-0.343 ***		-0.311 ***
		(<0.001)		*(<0.001)*		*(<0.001)*
Size	-0.007 ***	-0.004 ***	-0.007 ***	-0.005 ***	-0.008 ***	-0.006 ***
	(<0.001)	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*
Industry CF Vol	0.545 ***	0.529 ***	0.553 ***	0.516 ***	0.224 ***	0.208 ***
	(<0.001)	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*
I(R&D Intense)	0.070 ***	0.065 ***	0.068 ***	0.064 ***	0.064 ***	0.061 ***
	(<0.001)	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*
M/B	0.031 ***	0.027 ***	0.031 ***	0.027 ***	0.028 ***	0.024 ***
	(<0.001)	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*
Cap Ex	-0.201 ***	-0.244 ***	-0.197 ***	-0.233 ***	-0.231 ***	-0.264 ***
	(<0.001)	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*
Leverage	-0.270 ***	-0.263 ***	-0.272 ***	-0.264 ***	-0.274 ***	-0.267 ***
	(<0.001)	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*
Constant	0.154 ***	0.116 ***	0.156 ***	0.121 ***	0.167 ***	0.149 ***
	(<0.001)	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*
Fixed Effects	*None*	*None*	*Year*	*Year*	*Year, Industry*	*Year, Industry*
N	175,407	175,407	175,407	175,407	175,407	175,407
R2	0.408	0.421	0.412	0.425	0.443	0.453

Table 12

Numerical example: What drives growth in cash holdings in low cash flow firms?

This table reports predicted cash holdings for the median firm characteristics from the lowest decile of CF/assets during the periods (i) 1970-74 and (ii) 2011-2015 using coefficients from OLS regressions of cash holdings (cash/assets) on various determinants defined in the appendix. The full sample is 227,745 firm year observations over the period 1970-2015. Predicted cash is the product of the coefficients and median values for each respective subperiod.

	Coefficients		Median Values CF<0		Predicted Cash			
	1970-1974	2011-2015	1970-1974	2011-2015	(1)	(2)		
Cash Flow	0.118	0.322	-0.061	-0.159	(0.007)	(0.051)		
I(CF<0)	0.013	0.084	1	1	0.013	0.084		
Cash Flow x I(CF<0)	-0.160	-0.386	-0.061	-0.159	0.010	0.062		
Industry CF Vol	0.295	0.274	0.029	0.157	0.009	0.043		
Size	-0.004	-0.001	2.153	4.340	(0.009)	(0.006)		
R&D	-0.363	0.640	0.000	0.080	-	0.051		
M/B	0.023	0.022	0.926	1.900	0.021	0.042		
Cap Ex	-0.078	-0.457	0.042	0.014	(0.003)	(0.006)		
Leverage	-0.142	-0.243	0.397	0.085	(0.056)	(0.021)		
Constant	0.088	0.130			0.088	0.130		
							Increase	%
Predicted cash					0.064	0.327	0.263	
Contribution from level of cash flow					0.015	0.094	0.079	30%
Contribution from cash flow volatility					0.009	0.043	0.034	13%

Table 13

Cash Flow Sensitivity of Cash

This table reports results from OLS regressions estimated over the 1st 10 years and last 10 years of the sample (1970-79 and 2006-2015). Columns 1 and 3 report change in cash/assets regressed on cash flow and a constant. Columns 2 and 4 allow for non-linearity when cash flow are negative by adding an indicator of negative earnings and an interaction that takes the value of CF/assets when it is negative and zero otherwise. Columns 5 and 6 constrain the sample to the lowest three deciles of size (constrained firms) and estimate the model separately for positive and negative cash flow firms. Variables are defined in the appendix. Standard errors are clustered by firm and year. *, **, and *** indicate significance at the 10%, 5% and 1% levels respectively.

	1970-79		2006-2015			
	1	2	3	4	5	6
	All	All	All	All	Size Dec<=3 CF<0	Size Dec<=3 CF>0
Cash Flow	0.085 ***	0.124 ***	0.082 ***	0.186 ***	0.056 ***	0.278 ***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
I(CF<0)		0.005 ***		-0.004		
		(0.002)		*(0.122)*		
CF x I(CF<0)		-0.140 ***		-0.147 ***		
		0.000		*0.000*		
M/B	-0.004 ***	-0.005 ***	0.001	-0.001	0.004 ***	-0.001
	(0.010)	*(0.003)*	*(0.140)*	*(0.334)*	*(0.001)*	*(0.487)*
ln(Assets)	0.000	0.001	-0.002 ***	-0.002 ***	0.004 **	(0.008) ***
	(0.554)	*(0.144)*	*0.000*	*0.000*	*(0.020)*	*0.000*
Constant	-0.01 **	-0.019 ***	0.002	-0.004	-0.035 ***	0.013
	(0.041)	*0.000*	*(0.731)*	*(0.399)*	*0.000*	*(0.108)*
N	26,870	26,870	32,729	32,729	5,195	4,060
R2	0.038	0.049	0.029	0.037	0.017	0.071

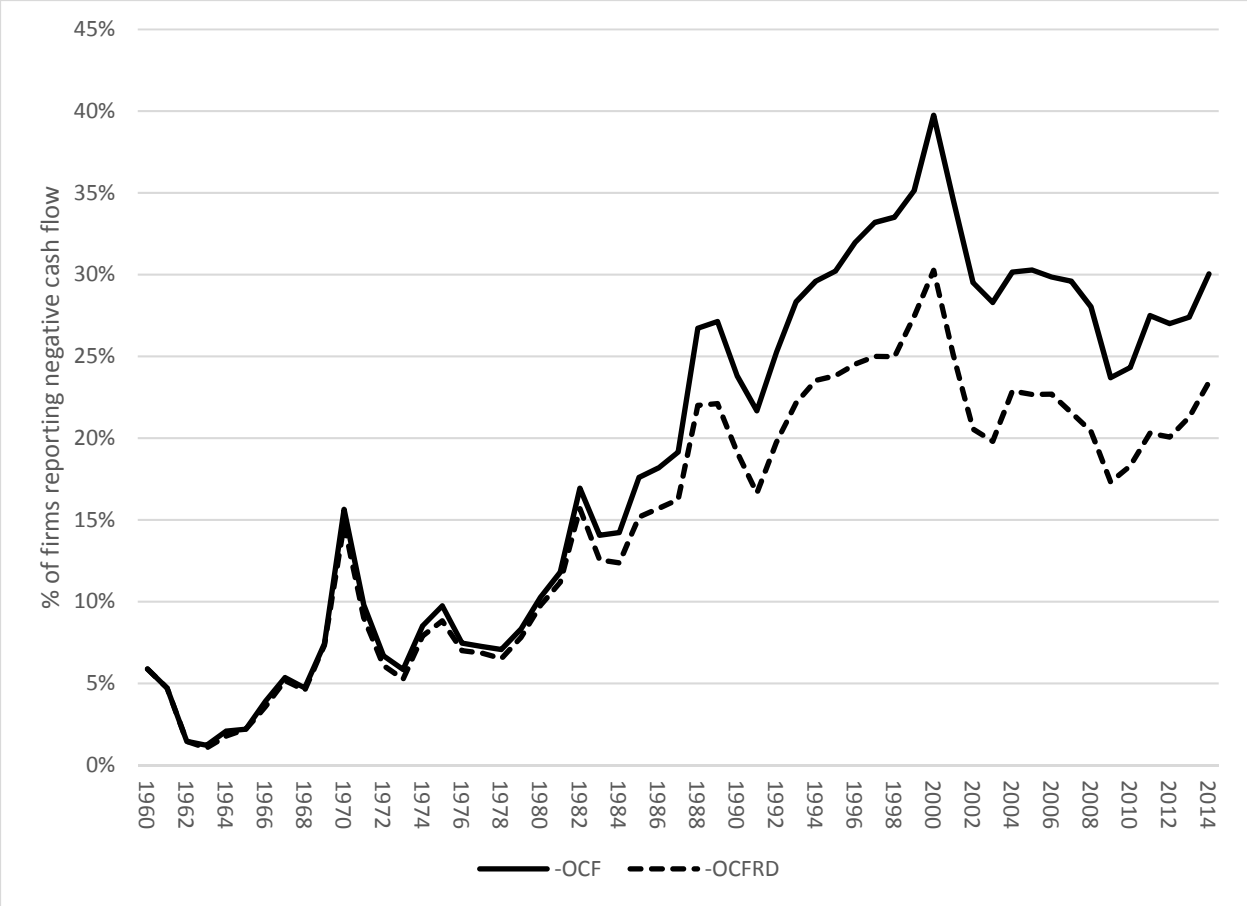


Figure 1. Prevalence of Negative Cash Flow. This chart reports the percentage of Compustat listed firms that report negative operating cash flow. –OCF is negative operating cash flow, -OCFRD is negative operating cash flow after adding back R&D expense. Detailed variable descriptions are available in the appendix.

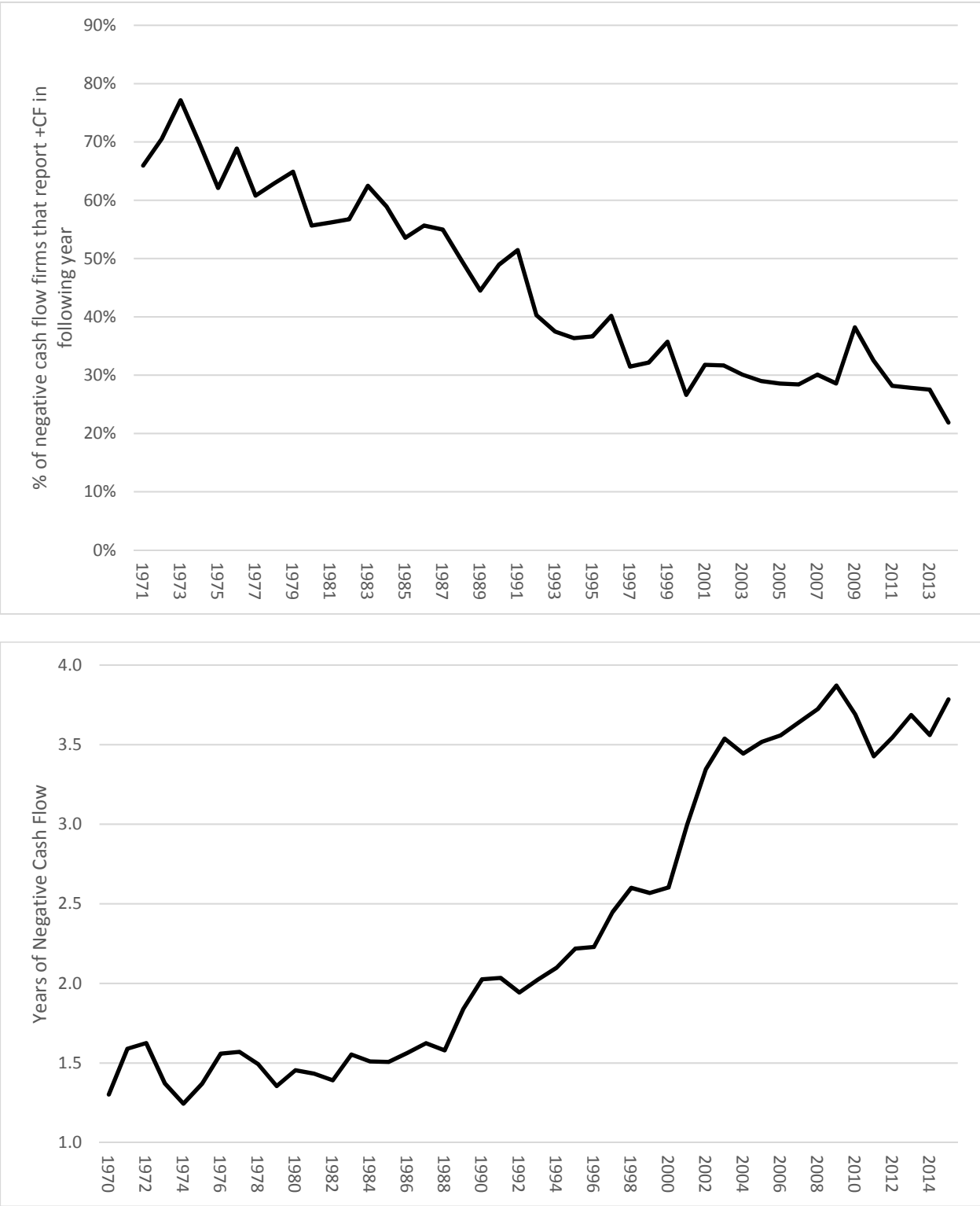


Figure 2. Persistence of Negative Cash Flow. Panel A: Proportion of Negative cash flow firms that report positive cash flow in the following year. Panel B: Average number of consecutive years of negative cash flow for firms that report negative cash flow.

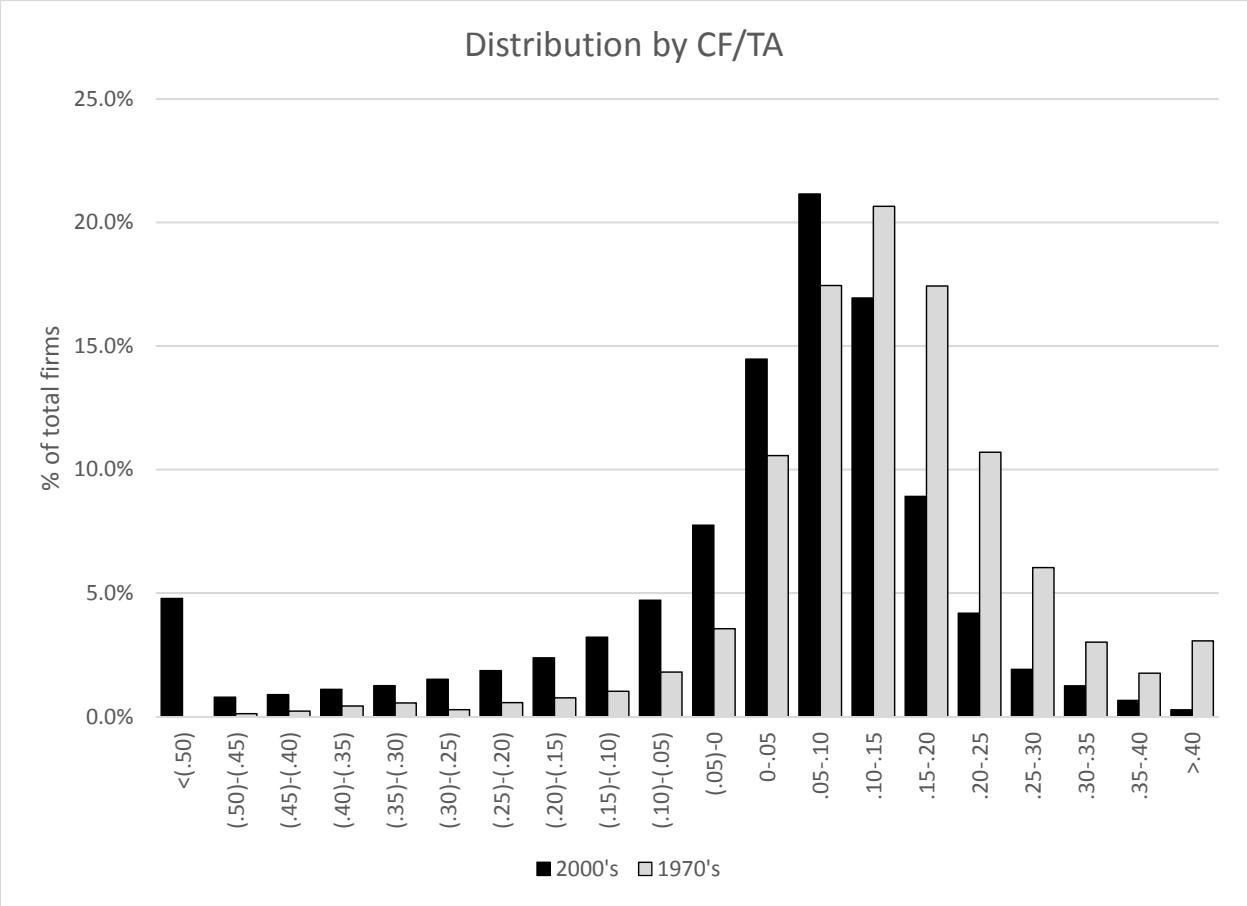


Figure 3. Distribution of Firms by Cash Flow over time. This chart reports the percentage of firm-year observations within each bin of operating cash flow during two subperiods: (i) 1970-79, (ii) 2000-2015.

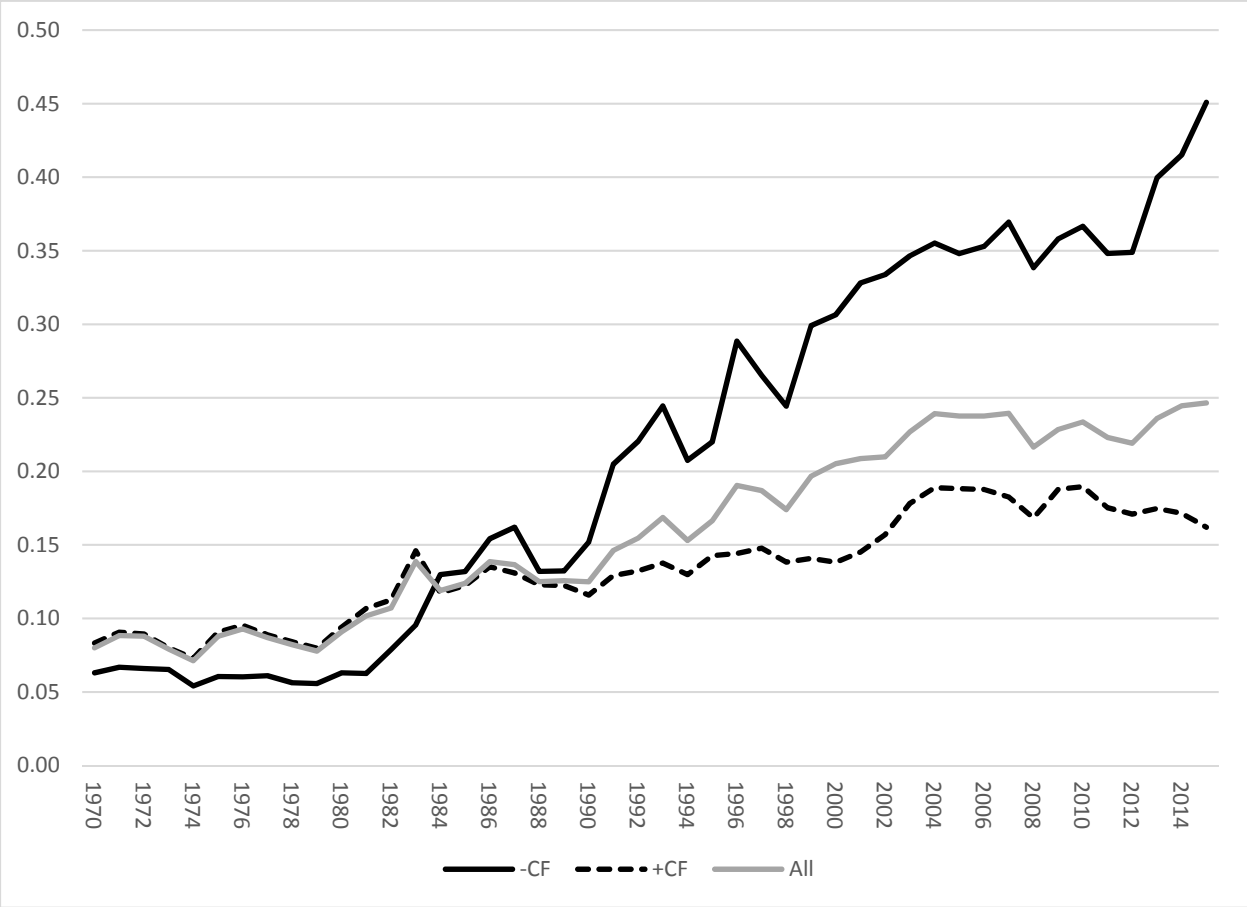


Figure 4. Evolution of Cash Holdings. This chart reports mean values of cash/total assets annually over 1970-2015 for the full sample (gray line) as well as two subsamples: positive cash flow firms (dotted line) and negative cash flow firms (solid black line).

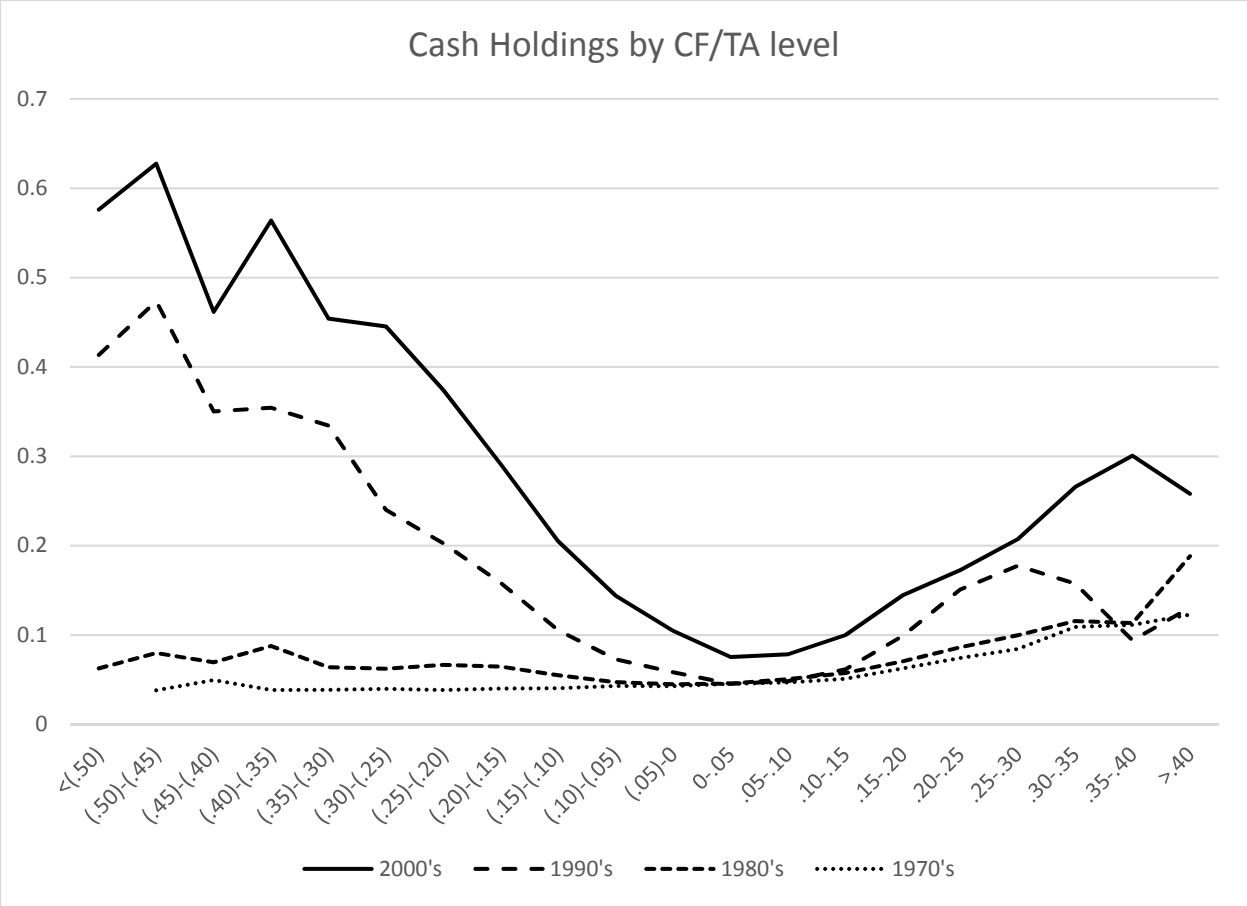


Figure 5. Convexity in the Relation between Cash Holdings and Cash Flow. This chart reports median values of cash/total assets for each bin of operating cash flow during four subperiods: (i) 1970-79, (ii) 1980-89, (iii) 1990-99, and (iv) 2000-2015.

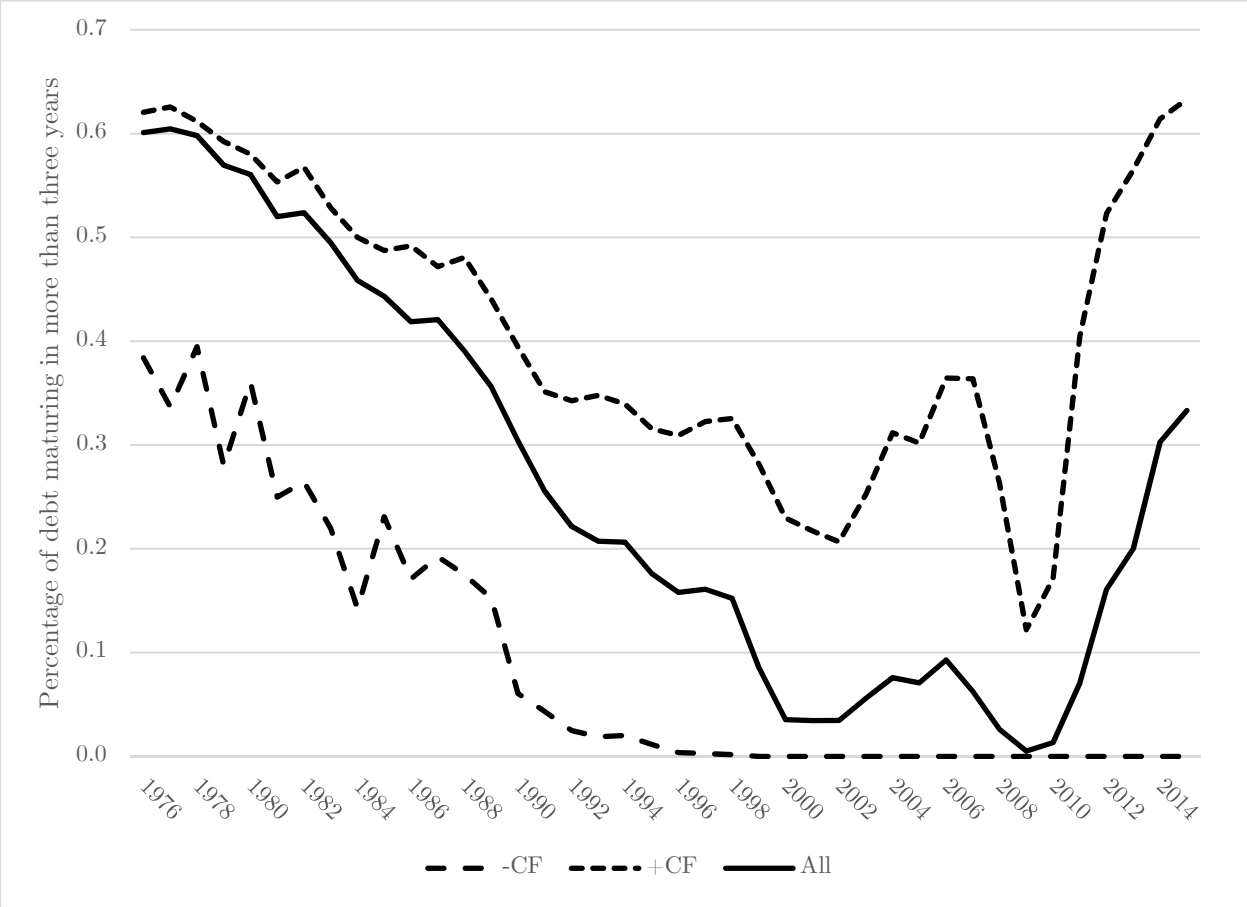


Figure 6. Debt maturity. This chart reports the median percentage of debt that matures in more than three years for the full sample, as well as the negative and positive cash flow subgroubs.

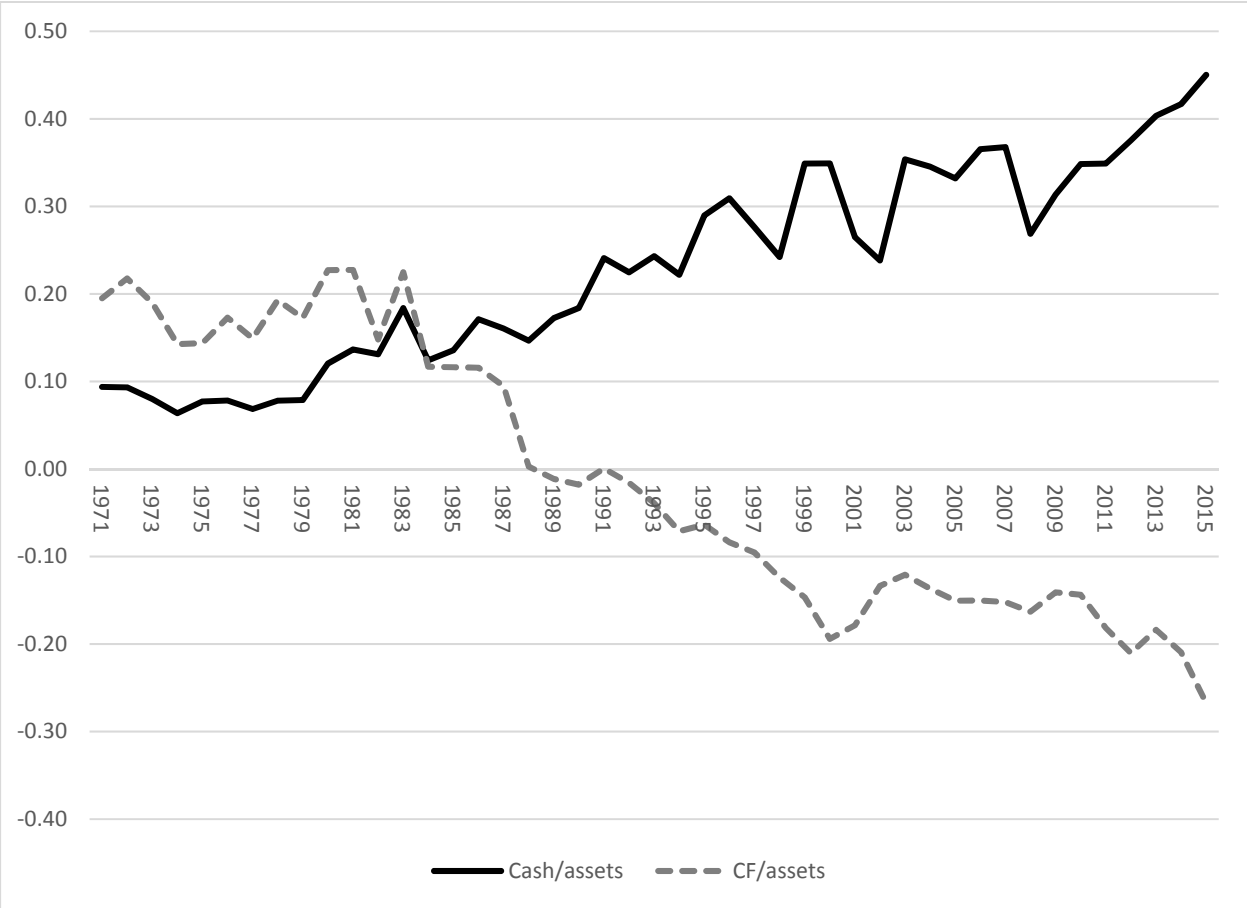


Figure 7. Equity Issuer Characteristics. This chart reports mean values of cash holdings and operating cash flow for all firms that initiate an equity issuance in a given year.

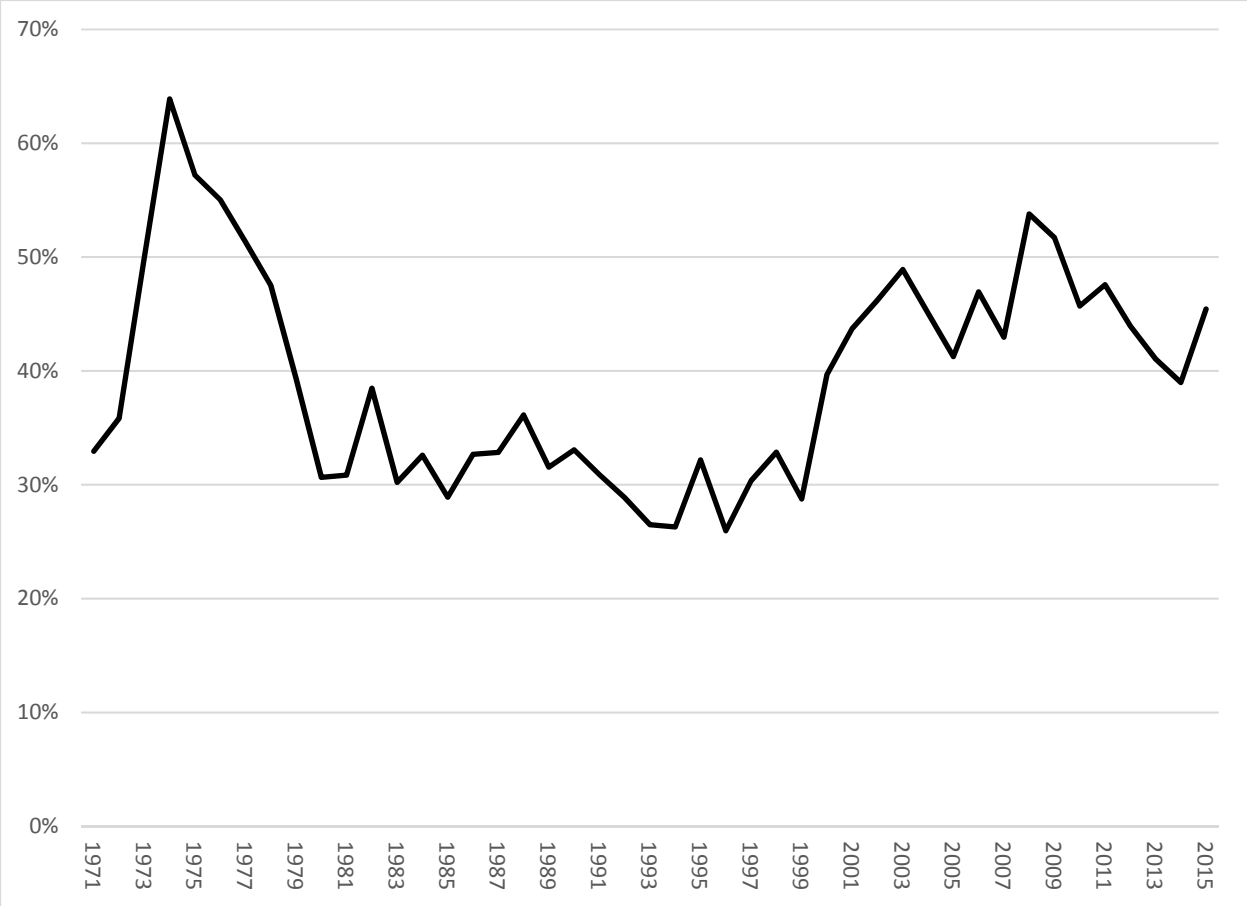


Figure 8. Cash Minus Issuance. This chart reports the proportion of equity issuers that held all proceeds in cash at the end of the year during which the issuance occurs.

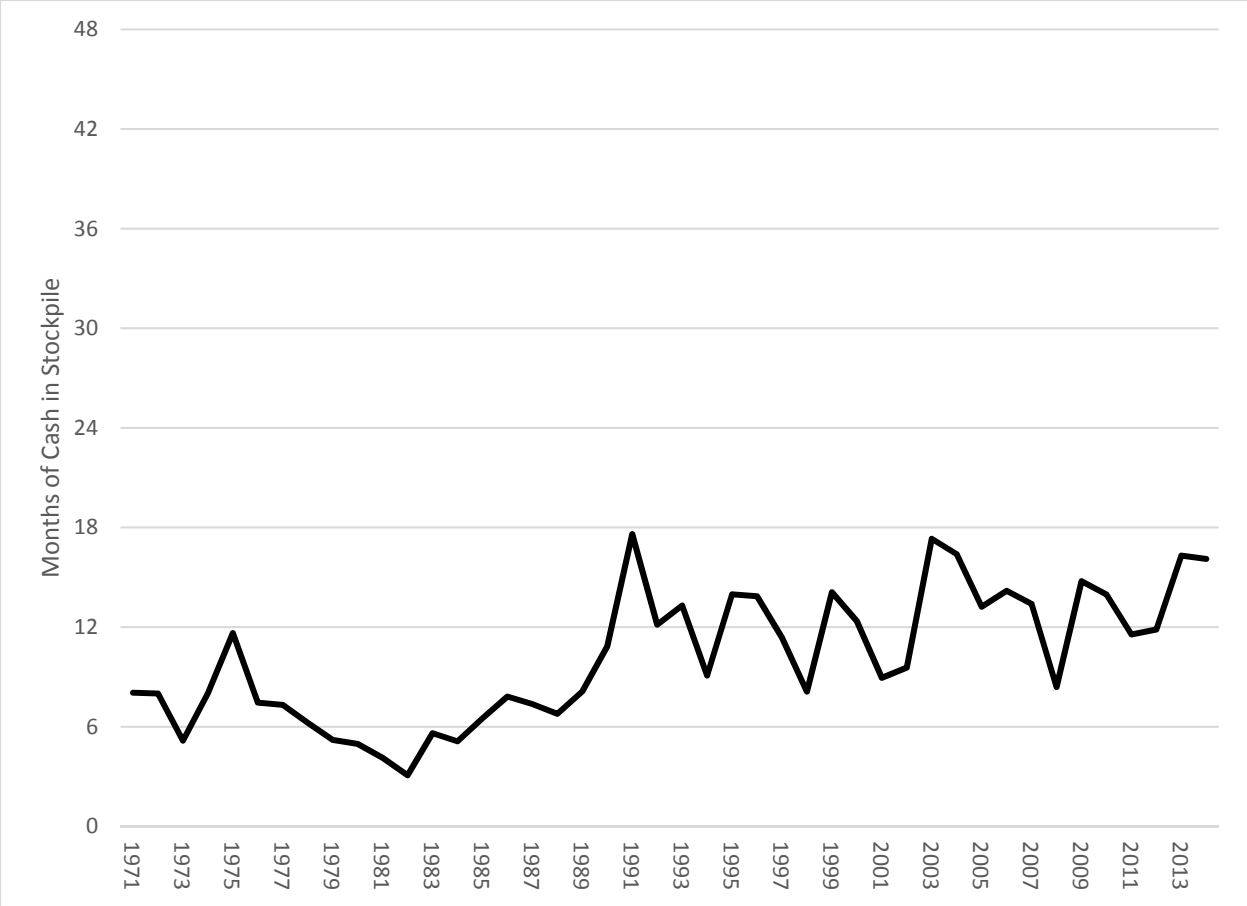
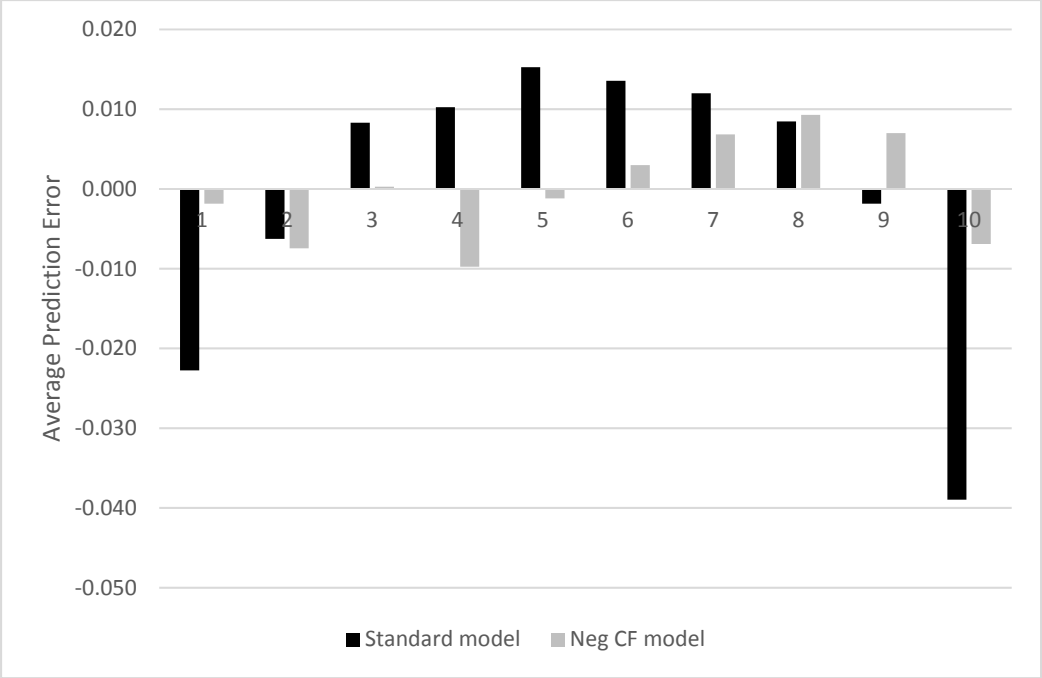


Figure 9. Median Runway for Equity Issuers with Negative Cash Flow. This chart reports the mean number of months of continued operations that could be sustained given current cash holdings. The sample includes all firms that both initiate an equity issuance and report negative cash flow in a given year.



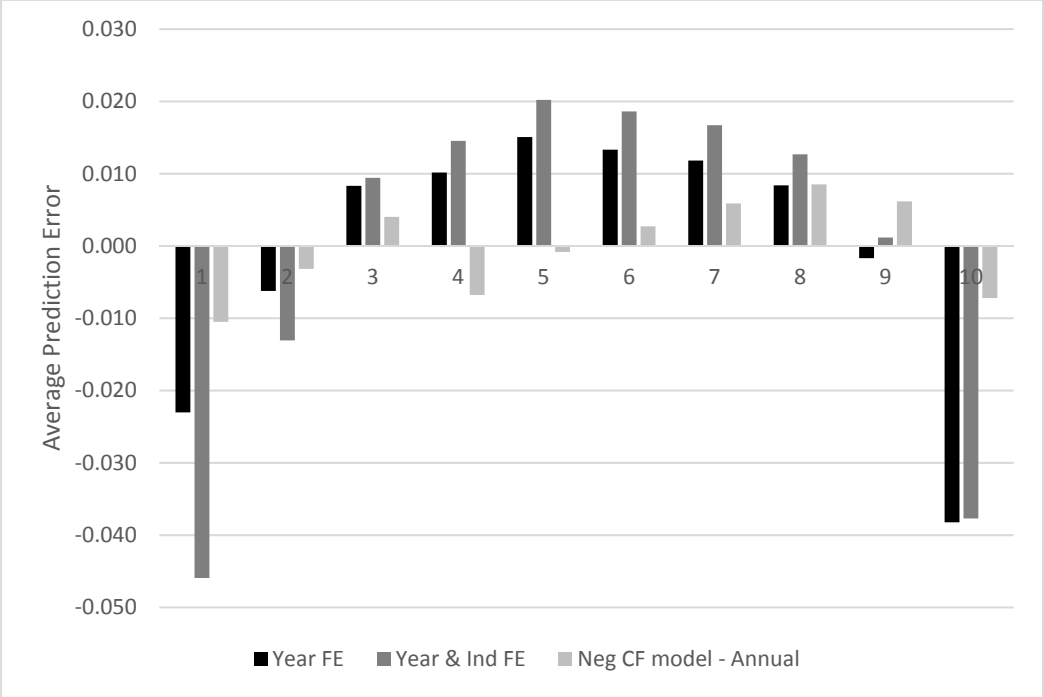


Figure 10. Prediction Error in Models of Cash Holdings. Panel A reports average prediction error from a standard model of cash/assets including cash flow, size, leverage, R&D intensity, industry cash flow volatility, capital expenditures and market-to-book ratio. The second series in panel A adds an indicator variable for negative cash flow and an interaction between negative cash flow and level of cash flow. Panel B reports prediction error from estimates using (i) the standard model with year fixed effects, (ii) year and industry fixed effects, and (iii) the negative earnings model from panel A estimated on annual cross sections. Both panels report average error sorted by cash flow decile where 1 is the lowest level of cash flow and 10 is the highest.

Analyst Effort Allocation and Firms' Information Environment*

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Abstract

We show that a firm's information environment is significantly impacted by the characteristics of the other firms its analysts cover. Analysts strategically allocate effort among portfolio firms by devoting more effort to firms that are relatively more important for their career concerns. Specifically, controlling for analyst and firm characteristics, we find that within each analyst's portfolio, firms ranked relatively higher based on market capitalization, trading volume, or institutional ownership receive more accurate, frequent, and informative earnings forecast revisions and stock recommendation changes that contain greater information content from that analyst. Firms' relative rank across analysts varies widely, so this is not a firm characteristic. As a result, even with explicit controls for firm characteristics, firms where a larger proportion of their analysts consider them as relatively more important are associated with more transparent information environments. Finally, we find that analysts who engage in a greater extent of career concerns-driven effort allocation are more likely to experience favorable career outcomes.

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1. Introduction

What determines the amount and quality of coverage a stock receives from an analyst? Prior research has identified many analyst and firm characteristics that affect analyst research (e.g., Clement (1999), Jacob, Lys, and Neale (1999), Clement, Reese, and Swanson (2003), Frankel, Kothari, and Weber (2006), Ljungqvist et al. (2007), Du, Yu, and Yu (2013), Bradley, Gokkaya, and Liu (2016), and Jiang, Kumar, and Law (2016)).[1] But the reality of analyst coverage portfolios suggests that analysts face competing demands for their time from the stocks they cover, and as a result how much coverage a stock receives from an analyst should depend not only on its own characteristics but also on the characteristics of other stocks the analyst follows. However, we know little about how the variation in stock characteristics *within* an analyst's portfolio impacts the way in which analysts provide research coverage on portfolio firms, and whether analysts' response to intra-portfolio firm differences has real consequences.

We aim to fill this void by examining how analysts allocate their effort among firms and whether their effort allocation decisions affect firm-level research quality and information transparency as well as their career outcomes. These are important questions that can lead to a more complete understanding of how analysts fulfill their information intermediary role, and of the constraints and incentives shaping their behavior. Answers to these questions can also provide new insights into the determinants of corporate transparency and improve empirical approaches to estimating the impact of an analyst on a firm's information environment.

Our investigation is built on the premise that financial analysts, like most economic agents, have limited time, energy, and resources (Kahneman (1973)), a notion that is consistent with extant evidence in the literature. For example, Clement (1999) shows that portfolio complexity measured by portfolio size has an adverse impact on analyst earnings forecast accuracy, and Cohen, Lou, and Malloy (2014) find that analysts with larger portfolios are less likely to ask questions on firms' earnings conference calls. Faced

[1] These variables include, e.g., the analyst's forecasting experience, portfolio complexity, employer size, employment history, cultural background, and political view and the firm's potential for generating investment banking business and trading commission and its institutional ownership.

with these constraints, analysts must be selective in allocating their attention and effort to firms in their portfolios.

As information intermediaries, analysts may choose to allocate their effort among firms based on their potential impact on a firm's information environment. For example, smaller firms with thinly traded stocks and less institutional following typically have more opaque information environments and thus are more difficult for outside investors to understand and evaluate. Therefore, investors as well as the firms themselves can benefit from more information production and dissemination by analysts. As a result, analysts could be expected to expend more effort researching these firms. We term this conjecture the "incremental impact" hypothesis.

Alternatively, analysts' career concerns may push them in a different direction. Analysts' compensation and upward mobility in the labor market depends on their reputation and ability to generate commission revenue for their brokerage houses and win favorable ratings from buy-side institutional clients (Groysberg, Healy, and Maber (2011)). Importantly, firms within an analyst's research portfolio can have differential impacts on the analyst's compensation, reputation, and mobility. For example, firms with large trading volumes and institutional ownership represent more lucrative sources of commission fee revenue for brokerage houses (Frankel, Kothari, and Weber (2006)). In addition, institutional investors participate in annual evaluations of sell-side analysts, and their assessments form the basis of the selection of "All-Star" analysts and the allocation of buy-side investors' trades and commissions across brokerage firms (Maber, Groysberg, and Healy (2014) and Ljungqvist et al. (2007)). In a similar vein, because large firms are more visible in the capital market, generating large trading activities and attracting significant institutional following, an analyst's performance in researching these firms may also have a larger impact on her compensation and reputation in the labor market (Hong and Kubik (2003)).

Given the heterogeneity along these dimensions among firms within an analyst's portfolio, the quality of the analyst's research services for each firm is likely to vary with the firm's relative importance for the analyst's career concerns. Based on this intuition, we develop a "career concerns" hypothesis, which contends that analysts devote more (less) effort to researching firms that are relatively more (less)

important from their career concern perspectives. We identify firms of relatively high (or low) importance to analysts using a firm's relative rank in an analyst's portfolio based on market capitalization, trading volume, and institutional ownership. Importantly, because a firm's relative rank is determined by not only its own characteristics but also those of other firms in an analyst's portfolio, there is wide variation in a firm's relative rank across analysts covering the firm. Aggregating the research efforts a firm receives from all of its analysts, the "career concerns" hypothesis further predicts that firms whose relative rank is high (or low) in a larger proportion of its analysts' portfolios are associated with more (less) transparent information environment and less (more) information asymmetry. This implies that a firm's information environment and hence cost of capital can be influenced by the characteristics of the *other* firms that its analysts follow.

To test these competing conjectures, we begin by analyzing the earnings forecasts and stock recommendations issued by a large sample of sell-side analysts from 1983 to 2012.[2] Evidence from our analysis lends strong support to the "career concerns" hypothesis. Specifically, analysts provide more accurate earnings forecasts and more frequent earnings forecast revisions for firms ranked higher based on market capitalization, trading volume and institutional ownership relative to other firms in the same analyst's portfolio. It is worth noting that these results are robust to controlling for a large array of pertinent firm and analyst characteristics. Our findings are also robust to controlling for analyst fixed effects, firm fixed effects, or analyst-firm pair fixed effects. The robustness to analyst-firm pair effects is especially notable because we are holding the pairing constant so that variation in the importance of the firm to the analyst comes largely from variations in the *other* firms that the analyst covers. In addition, we find that the impact of a firm's relative importance on earnings forecast behavior is stronger for "busy" analysts, i.e., those covering larger portfolios. This evidence is consistent with the intuition that larger

[2] Our examination of earnings forecasts and stock recommendations does not imply that they are the sole metrics based on which analysts are assessed and rewarded. In fact, institutional investors and brokerage houses evaluate analysts more broadly based on their knowledge and understanding of firms and industries and their activities of producing value relevant information or helping institutional clients obtain such information (Brown et al. (2015), Groysberg, Healy, and Maber (2011), and Maber, Groysberg, and Healy (2014)). We assume that the properties of earnings forecasts and stock recommendations are signals of the effort and resources devoted by analysts to all of these activities related to a given firm.

portfolios are more likely to hit the constraint created by analysts' limited time, energy, and resources, making it even more critical for the analysts to be strategic in their research activities. As such, it lends more credence to our "career concerns" hypothesis.

Further analyses suggest that the stock market recognizes the effort allocation incentives of analysts. Specifically, we find that earnings forecast revisions and stock recommendation changes issued by analysts on firms that are relatively more important in their portfolios elicit stronger stock price reactions, indicative of analyst research on these firms conveying greater information content.

We then extend our investigation to study the effects of analysts' career concerns-driven effort allocation on firms' information environment. Our results show that firms where a larger proportion of their analysts consider them relatively more important are associated with lower bid-ask spreads, higher stock market liquidity, and lower costs of capital. This is consistent with the interpretation that analysts commit more effort to research and information production for these firms, thereby contributing to more transparent information environments. We also exploit exogenous losses of analyst coverage due to brokerage house closures and mergers and find that firms losing coverage by analysts who rank them as relatively more important experience greater declines in information transparency, compared to firms losing coverage by analysts who rank them as relatively less important. Thus, analysts' effort allocation decisions have real consequences for firms and investors.

Finally, we examine the career outcome implications of analysts' effort allocation. If the pattern of analyst effort allocation we document is a rational response to career concerns, we expect favorable career outcomes to be related to the degree to which analysts engage in such effort allocation. We measure an analyst's engagement of career concern-based effort allocation by the differences in earnings forecast accuracy and frequency between the higher and lower ranked firms within the analyst's portfolio. Consistent with our expectation, we find that the extent of an analyst's career concern-based effort allocation is significantly and positively related to the probability of the analyst being voted as an "All Star" and moving to more prestigious brokerage houses. The explanatory power of the differential forecast frequency and accuracy between high and low ranked firms is incremental to the analyst's

average forecast frequency and accuracy for her portfolio. These results provide a logical explanation for the analyst effort allocation pattern we observe.

Our study makes several contributions that advance our understanding of the determinants of analyst behavior and firms' information environment. First, we contribute to the sell-side analyst literature by exploring within-analyst portfolio variations in analyst behavior. This approach represents a novel departure from as well as an important complement to prior studies focusing on either cross-analyst or cross-firm variations. It enables us to provide new insights into how analysts allocate their limited attention and resources to firms within their portfolios. Specifically, our findings go beyond the average effect of analyst and firm attributes and highlight the fact that the same analyst does not treat all firms in her portfolio equally and that the same firm does not receive equal amounts of attention and effort from all the analysts covering it. Instead, analysts strategically allocate more research effort to firms that are relatively more important for their career concerns.

In addition, we show that a firm's aggregate relative importance across its analysts has an effect on its information environment incremental to firm and analyst characteristics. Given that a firm's relative rank in an analyst's portfolio is partly determined by characteristics of other firms in the portfolio, our finding suggests that the quality of a firm's information environment is not entirely a function of its own attributes but also those of firms with which it shares analyst coverage.

Our results also suggest that the common approach of using the number of analysts following a firm as a measure of the firm's information environment can benefit from incorporating the firm's average relative importance in its analysts' portfolios. A larger number of analysts covering a firm does not necessarily translate into more information production and a more transparent information environment for the firm if it often finds itself at the bottom of its analysts' priority lists and thus receives little research attention.

Finally, our investigation sheds new light on factors that influence analysts' career outcomes. Specifically, our evidence suggests that the way in which analysts allocate their effort among portfolio firms is an important determinant of their labor market outcomes. Prior research finds that an analyst's

average earnings forecast accuracy has a significant impact on her career prospects (e.g., Mikhail, Walther, and Willis (1999) and Hong and Kubik (2003)). We show that an analyst's forecasting performance differential between the high and low ranked firms within her portfolio, which captures the extent of the analyst's career concern-based effort allocation, matters as well.

Before we move on to the empirical part of the paper, it is important to discuss the determination of an analyst's portfolio and whether it affects our research question and findings. The size and composition of an analyst's portfolio are driven by a multitude of factors, some of which are outside analysts' or brokerage firms' control, such as the number of companies, complexity, and major players in an industry. However, brokerage firms and analysts typically have at least some discretion over how many and which firms an analyst covers. For example, conversations with sell-side analysts, confirmed by our sample descriptive statistics, suggest that more seasoned analysts with higher quality and better reputation have more control over their research portfolios and tend to cover more firms. To the extent that analyst portfolios are determined entirely by exogenous forces and analysts or brokers do not have any discretion, it is a fairly straightforward question and empirical exercise with respect to how analysts allocate their efforts trying to maximize their utility function defined by career concern considerations. Alternatively, if analysts have full control over which firms are included in their portfolios and only cover firms that are important to them in some respect, e.g., trading commission or investment banking business, then ex ante it will be less likely for us to find evidence of analysts playing favorites among portfolio firms. However, even with the endogenous determination of analyst portfolios, our career concerns hypothesis would continue to be relevant as long as there is variation in the relative importance of firms within an analyst's portfolio. In fact, we find stronger evidence of career concerns-driven effort allocation when there is larger variation in firms covered by an analyst. In addition, the endogenous selection of portfolio firms implies that our findings represent a lower bound of the extent of strategic effort allocation by analysts, because firms of the least importance are likely not even included in analyst portfolios.

The rest of the paper proceeds as follows. Section 2 discusses the data sources, sample, and key variables. Section 3 examines analysts' earnings forecasts and stock recommendations and presents

evidence of analysts allocating efforts based on career concerns. Section 4 shows the real effects of analyst effort allocation decisions on firm information asymmetry and costs of capital. Section 5 presents results on the implication of analysts' strategic effort allocation for their career outcomes. Section 6 reports some additional analyses. Section 7 concludes the paper.

2. Sample description, variable construction, and summary statistics

The dataset used in our study is constructed from multiple sources. Analyst earnings forecasts and stock recommendations are from Institutional Broker Estimate System (*I/B/E/S*). Firm characteristics and stock returns are obtained from COMPUSTAT and CRSP. Information on institutional ownership is from the Thomson 13F database. Our sample period is from 1983 to 2012. Following prior literature, e.g., Clement (1999), we restrict the sample to earnings forecasts made during the first 11 months of a fiscal year, i.e., with a minimum forecast horizon of 30 days.

Our primary measure of analyst effort is the accuracy of an analyst's earnings forecast for a firm, which is based on the forecast made by the analyst that is closest to the firm's fiscal year end. We construct the analyst forecast accuracy measure by comparing an analyst's absolute forecast error on a firm to the average absolute forecast error of other analysts following the same firm during the same time period. This measure is initially developed by Clement (1999) to remove firm-year effects in analyst forecast accuracy and is widely adopted in the literature (e.g., Malloy, 2005; Clement et al., 2007; De Franco and Zhou, 2009; Horton and Serafeim, 2012; Bradley, Gokkaya, and Liu, 2016). Specifically, the relative earnings forecast accuracy ($PMAFE_{i,j,t}$) is computed as the absolute forecast error ($AFE_{i,j,t}$) of analyst i for firm j in year t minus the mean analyst absolute forecast error for firm j at year t ($MAFE_{j,t}$), then scaled by the mean absolute forecast error for firm j at year t to reduce heteroskedasticity (Clement, 1998). Specifically, $PMAFE_{i,j,t}$ is formally defined as:

$$PMAFE_{i,j,t} = \frac{AFE_{i,j,t} - MAFE_{j,t}}{MAFE_{j,t}}$$

$PMAFE_{i,j,t}$ is an analyst's forecast accuracy *relative to* all other analysts covering the same firm during the same time period and thus filters out differences across companies, year and industry (Ke and Yu, 2006). Lower values of *PMAFE* correspond to more accurate forecasts.

Our second measure of analyst effort is the frequency of earnings forecast updates, which is equal to the number of annual forecasts made by an analyst for a firm during a fiscal year with a minimum forecast horizon of 30 days. This variable has been used by prior studies to measure the amount of analyst effort (e.g., Jacob, Lys, and Neale (1999) and Merkley, Michaely, and Pacelli (2016)). However, its caveat is that it does not directly speak to the quality of analyst research on a given firm.

We construct a number of analyst and forecast characteristics that previous research has identified as important factors explaining analyst performance. Specifically, we control for analyst experience because Clement (1999) shows that it is related to forecast accuracy. We consider both general and firm-specific forecasting experience, which are calculated, respectively, as the total number of years that analyst *i* appeared in *I/B/E/S* ($Gexp_i$) and the total number of years since analyst *i* first provided an earnings forecast for firm *j* ($Fexp_{ij}$). We measure the resources available to an analyst using an indicator variable that is equal to one if the analyst works for a top-decile brokerage house ($Top10_i$) based on the number of analysts employed, and zero otherwise. This variable can also serve as an indicator for analyst ability, to the extent that larger brokerage houses attract more talented analysts. We also measure the complexity of an analyst's portfolio by the number of firms in analyst *i*'s portfolio ($PortSize_i$) and the number of 2-digit SICs represented by these firms ($SIC2_i$). Finally, we control for the number of days (AGE_{ij}) between analyst *i*'s forecast for firm *j* and the firm's fiscal year end. Clement (1999) and Clement and Tse (2005) find that *AGE* is positively related to relative forecast errors, emphasizing the need to control for timeliness. Appendix A provides detailed definitions of these variables.

Because the *I/B/E/S* database is left censored, we cannot determine how much experience analysts have prior to the first year of available data. To mitigate this problem, we follow Clement (1999) to exclude analysts who appear in the first year of the database (1983). Forecasts made in 1984 are also

excluded from our analysis because there would be little variation in the experience variables for that year (i.e., the experience variables can take on the value of only 0 or 1 in 1984).[3]

<Insert table 1 here >

Table 1 provides summary statistics on the main variables used throughout this paper. Panel A presents the unadjusted values. The median absolute forecast error is 0.07, and the median frequency of forecast revisions in a year is 3. The median analyst in our sample has been providing forecasts for 4 years, and covering the typical firm in our sample for 2 years. The median number of days between forecasts and the fiscal year end is 73. The median analyst covers 14 firms each year, which represents 3 distinct 2-digit SIC codes. Approximately 49% of forecasts are issued by analysts working for a top-decile brokerage house based on the number of analysts employed by each brokerage. These values are comparable to those in prior studies (Clement and Tse, 2005; Clement, Koonce, and Lopez, 2007; Bradley, Gokkaya, and Liu, 2016).

Panel B of Table 1 presents firm-year-mean-adjusted values. Clement (1999) finds that removing firm-year effects from dependent and independent variables improves the likelihood of identifying performance differences across sell-side analysts compared to a model that includes firm and year fixed effects. This is due to a firm's earnings predictability varying over time. We observe that the median values in Panel B are comparable to those reported in prior studies (e.g. Clement, 1999; Clement, Koonce, and Lopez, 2007; Bradley, Gokkaya, and Liu, 2016).

Our key explanatory variables are the measures that capture the relative importance of a firm in an analyst's portfolio. We first construct the measures based on the firm's market capitalization at the previous year end. To capture the relative importance of a specific firm for analysts following multiple firms, we create a dummy variable *High*, which takes the value of 1 if a firm's market capitalization is in the top quartile of all firms the analyst covers in that year, and zero otherwise. We also create a dummy variable *Low*, which takes the value of 1 if a firm's market capitalization is in the bottom quartile of all

[3] Our results are robust to the inclusion of those observations in 1983 and 1984.

firms the analyst covers in that year, and zero otherwise.[4] We also construct the *High* and *Low* indicators based on a firm's trading volume in the prior year and institutional ownership at the previous year end. Our goal here is not to take a stand on which measure of relative importance is most accurate. Rather, by using three different metrics, we hope to ensure that whatever pattern of analyst effort allocation we find is robust across alternative measures.

There is considerable variation in a firm's relative ranking across analysts. For example, using a firm's market capitalization to capture its relative importance, we find that conditional on a firm being ranked as high by at least one analyst, only 37% of the other analysts covering the firm rank it as high. Conditional on a firm being ranked as low by at least one analyst, the firm is ranked low by 56% of other analysts.

Panel C of Table 1 provides a comparison of several analyst forecast and firm characteristics between firms in the *High* and *Low* portions of analyst portfolios. Not surprisingly, we find that compared to firms in the *Low* group, firms in the *High* group are larger, more actively traded, and receive more institutional investment. They also receive more frequent and more accurate earnings forecasts from analysts, providing some preliminary support for our career concerns hypothesis.

3. Evidence on how analysts allocate effort

In this section, we examine how analysts allocate their effort across firms in their portfolios. We measure analyst effort using the earnings forecast accuracy and revision frequency.

3.1. Earnings forecast accuracy

Our career concerns hypothesis predicts that analysts make more accurate earnings forecasts for firms that are relatively more important in their portfolios. To test this prediction, we regress an analyst's relative forecast accuracy on a firm ($PMAFE_{i,j,t}$) on our key explanatory variables, the *High* and *Low* indicators, along with an array of analyst characteristics that previous research has identified as related to

[4] We require analysts covering at least four firms in a given year. Our results still hold without this requirement.

differences in relative forecast accuracy among analysts. To ensure that the *High* and *Low* indicators do not simply pick up the effects of the variables they are based on, we also control for a set of firm characteristics, even though the dependent variable by construction is free of firm-year effects.[5] More specifically, the model is specified as follows.

$$\begin{aligned} PMAFE_{i,j,t} = {} & \beta_0 + \beta_1 High_{i,j,t} + \beta_2 Low_{i,j,t} + \beta_3 DGexp_{i,j,t} + \beta_4 DFexp_{i,j,t} + \beta_5 DAge_{i,j,t} + \beta_6 DPortsize_{i,j,t} \\ & + \beta_7 DSIC2_{i,j,t} + \beta_8 DTop10_{i,j,t} + \beta_9 All\text{-}star_{i,j,t} + \beta_{10} Size_{j,t} + \beta_{11}\, Log(Trading\ Volume)_{j,t} \\ & + \beta_{12} Institutional\ Holding_{j,t} + \beta_{13} BM_{j,t} + \beta_{14} Past\ Ret_{j,t} + \beta_{15} No.\ of\ Analysts_{j,t} + \varepsilon_{i,j,t} \qquad (1) \end{aligned}$$

The "*D*" preceding some variables indicates that these variables are de-meaned at the firm-year level to remove firm-year fixed effects. The standard errors are estimated by double clustering at the firm and analyst level. Note that while our test is stated in terms of forecast accuracy, the dependent variable in this regression is an analyst's relative forecast error. Lower relative forecast errors indicate higher forecast accuracy. Based on the career concerns hypothesis, we expect the coefficient of *High* (*Low*) to be negative (positive).

<Insert Table 2 Here >

Panel A of Table 2 reports the baseline regression results. In column (1), the relative importance of a specific firm in an analyst portfolio is measured using its equity market capitalization. As predicted, the coefficient on *High* is negative and statistically significant at the 1% level, while the coefficient on *Low* is positive and statistically significant at the 1% level. These results indicate that analysts make more accurate earnings forecasts for firms that are relatively more important in their portfolios and are consistent with the prediction of our career concerns hypothesis that analysts devote more resources to researching these firms. Economically, firms that belong to the relatively more important group receive earnings forecasts that are on average 2.383% more accurate than firms not in that group. Similarly, firms

[5] Our results are robust without controlling for firm characteristics.

that belong to the relatively less important group receive earnings forecasts that are on average 1.905% less accurate. The average difference in earnings forecast accuracy between the high and low groups of firms is 4.288% (=1.905-(-2.383)). To put this effect into context, we compare it to the effects of some other determinants of forecast accuracy. We find that the high-low accuracy differential is equivalent to the effect of over 17 years of general forecasting experience, over 6.8 years of firm-specific forecasting experience, 1.70 times the effect of working for a top-decile brokerage firm and about the same as the effect of being an all-star analyst. We obtain very similar results when we measure the relative importance of a firm by trading volume in column (2) or by institutional ownership in column (3).

The coefficients on control variables are mostly consistent with previous studies (e.g., Clement (1999)). For example, analysts with more general or firm-specific forecasting experience issue more accurate earnings forecasts, while analysts covering more industries issue less accurate forecasts. Analysts employed by the largest brokerage houses have better forecasting performance, which could be due to more resources being available at large brokerage houses or analysts working for large brokerage houses being more talented. More stale forecasts tend to be less accurate.[6]

In further analysis, we augment the regression model specified in equation (1) by controlling for analyst fixed effects.[7] Doing so can help us focus on the within-analyst variations in the *High* and *Low* indicators and mitigate the concern that our findings are driven by some time-invariant analysts' characteristics such as experience or talent. Results in Panel B of Table 2 show that the coefficient on *High* continues to be significantly negative while the coefficient on *Low* remains significantly positive. The magnitude of the coefficients is slightly different from that in Panel A. For example, based on equity market capitalization, the relative earnings forecast error is 1.582% lower for relatively more important firms and 1.536% higher for relatively less important firms. These results indicate that for the same

[6] Our results are also robust to controlling for how long an analyst has covered a firm's industry and whether there is investment banking relationship between a firm and an analyst's employer. We identify investment banking relationships based on whether the analyst's employer has been a lead underwriter or co-manager of the firm's equity offering (IPO or SEO).

[7] Our sample includes about 7,200 unique analysts, 10,500 unique firms, and 200,500 analyst-firm pairs.

analyst, firms that are more important in her portfolio receive more accurate earnings forecasts than firms that are less important in her portfolio.

In Panel C, we replace the analyst fixed effects with firm fixed effects and in Panel D, we replace them with analyst-firm pair fixed effects. These alternative specifications serve two important purposes. First, they accentuate the within-firm variations or variations within each analyst-firm pair. Second, they allow us to control, at least indirectly, for the costs faced by analysts in covering a firm, which may affect their effort allocation decisions. To the extent that certain firm characteristics are related to how difficult or costly it is for analysts to cover the firm, our firm fixed-effects will absorb all of these characteristics. If some analysts are particularly good at covering a particular industry or firm, this effect will be absorbed by our analyst-firm fixed effects. Thus, while we recognize that the cost of covering firms is not equal, our firm and analyst-firm pair fixed effects justify our focus on the relative benefits of coverage, which, given our empirical approach, should also rank firms on relative net benefits.

We find that the coefficients on the *high* and *low* indicators retain their signs and statistical significance. These results suggest that for the same firm (as in Panel C) or the same firm covered by the same analyst (as in Panel D), the accuracy of forecasts received by the firm varies with its relative importance in the analyst's portfolio. The fact that the results are robust to analyst-firm pair fixed effects is particularly reassuring because in these regressions, the variation in relative rankings comes primarily from changes in what *other* firms are in the analyst's portfolio, as well as changes in the subject firm over time *after* it was originally added. This identification approach relies on time-series variation in a firm's high/low status within the analyst's portfolio. One concern would be that there is not enough such variation. It turns out, however, that changes in the composition of an analyst's portfolio are frequent enough that conditional on a firm being ranked high (low) by an analyst, this firm has an 18% (25%) probability of being ranked non-high (non-low) in the following year by the same analyst.

Gormley and Matsa (2014) show that de-meaning variables may produce inconsistent estimates and distort the results, and suggest using the raw values of variables and controlling for fixed effects instead. Therefore, we estimate an alternative specification of model (1), in which we control for firm-

year pair fixed effects in lieu of de-meaning the dependent variable as well as some of the independent variables. Table 3 presents the regression results. We continue to find a significantly negative coefficient for the *High* indicator and a significantly positive coefficient for the *Low* indicator, allowing us to conclude that de-meaning variables does not have a material impact on statistical inferences in our context. Therefore, we use the de-meaned specification as our main model to be consistent with the prior literature on analysts, and when necessary show robustness to the non-demeaned specification. Overall, the results from Tables 2 and 3 lend strong support to the career concerns hypothesis.[8]

3.2. Earnings forecast revision frequency

Earnings forecast update frequency is another widely used proxy for analyst effort in the literature (e.g., Jacob, Lys, and Neale (1999) and Merkley, Michaely, and Pacelli (2016)). Based on the career concerns hypothesis, we expect firms of relatively high importance within an analyst's portfolio to receive more frequent earnings forecast updates. We reestimate equation (1) in Section 3.1 while replacing the dependent variable with the earnings forecast update frequency (*FREQ*), measured as the number of annual forecasts issued by an analyst each year during the 360 to 30 days prior to a covered company's fiscal year end (Groysberg, Healy, and Maber (2011)). Appendix B presents the results. Consistent with our hypothesis, we find that analysts update earnings forecasts more frequently for firms that are relatively more important in their portfolios. Economically, the average difference in the earnings forecast frequency between the high and low groups of firms based on their equity market capitalization is equivalent to the effect of about 12.3 years of general forecasting experience, 1.07 years of firm-specific forecasting experience, 0.83 times of the effect of being employed at a top-decile brokerage firm and 0.60 times of the effect of being an all-star analyst. Our results are also robust to controlling for analyst fixed effects, firm fixed effects, and analyst-firm pair fixed effects.

[8] We also examine the likelihood of an analyst being a leader or follower in issuing earnings forecasts for a firm. Untabulated results show that analysts are neither more likely to be leaders nor followers when making forecasts on their most important firms in their portfolio, but there is some evidence that they are more likely to be followers when it comes to their least important firms. These findings are consistent with analysts devoting less effort to the least important firms.

3.3. Busy analysts

The career concerns hypothesis is built on the fact that analysts have limited time, energy, and resources. Faced with these constraints, analysts devote more effort to collecting and analyzing information for relatively more important firms in their portfolios. When analysts cover many firms, these constraints would be more binding and have a larger impact on analyst behavior. Therefore, we expect to observe stronger patterns of effort allocation among "busy" analysts, i.e., those who cover a large portfolio of firms. To formally test this prediction, we define "busy" analysts as those whose portfolio size in a given year is greater than the sample median and classify the other analysts as "non-busy". We then re-estimate the forecast accuracy regression for busy and non-busy analysts separately. We expect that the difference in forecast accuracy between the high and low groups of firms is more pronounced for busy analysts. On the other hand, a countervailing effect may also be at work. In particular, we find that analysts with larger portfolios tend to have significantly longer general forecasting experience and are more likely to be all-stars and employed by the largest brokerage houses.[9] To the extent that "busy" analysts have more experience, higher ability, and more resources at their disposal, there may be a lesser need for them to ration efforts to firms of low importance so as to devote more attention to firms of high importance.

<Insert Table 4 Here >

Table 4 presents the regression results, with Panels A and B for busy and non-busy analysts, respectively. We find that for non-busy analysts, the coefficients on the *High* and *Low* dummies continue to be negative and positive respectively, but their statistical significance is relatively low, with the *High* dummy's coefficient only significant in one out of three models. In contrast, for busy analysts, the coefficients on the *High* and *Low* dummies are highly significant with the expected signs in all models. Moreover, when we compare the coefficients between the subsamples, we find that the coefficient on the

[9] In our sample, an analyst's portfolio size is significantly and positively related to the analyst's general forecasting experience, whether the analyst works for a top broker, and whether the analyst is an all-star, with the correlation coefficients being 0.239, 0.065, and 0.115, respectively.

High dummy is always more negative for busy analysts than for non-busy analysis (with the *p*-value for the between-subsample difference being 0.041, 0.003, and 0.011 across the three models), and that the coefficient on the *Low* dummy is always more positive for busy analysts than for non-busy analysis (with the *p*-value for the between-subsample difference being 0.001, 0.013, and 0.001). As a result, the high-low coefficient difference is much larger for busy analysts (ranging from 3.7% to 5.8%) than for non-busy analysts (from 1.4% to 2.0%). This is consistent with our conjecture that busy analysts face greater time and resource constraints and thus engage in more strategic effort allocation among firms in their portfolios.[10]

3.4. Further evidence on analyst effort allocation: Stock price impact of analyst research

Given our evidence of analysts issuing more accurate and frequent earnings forecasts for relatively more important firms in their portfolios, we next investigate the stock market reactions to their earnings forecast revisions and stock recommendations. If investors recognize that analysts allocate time strategically across firms, we expect stronger market reactions to analysts' research on relatively more important firms in their portfolios. Analyzing the stock market reactions to analyst research can also address a potential caveat with using the earnings forecast accuracy measure. Specifically, analysts can potentially produce more accurate earnings forecasts by piggybacking on the information produced by other analysts and revealed through their published research including earnings forecasts. If an analyst's earnings forecast largely reflects the information contained in previously published research by other analysts, it would carry little new information content even though it may be more accurate. Therefore, we would expect its stock price impact to be muted at best. On the other hand, if the analyst's forecast indeed carries significant information content, its release should generate stronger stock market reactions.

3.4.1. Stock price reactions to analyst earnings forecast revisions

[10] We find similar results when defining analyst "busyness" based on the number of industries (based on 2-digit SIC) they cover.

We first examine the market reaction to forecast revisions. We expect to observe more pronounced market reaction to forecast revisions issued by analysts for their relatively more important firms. To test this prediction, we estimate the following regression model.

$$
\begin{aligned}
CAR_{i,j,t} = {} & \beta_0 + \beta_1 FR{*}High_{i,j,t} + \beta_2 FR{*}Low_{i,j,t} + \beta_3 FR_{i,j,t} + \beta_4 High_{i,j,t} + \beta_5 Low_{i,j,t} + \beta_6 Gexp_{i,j,t} \\
& + \beta_7 Fexp_{i,j,t} + \beta_8 Age_{i,j,t} + \beta_9 Portsize_{i,j,t} + \beta_{10} SIC2_{i,j,t} + \beta_{11} Top10_{i,j,t} + \beta_{12} All\text{-}star_{i,j,t} \\
& + \beta_{13} Size_{j,t} + \beta_{14}\, Log(Trading\ Volume)_{j,t} + \beta_{15} Institutional\ Holding_{j,t} + \beta_{16} BM_{j,t} + \beta_{17} Past\ Ret_{j,t} \\
& + \beta_{18} No.\ of\ Analysts_{j,t} + Year\ FE + \varepsilon_{i,j,t} \qquad (2)
\end{aligned}
$$

This model is similar to that used by Bradley, Gokkaya and Liu (2016). The dependent variable is the cumulative market-adjusted abnormal stock returns over a 3-day event window (-1, 1) around a forecast revision.[11] The key independent variables are the forecast revision (*FR*) and its interaction terms with *High* and *Low*. We control for other analyst and firm characteristics as in equation (1) as well as year fixed effects, and adjust standard errors for clustering at the firm and analyst level. We define forecast revision *(FR*) as the difference between the new forecast and the old forecast, scaled by the absolute value of the old forecast.[12] A positive *FR* represents an upward revision, and a negative *FR* represents a downward revision.

<Insert Table 5 Here >

Table 5 presents the regression results. Columns (1)-(3) are based on using the market capitalization, trading volume, and institutional ownership to measure the relative importance of firms. We find that the coefficient on forecast revision *(FR*) is significantly positive. This suggests that the stock market responds positively to upward revisions and negatively to downward revisions, and larger forecast revisions elicit greater stock price reactions. More relevant for our purpose are the interaction terms between forecast revision and the *High* and *Low* indicators. We find that *High*FR* has a

[11] The abnormal stock returns are denominated in percentage points, and we exclude analyst forecast revisions as well as stock recommendation changes that coincide with firms' earnings announcements.

[12] Our results are robust if we deflate the forecast revision by stock price.

significantly positive coefficient in two out of three models while *Low*FR* has a significantly negative coefficient in all three model specifications. These results indicate that conditional on the direction and magnitude of forecast revisions, the stock market reacts more strongly to forecast revisions issued by analysts for relatively more important firms in their portfolios. In other words, the forecast revisions received by relatively more important firms in an analyst's portfolio tend to be more informative. This is again consistent with the career concerns hypothesis, which predicts greater information production effort by analysts on these firms.

3.4.2. Stock price reactions to stock recommendations

Next we examine the market reaction to stock recommendation revisions. Loh and Mian (2006) find that analysts who have superior forecast accuracy also issue more informative stock recommendations. Brown et al. (2015) document that analysts' top motivation for issuing accurate forecasts is to use these forecasts as inputs for their corresponding stock recommendations. Therefore, we expect stronger market reactions to stock recommendations issued by analysts on their relatively more important firms. We estimate the following regression model to test our prediction.

$$CAR_{i,j,t} = \beta_0 + \beta_1 High_{i,j,t} + \beta_2 Low_{i,j,t} + \beta_3 Gexp_{i,j,t} + \beta_4 Fexp_{i,j,t} + \beta_5 Portsize_{i,j,t} + \beta_6 SIC2_{i,j,t} + \beta_7 Top10_{i,j,t} + \beta_8 All\ star_{i,j,t} + \beta_9 Lag\ recommendation_{i,j,t} + \beta_{10} Size_{j,t} + \beta_{11} Log(Trading\ Volume)_{j,t} + \beta_{12}\ Institutional\ Holding_{j,t} + \beta_{13} BM_{j,t} + \beta_{14} Past\ Ret_{j,t} + \beta_{15} No.\ of\ Analysts_{j,t} + Year\ FE + \varepsilon_{i,j,t} \quad (3)$$

The dependent variable is the cumulative 3-day market-adjusted abnormal stock return around a stock recommendation revision. The key explanatory variables are the *High* and *Low* indicators which capture the relative importance of a firm in an analyst's portfolio. We control for year fixed effects and adjust standard errors for clustering at the firm and analyst level. Following prior literature (e.g., Kecskes, Michaely, and Womack (2016)), we run separate regressions on recommendation upgrades and downgrades because of the asymmetric market reactions they elicit. Specifically, investors consider

downgrades more credible and informative than upgrades, because the latter may be driven by analysts' conflicts of interest, namely, their incentive to please firm management and drum up order flow.

<Insert Table 6 Here >

Panel A of Table 6 presents results for downgrades. Columns (1) to (3) correspond to the three different ways of ranking the relative importance of firms within an analyst's portfolio. We find that market reactions are stronger (weaker) for downgrades issued by analysts on their relatively more (less) important firms. In all specifications, the coefficients on *High* (*Low*) are significantly negative (positive) at the 1% level. In terms of economic significance, the coefficients in column (1) suggest that market reactions to downgrades are 54.8 basis points stronger for firms ranked relatively high in an analyst's portfolio and 33.3 basis points weaker for firms ranked relatively low in an analyst's portfolio. These results indicate that the informativeness of stock recommendations is related to a firm's ranking within an analyst's portfolio.

Panel B of Table 6 presents results for upgrades. The coefficients on *High* are significantly positive in all specifications, and the coefficients on *Low* are negative in all specifications but significant only in column (2). As a gauge of economic significance, the coefficients in column (1) indicate that stock market reactions are 15.2 basis points higher for firms with relatively high rankings, and 13.1 basis points lower for firms with relatively low rankings. The relatively weaker statistical and economic significance of the results for upgrades are likely due to their generally lower information content compared to downgrades.

4. The real effects of analyst career concerns on firm information environment

The results from Sections 3 are consistent with analysts devoting more effort to information production for relatively more important firms in their portfolios. A direct implication of our evidence is that everything else being equal, firms that on average are ranked high in relative importance across their analysts' portfolios should have more transparent information environments. In this section, we test this

conjecture by examining the effects of analyst effort allocation on firms' information asymmetry and costs of equity capital.

Different from the previous section, where we conduct tests at the analyst-firm-year level, the analysis in this section is at the firm-year level. We construct two variables to capture a firm's average relative ranking across all of its analysts. Specifically, we define *%High* (*%Low*) as the proportion of a firm's analysts who rank the firm high (low) in their portfolios. A higher value of *%High* implies that collectively more analyst effort is allocated to the firm while a higher value of *%Low* implies that collectively less analyst effort is allocated to the firm. Therefore, we expect a firm's information asymmetry and costs of capital to decrease with *%High* and increase with *%Low*. Appendix C reports the summary statistics of the dependent and independent variables used in this section. Panels A and B are based on two different samples, one for the information asymmetry analysis and the other for the costs of capital analysis.

4.1. Information asymmetry: Bid-ask spread and stock market liquidity

We follow the literature to measure a firm's information asymmetry in two ways. First, we compute a stock's bid-ask spread as a percentage of the stock price. A lower bid-ask spread implies lower information asymmetry. Second, we compute the Amihud (2002) stock illiquidity measure, which is defined as the natural log of one plus the ratio of the absolute stock return to the dollar trading volume and scaled by 1,000,000.[13] The key independent variables are *%High* and *%Low*. We control for a wide array of variables that have been shown to affect firms' information asymmetry. In particular, we control for firm size, trading volume, and institutional holding and their quadratic forms to ensure that *%High* and *%Low* are not simply picking up the effects of these firm characteristics. Our regression model is specified as follows.

[13] Following prior literature, we exclude firms with stock prices below $5.

$$\textit{Bid-ask spread or Amihud illiquidity measure}$$

$$= \beta_0 + \beta_1 \%High + \beta_2 \%Low + \beta_3 No.\ of\ Analysts + \beta_4 Size + \beta_5 Size^2 + \beta_6 Log(Trading\ Volume)$$

$$+ \beta_7 Log(Trading\ Volume)^2 + \beta_8\ Institutional\ Holding + \beta_9\ Institutional\ Holding^2 + \beta_{10} Log(Stock\ Price)$$

$$+ \beta_{11} BM + \beta_{12} Leverage + \beta_{13} Past\ Ret + \beta_{14} ROA + \beta_{15} Volatility + Year\ FE + Firm\ FE + \varepsilon \qquad (4)$$

<Insert Table 7 Here >

Panel A of Table 7 presents the results from the bid-ask spread regressions. Consistent with our conjecture, the coefficients on *%High* are significantly negative in all three specifications and the coefficients on *%Low* are significantly positive in two specifications. These results indicate that a firm which is ranked high by a larger proportion of its analysts has lower information asymmetry as measured by the bid-ask spreads. Economically, the coefficient estimates in column (1) suggest that, for a one standard deviation increase in *%High*, a firm's bid-ask spread on average decreases by 2.86 basis points (= -0.118×0.242×100) or 2.40% (=2.86/119).[14] Similarly, for a one standard deviation increase in *%Low*, a firm's bid-ask spread increases by 1.40 (=0.039×0.359×100) basis points or 1.17% (=1.40/119). As a comparison, for a one standard deviation increase in *No. of Analysts*, a firm's bid-ask spread on average decreases by 1.97 basis points (=-0.003×6.557×100) or 1.66% (=1.97/119).[15] Therefore, the economic significance of *%High* and *%Low* is on par with that of *No. of Analysts*.

Coefficients on control variables are generally consistent with the literature. For example, the bid-ask spread decreases with the number of analysts covering a firm, firm size, trading volume, institutional holding, stock return, and increases with stock volatility.

Panel B of Table 7 presents the results from the regressions of the Amihud illiquidity measure. We find that firms covered by more analysts who rank them high (low) enjoy higher (lower) stock market liquidity. Our results in Table 7 are robust to an alternative specification in which we replace *%High* (or *%Low)* with a dummy variable equal to one if a majority of a firm's analysts rank the firm high (or low) in their portfolios.

[14] The standard deviation of *%High* (*%Low*) in our sample is 0.242 (0.359). The mean value of bid-ask spread in our sample is 119 basis points. Please see Panel A of Appendix C.
[15] The standard deviation of *No. of Analyst*s in our sample is 6.557.

4.2. Costs of equity capital

To examine the effect of analyst effort allocation on firms' costs of equity capital, we use the residual income valuation model developed by Gebhardt, Lee, and Swaminathan (2001) to estimate the implied cost of capital (ICOC). The basic premise of the residual income model is that the ICOC is the internal rate of return that equates the current stock price to the present value of the expected future sequence of residual incomes or abnormal earnings. As in equation (5), the key explanatory variables are *%High* and *%Low* and we control for the raw values of firm size, trading volume, and institutional holding and their quadratic forms. The other control variables are from Gebhardt, Lee, and Swaminathan (2001). The regression model is specified as follows:

$$ICOC = \beta_0 + \beta_1 \%High + \beta_2 \%Low + \beta_3 No\ of\ Analysts + \beta_4 Size + \beta_5 Size^2 + \beta_6 Log(Trading\ Volume)$$
$$+ \beta_7 Log(Trading\ Volume)^2 + \beta_8\ Institutional\ Holding + \beta_9\ Institutional\ Holding^2 + \beta_{10} MAE\ of\ forecasts$$
$$+ \beta_{11} Earnings\ variability + \beta_{12} Dispersion\ of\ analyst\ forecasts + \beta_{13} BM + \beta_{14} Leverage + \beta_{15} Past\ Ret$$
$$+ \beta_{16} Long\text{-}term\ growth + \beta_{17} Beta + \beta_{18} Volatility + Year\ FE + Firm\ FE + \varepsilon \qquad (5)$$

<Insert Table 8 Here >

Table 8 presents the regression results. We find that a firm's ICOC decreases with the percentage of analysts that rank the firm high in their portfolios and increases with the percentage of analysts that rank the firm low in their portfolios. The coefficients on *%High* are all significantly negative and the coefficients on *%Low* are positive and significant in two out of three specifications. Economically, the coefficient estimates in column (1) suggest that, for a one standard deviation increase in *%High* or *%Low*, a firm's implied cost of capital on average decreases by 1.08% (=-0.259×0.274/(0.0654×100)) or increases by 0.89% (=0.193×0.303/(0.0654×100)).[16] As a comparison, for a one standard deviation increase in *No. of Analysts*, a firm's implied cost of capital on average decreases by 0.99% (=-

[16] The mean implied cost of capital for our sample firms is 0.0654. Please see Panel B of Appendix C.

0.009×7.158/ (0.0654×100)). Therefore, the economic impact of *%High* and *%Low* is similar to that of *No. of Analysts.*

Overall, our analysis in this section shows that a firm that is considered relatively more important by a larger proportion of its analysts has lower information asymmetry, better stock market liquidity, and a lower cost of capital. These results are consistent with analysts producing more information for relatively more career-important firms in their portfolios, and suggest that when evaluating the impact of analyst coverage on a firm's information environment, it is important to consider not only the number of analysts providing coverage but also the firm's average relative importance in the analysts' portfolios.

4.3. The effects of exogenous losses of analyst coverage

For a sharper identification of the effects of analyst effort allocation on firm information environments, we exploit exogenous losses of analyst coverage due to brokerage house closures and mergers as a quasi-natural experiment. Kelly and Ljungqvist (2012) document that information asymmetry increases following analyst coverage termination caused by brokerage house closures and mergers. We examine if the effect is stronger (or weaker) for firms losing coverage by an analyst who ranks the firm high (or low).

There are 38 brokerage house closures and mergers during our sample period.[17] We first identify firms that experienced losses of analyst coverage caused by brokerage closures or mergers. For broker mergers, we focus only on analyst coverage terminations where a stock was covered by an analyst from both the acquirer and target brokers before the merger, and by only one surviving analyst after the merger (e.g., Kelly and Ljungqvist (2012) and Derrien and Kecskes (2013)). To remove the common factors that affect the information environment of similar firms at the same time, we follow Kelly and Ljungqvist (2012) and Daniel, Grinblatt, Titman, and Wermers (DGTW, 1997) to construct a control group for each treatment firm. Specifically, for each firm experiencing analyst coverage losses, a control group is formed by selecting stocks with the same size and book-to-market quintile assignment in the month of June prior

[17] Our sample of brokerage house mergers and closures comes from Wang, Xie, and Zhang (2016).

to the analyst loss, subject to the conditions that control firms (1) were covered by one or more analysts in the three months before the event; and (2) were not themselves subject to a coverage termination in the quarter before and after the event. We select up to five control stocks that are closest to the treatment stock in terms of the relevant pre-event information asymmetry measure. We then employ a difference-in-differences (DiD) approach to compare the change in the information environment of control firms to treatment firms. We further split the treatment firms into *High* and *Low* groups based on each treatment firm's ranking (high or low) in the lost analyst's portfolio in the year before the brokerage house closures and mergers. Based on market capitalization, we have 463 treatment firms in the *High* group and 214 treatment firms in the *Low* group.

<Insert Table 9 Here >

Table 9 reports the differences in the mean DiD between the *High* and *Low* groups for the bid-ask spread and Amihud illiquidity measures. Following Kelly and Ljungqvist (2012), we compute the changes in a firm's bid-ask spread and stock illiquidity from three (or six) months before an analyst coverage loss to three (or six) months afterwards. Specifically, we calculate the average bid-ask spread and stock illiquidity using daily stock price and returns data over a three- (or six-) month estimation window ending ten days before a termination event and a three- (or six-) month estimation window starting ten days after the termination event.

Results in Panel A show that the differences in the mean DiD between the *High* and *Low* groups of treatment firms are positive and statistically significant in all cases. This suggests that firms losing coverage from an analyst who ranks them high experience significantly larger increases in bid-ask spreads compared to firms losing coverage from an analyst who ranks them low. In Panel B, firms in the *High* group also experience larger increases in the Amihud illiquidity measure due to analyst coverage losses, and the differences in the mean DiD between the *High* and *Low* groups are statistically significant when firms are ranked by market capitalization and institutional ownership. Overall, results in this section provide further support for our conjecture that analysts devote more effort to information production for

relatively more important firms in their portfolios, helping to create more transparent information environments for these firms.[18]

5. Strategic effort allocation and analyst career outcomes

The evidence presented so far in the paper suggests that analysts respond to career concern incentives in strategically allocating their effort among portfolio firms. A question that naturally arises from our finding is whether the extent of analysts' strategic effort allocation has any impact on their career outcomes. Specifically, if an analyst indeed devotes more effort to, and produces higher-quality research for, firms with greater visibility, more institutional following, and greater brokerage commission potential, we expect the analyst to experience more favorable career outcomes. We test this conjecture by examining two measurable career outcomes – being voted an "All Star," and moving up to a more prestigious brokerage firm. We expect that a higher degree of career concern-based effort allocation increases the likelihood of both outcomes.

We capture the extent of such effort allocation by the difference in forecast frequency and accuracy between the *high* and *low* groups of firms in an analyst's portfolio. The rationale behind this approach is that in the absence of strategic effort allocation we should not expect to observe any difference in the relative frequency and accuracy of forecasts issued by the same analyst to firms in her portfolio. This is because an analyst's forecast behavior for each firm is measured relative to other analysts covering the same firm in the same year, effectively removing firm-year effects from our forecast frequency and accuracy measures. Therefore, analyst effort allocation is the only logical explanation for any observed difference in these measures between the high and low groups of firms within an analyst's portfolio.

[18] The identification strategy used in this section is less well suited for the implied cost of capital measure, because its estimation is based on many inputs that are unlikely to change much over our short event windows, such as the historical dividend yield, expected earnings per share, and the long-term GDP growth rate.

We estimate a logit regression to investigate how strategic effort allocation affects the probability of an analyst being voted an "All Star". We extract the annual list of "All Star" analysts from the October issues of *Institutional Investor* magazine. The dependent variable is a dummy variable that is equal to one if an analyst is named an "All Star" in a particular year and zero otherwise. The key independent variables are the differences in relative forecast frequency and accuracy between the high and low groups within each analyst's portfolio. We include the analyst's general forecasting experience, portfolio size, number of industries covered, average forecast frequency and accuracy for portfolio firms, average portfolio firm size, as well as whether the analyst was an "All Star" in the previous year. Our model is specified as follows.

$$Pr(Voted\ All\text{-}star) = \beta_0 + \beta_1(Diff(High\text{-}Low)\ in\ DFREQ) + \beta_2(Diff(High\text{-}Low)\ in\ PMAFE) + \beta_3 GExp + \beta_4 Portsize + \beta_5 SIC2 + \beta_6 Brokerage\ Size + \beta_7 Average\ PMAFE + \beta_8 Average\ DFREQ + \beta_9 Average\ Firm\ Size + \beta_{10} lag(All\ star) + Year\ FE + \varepsilon \quad (6)$$

<Insert Table 10 Here >

Panel A of Table 10 presents the regression results. For each specification, we have separate regressions using market capitalization, trading volume, and institutional ownership to define the high vs. low groups. We find that in all model specifications, the high-low group difference in relative forecast frequency has a significant and positive coefficient and the high-low group difference in relative forecast errors has a significant and negative coefficient. Note that for analysts who strategically allocate their efforts, we expect a positive difference in the relative forecast frequency and a negative difference in forecast errors between high and low groups. Thus, our results suggest that analysts who engage in a greater extent of strategic effort allocation are more likely to be voted "All Star". This is consistent with our earlier conjecture and provides a rational justification for the analyst effort allocation pattern we observe in the data.

With respect to the control variables, their coefficients are largely in line with extant evidence in the literature. For example, analysts who cover larger portfolios with larger firms, work for larger

brokerage firms, issue more frequent and more accurate earnings forecasts for average portfolio firms are more likely to be voted "All Stars". There is also significant evidence of persistence in analysts being named "All Star" in consecutive years.[19]

Next, we investigate the effect of strategic effort allocation on the likelihood of an analyst being promoted. Following Hong and Kubik (2003), we define analyst promotion as cases in which an analyst moves from a low-status brokerage house to a high-status one. Each year we classify the top ten brokerage houses employing the most analysts as high-status and the rest as low-status.[20] We find that during our sample period, 9.77% of the analysts switch brokerage houses each year. Of those analysts that switch employers, 14.29% of them move from a low-status brokerage house to a high-status one, a frequency that is comparable to that reported by Hong and Kubik (2003). Following Hong and Kubik (2003), we measure analyst performance over a 3-year period. Therefore, in the regression model specified below, *Diff(High-Low) in DFREQ*, *Diff(High-Low) in PMAFE*, *Average DFREQ*, and *Average PMAFE* are calculated as the averages over the previous 3 years.

$$\begin{aligned} Pr(Being\ Promoted) = {} & \beta_0 + \beta_1(Diff(High\text{-}Low)\ in\ DFREQ) + \beta_2(Diff(High\text{-}Low)\ in\ PMAFE) + \beta_3 GExp \\ & + \beta_4 Portsize + \beta_5 SIC2 + \beta_6 Brokerage\ Size + \beta_7 Average\ PMAFE \\ & + \beta_8 Average\ DFREQ + \beta_9 Average\ Firm\ Size + Year\ FE + \varepsilon \qquad (8) \end{aligned}$$

Panel B of Table 10 reports the regression results.[21] Similar to the results in Panel A, the high-low group difference in relative forecast frequency has a significant and positive coefficient and the high-low group difference in relative forecast errors has a significant and negative coefficient in two out of three

[19] We also examine the probability of an analyst being a first-time all-star and obtain qualitatively similar results. The probability of an analyst being a first-time all-star in our sample is 1.85%.

[20] We also make sure that an analyst's promotion is not driven by a brokerage house's status change. That is, we require that the analyst's former employer is a low-status brokerage house in both year t and year t+1, and her new employer is a high-status one in both year t and year t+1.

[21] The sample used for the promotion analysis is smaller because this test is conditional on an analyst working at a low-status brokerage house in the base year t and we require each analyst to have at least three years of earnings forecast data.

specifications. These results suggest that analysts who engage in a greater extent of strategic effort allocation are more likely to move up to more prestigious brokerage houses.

6. Additional Analysis

6.1. Heterogeneity among firms within an analyst's portfolio

Some analyst portfolios are characterized by large differences between their high and low firms, while other analysts cover relatively similar firms, so that there is not as much of a difference, and hence less incentive for strategic effort allocation. The idea is that in analyst portfolios with large variations in market capitalization, trading volume, or institutional ownership, the high and low designations are likely to be more meaningful indicators of firms' relative importance to analyst career concerns and thus more powerful predictors of analyst effort allocation. To test this conjecture, we first compute the standard deviation of market capitalization, trading volume, and institutional ownership for each analyst portfolio in each year and partition our sample into subsamples based on whether the within-portfolio variation along a particular dimension is above or below the sample median. We then repeat our analysis in Section 3 in these subsamples. In untabulated results, we find that analysts covering portfolios with larger variations in market capitalization, trading volume, or institutional ownership indeed engage in a greater extent of strategic effort allocation.

6.2. Alternative measure for analyst forecast accuracy

We repeat the analyst forecast accuracy analysis using an alternative measure of forecast accuracy suggested by Clement and Tse (2005), which is defined as follows.

$$Accuracy_i = \frac{\mathrm{Max(AFE)} - \mathrm{AFE}_i}{\mathrm{Max(AFE)} - \mathrm{Min(AFE)}}$$

This alternative proxy increases with forecast accuracy, while *PMAFE* decreases with forecast accuracy. In untabulated results, we continue to find that analysts issue more (less) accurate forecasts for firms that are relatively more (less) important within their portfolios.

6.3. Coverage termination

We examine analysts' decision to terminate coverage on a firm as another indicator of effort allocation. Our career concerns hypothesis predicts that analysts are less (more) likely to stop providing research coverage for firms that are relatively more (less) important in their portfolios. We define coverage termination as instances in which an analyst does not issue earnings forecasts for a firm for an entire year but she did so in the previous year. In our sample, the unconditional probability of a firm being dropped by an analyst is 15.3%, and the likelihood decreases to 12.9% if the analyst ranks the firm high and increases to 19.5% if the analyst ranks the firm low. For more reliable inferences, we estimate a logistic regression where the dependent variable is equal to one if a firm loses coverage by an analyst in a given year and the key explanatory variables are the *High* and *Low* indicators reflecting a firm's relative importance in the analyst's portfolio. We control for firm and analyst characteristics included in previous tables, the analyst's prior forecast accuracy for the firm, and analyst-firm pair fixed effects. Untabulated results show that an analyst is more likely to stop coverage for a firm that is ranked low in her research portfolio, and this is especially the case when her prior forecast accuracy is poor for the firm. These findings provide further support for the career concerns hypothesis.

7. Conclusion

We provide evidence on how financial analysts treat firms in their portfolios differently and the implications this has for the information environment of the firms they follow. Analysts devote more effort to researching firms that are more important for their career concerns. Specifically, within each analyst's portfolio, firms ranked relatively higher based on market capitalization, trading volume, or institutional ownership receive more frequent earnings forecast revisions and more accurate earnings forecasts. These findings are robust to controlling for firm and analyst characteristics and the inclusion of firm fixed effects, analyst fixed effects, and, importantly, analyst-firm pair fixed effects. Earnings forecast revisions and stock recommendation changes issued by analysts for the relatively more important firms in

their portfolios also generate significantly stronger stock price reactions. This pattern of analysts strategically allocating their effort among portfolio firms is especially strong when they have larger research portfolios.

Analysts' career concern-based effort allocation also carries real consequences for firms. Specifically, firms covered by more analysts who rank them as more important in their portfolios have, on average, more transparent information environments, characterized by lower bid-ask spreads, stock market illiquidity, and costs of equity capital. Thus, the information environment of a firm is determined in part by what other firms its analysts cover. The marginal impact of a new analyst on a firm's spreads, liquidity and cost of capital varies with the firm's relative rank within the new analyst's portfolio. Researchers studying the impact of analysts on firms should take into account these analyst portfolio effects.

Finally, as a logical justification for the observed effort allocation pattern, we find that analysts who engage in a greater extent of strategic effort allocation are more likely to be voted "All Stars" by institutional investors and move up to more prestigious brokerage houses. Overall, our entire body of evidence is consistent with the hypothesis that driven by career concerns, analysts strategically allocate their effort among firms in their portfolios, which is reflected in the frequency, accuracy, and informativeness of their research.

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Appendix A: Variable Definitions

Variable	Definition
%High	The percentage of a firm's analysts who rank the firm high in their portfolios in year *t*.
%Low	The percentage of a firm's analysts who rank the firm low in their portfolios in year *t*.
AFE	The absolute forecast error of analyst *i* for firm *j*, calculated as the absolute value of the difference between analyst *i*'s earnings forecast for firm *j* and the actual earnings reported by firm *j*
Age	The age of analyst *i*'s forecast (*Age*) is defined as the number of days between analyst *i*'s forecast for firm *j* and the firm's fiscal year end.
All-star	Indicator variable is one if the analyst is named to Institutional Investor's all-star team in current year, and zero otherwise.
Amihud illiquidity	The natural log of one plus the ratio of the absolute stock return to the dollar trading volume and scaled by 10^6.
Average DFREQ	The average DFREQ of all the firms covered by analyst *i* in year *t-1*.
Average PMAFE	The average PMAFE of all the firms covered by analyst *i* in year *t-1*.
Average firm size	The average size of the all the firms covered by analyst *i* in year *t-1*.
Beta	Market beta of a firm based on a five-year rolling regression using monthly data and the value-weighted CRSP index.
Bid-ask spread	Computed as 100 * (ask–bid) / [(ask+bid) / 2] using daily closing bid and ask prices from CRSP
BM	Book value of equity in the fiscal year prior to the earnings forecast divided by the current market value of equity.
Brokerage size	The total number of analysts working at a given analyst *i*'s brokerage house.
CAR	Three-day CRSP value-weighted market-adjusted cumulative abnormal return. Values are multiplied by 100.
DAge	The age of analyst *i*'s forecast (Age) minus the average age of forecasts issued by analysts following firm *j* at year *t*, where age is defined as the age of forecasts in days at the minimum forecast horizon date.

DFExp	The total number of years since analyst *i*'s first earnings forecast for firm *j* (FExp) minus the average number of years I/B/E/S analysts supplying earnings forecasts for firm *j* in year *t*.
DFREQ	The number of earnings forecast revisions issued by analyst *i* for firm *j* in year *t*, minus the average number of earnings forecast revisions issued by all analysts for firm *j* in year *t*.
DGExp	The total number of years that analyst *i*'s appeared in *I/B/E/S* (*GExp*) minus the average tenure of analysts supplying earnings forecasts for firm *j* in year *t*.
Diff(High-Low) in DFREQ	The average DFREQ of firms in the high group of an analyst's portfolio minus the average DFREQ of firms in the low group of the analyst's portfolio in year *t-1*.
Diff(High-Low) in PMAFE	The average PMAFE of firms in the high group of an analyst's portfolio minus the average PMAFE of firms in the low group of the analyst's portfolio in year *t-1*.
Dispersion of analyst forecasts	The coefficient of variation of the current FY1 forecast.
DPortsize	The number of firms followed by analyst *i* for firm *j* in year *t* (*Portsize*) minus the average number of firms followed by analysts supplying earnings forecasts for firm *j* in year *t*.
DSIC2	Number of 2 digit SICs followed by analyst *i* in year *t* (*SIC2*) minus the average number of 2-digit SICs followed by analysts following firm *j* in year *t*.
DTop10	Indicator variable is one if analyst works at a top decile brokerage house (*Top10*) minus the mean value of top decile brokerage house indicators for analysts following firm *j* in year *t*.
Earnings variability	The coefficient of the variation of annual earnings over the previous five years.
FExp	The total number of years since analyst *i*'s first earnings forecast for firm *j* in year *t*.
FREQ	The number of earnings forecast revisions issued by analyst *i* for firm *j* in year *t*.
FR	Analyst forecast revision following Ivkovic and Jegadeesh (2004). The difference between an analyst's revised forecast and the previous forecast scaled by the absolute value of the previous forecast. The denominator is set equal to .01 if the absolute value of the previous forecast is smaller. Values are multiplied by 100 and are truncated between -50% and 50%.
GExp	The total number of years that analyst *i*'s appeared in I/B/E/S in year *t*.

High	A dummy variable which takes the value of 1 if the firm's market capitalization (or trading volume, institutional ownership) is in the top quartile of all firms the analyst covers in that year, zero otherwise.
Institutional holding	The percentage of a firm's equity held by all institutions at the end of year *t-1*.
Institutional ownership	The dollar amount of institutional investment in firm *j*, calculated as firm *j*'s market capitalization at the end of year *t-1* multiplied by the percentage of equity held by all institutions.
Leverage	Long term debt plus debt in current liabilities divided total assets
Long-term growth	Long-term growth in earnings; the mean long-term earnings growth rate from I/B/E/S.
Low	A dummy variable which is an indicator variable equal to one if the firm's market capitalization (or trading volume, institutional ownership) is in the lower quartile of all firms the analyst covers in that year, zero otherwise.
MAE of forecasts	The average mean absolute error of the last five annual I/B/E/S consensus forecasts
No. of analysts	The number of unique analysts issuing earnings forecasts for firm *j* in year *t*.
Past Ret	CRSP VW-index adjusted buy-and hold abnormal returns over six months prior to the announcement date of the earnings forecast.
PMAFE	The proportional mean absolute forecast error calculated as the difference between the absolute forecast error (AFE) for analyst *i* on firm *j* in year *t* and the mean absolute forecast error (MAFE) for firm *j* in year *t* scaled by the mean absolute forecast error for firm *j* in year *t*.
Portsize	The number of firms followed by analyst *i* in year *t*.
ROA	Return on assets, calculated as net income before extraordinary items and discontinued operations divided by total assets
SIC2	The number of 2-digit SICs represented by firms followed by analyst *i* in year *t*.
Size	The natural log of market capitalization of the covered firm (in $thousands) at the end of year *t*-1.
Top10	Indicator variable that is equal to one if an analyst works at a top decile brokerage house in year *t*.

Trading volume	The annual trading volume (in thousand shares) for a firm *j* in year *t-1*
Volatility	Daily stock return volatility for firm *j* in year *t*

Appendix B: Earnings Forecast Update Frequency

This table presents OLS regression results for analyst earnings forecast update frequency for the full sample. The dependent variable is the de-meaned analyst forecast update frequency (*DFREQ*) in all regressions. The primary variables of interest are *High* and *Low*. *High* is a dummy variable which takes the value of 1 if the firm's market capitalization (or trading volume, institutional ownership) is in the top quartile of all firms the analyst covers in that year, zero otherwise. *Low* is a dummy variable which is an indicator variable equal to one if the firm's market capitalization (or trading volume, institutional ownership) is in the lower quartile of all firms the analyst covers in that year, zero otherwise. See Appendix A for a description of control variables. t-statistics are in parentheses with heteroskedastic-consistent standard errors clustered at the firm and analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Variables	(1) Market cap	(2) Trading volume	(3) Ownership
High	0.055***	0.034***	0.043***
	(5.12)	(3.42)	(4.17)
Low	-0.080***	-0.049***	-0.072***
	(7.66)	(5.24)	(6.53)
DGExp	-0.011***	-0.012***	-0.011***
	(4.03)	(4.10)	(4.03)
DFExp	0.126***	0.127***	0.127***
	(28.07)	(28.13)	(28.05)
DAge	-0.011***	-0.011***	-0.011***
	(97.76)	(97.74)	(97.75)
DPortsize	0.006***	0.006***	0.006***
	(4.22)	(4.15)	(4.19)
DSIC2	-0.043***	-0.043***	-0.043***
	(9.22)	(9.13)	(9.16)
DTop10	0.162***	0.159***	0.161***
	(8.10)	(7.96)	(8.08)
All-star	0.228***	0.222***	0.227***
	(8.07)	(7.90)	(8.04)
Size	-0.015**	-0.014**	-0.015**
	(2.23)	(2.14)	(2.19)
Log(trading volume)	0.001	-0.005	0.002
	(0.19)	(0.91)	(0.50)
Institutional holding	-0.008	0.002	-0.039**
	(0.44)	(0.11)	(2.07)
BM	0.001	-0.009	-0.002
	(0.09)	(0.68)	(0.16)
Past Ret	0.006	0.007	0.006
	(0.70)	(0.71)	(0.68)
# of Analysts	0.001	0.001	0.001
	(0.80)	(0.71)	(0.61)
# of observations	529,896	529,896	529,896
R^2	0.237	0.237	0.237

Appendix C: Summary Statistics for Variables in the Information Environment Analysis

This table reports descriptive statistics of the variables used in information environment analysis. Panel A reports the summary statistics of 64,011 firm-year observations in Table 7 and Panel B report the summary statistics of 34,219 firm-year observations in Table 8.

Panel A: Summary statistics for Table 7

Variables	Mean	Q1	Median	Q3	Std
Bid-ask spread	1.194	0.128	0.768	1.814	1.370
Amihud illiquidity	0.100	0.001	0.007	0.046	0.290
% high (market cap)	0.134	0.000	0.000	0.182	0.242
% low (market cap)	0.325	0.000	0.200	0.556	0.359
% high (trading volume)	0.127	0.000	0.000	0.167	0.238
% low (trading volume)	0.346	0.000	0.222	0.625	0.368
% high (ownership)	0.129	0.000	0.000	0.167	0.235
% low (ownership)	0.321	0.000	0.200	0.500	0.356
No. of Analysts	7.704	3.000	6.000	10.000	6.557
Size	13.701	12.490	13.547	14.773	1.635
Log(trading volume)	11.766	10.506	11.732	12.948	1.770
Institutional holding	0.530	0.329	0.541	0.734	0.251
BM	0.689	0.480	0.713	0.911	0.269
Leverage	0.223	0.054	0.196	0.343	0.192
Price	27.426	13.200	22.726	36.088	19.033
Past Ret	0.177	-0.112	0.115	0.381	0.521
ROA	0.038	0.011	0.042	0.084	0.106
Volatility	0.027	0.018	0.024	0.034	0.013

Panel B: Summary statistics for Table 8

Variables	Mean	Q1	Median	Q3	Std
Implied cost of capital	0.065	0.044	0.066	0.085	0.031
% high (market cap)	0.189	0.000	0.000	0.286	0.274
% low (market cap)	0.233	0.000	0.100	0.375	0.303
% high (trading volume)	0.180	0.000	0.000	0.263	0.271
% low (trading volume)	0.254	0.000	0.111	0.429	0.316
% high (ownership)	0.185	0.000	0.000	0.286	0.267
% low (ownership)	0.223	0.000	0.091	0.333	0.294
No. of Analysts	10.005	5.000	8.000	14.000	7.158
Size	14.343	13.197	14.252	15.390	1.571
Log(trading volume)	12.360	11.178	12.348	13.505	1.696
Institutional holding	0.605	0.444	0.628	0.786	0.225
MAE of forecasts	0.107	0.028	0.061	0.140	0.320
Earnings variability	0.390	0.170	0.279	0.504	0.931
Dispersion of analyst forecasts	0.166	0.036	0.080	0.183	0.246
BM	0.683	0.485	0.704	0.894	0.253

Leverage	0.225	0.078	0.211	0.340	0.173
Past Ret	0.171	-0.094	0.113	0.348	0.442
Long-term growth (%)	14.484	9.682	13.000	17.800	8.237
Beta	1.086	0.631	1.003	1.410	0.647
Volatility	0.025	0.016	0.022	0.031	0.012

Table 1: Summary Statistics

This table reports descriptive statistics of analyst characteristics of our main variables used throughout this paper. Earnings forecast accuracy (*PMAFE*) is defined as the difference between the absolute forecast error for analyst i for firm j and the mean absolute forecast error at year t scaled by the mean absolute forecast error for firm j at year t. See Appendix A for a description of control variables. Analyst data are from I/B/E/S from 1983 to 2012, stock price data are from CRSP, and firm characteristics are obtained from Compustat. In Panel C, the notation *** indicates statistical significance at the 1% level.

Panel A: Summary statistics

Variables	Mean	Q1	Median	Q3	Std
AFE	0.25	0.02	0.07	0.21	0.60
FREQ	3.59	2	3	5	2.38
AGE	114.70	60	73	154	83.39
GEXP	5.05	2	4	7	4.37
FEXP	3.20	1	2	4	2.68
PORTSIZE	17.01	10	14	20	13.49
SIC2	4.17	2	3	5	3.13
TOP10	0.49	0	0	1	0.50

Panel B: De-meaned summary statistics

Variables	Mean	Q1	Median	Q3	Std
PMAFE	0	-0.57	-0.15	0.24	0.86
DFREQ	0	-1.05	0.00	1.00	1.75
DAGE	0	-45.81	-17.67	26.25	72.81
DGEXP	0	-2.42	-0.33	1.88	3.62
DFEXP	0	-1.27	-0.21	0.84	2.16
DPORTSIZE	0	-5.00	-0.97	3.27	8.93
DSIC2	0	-1.19	-0.29	0.75	2.09
DTOP10	0	-0.43	0.00	0.42	0.44

Panel C: Comparison between firms in the high and low groups

	Market Cap			Trading Volume			Institutional Ownership		
Variables	High	Low	Diff	High	Low	Diff	High	Low	Diff
FREQ	3.821	3.377	***	3.876	3.337	***	3.787	3.315	***
DFREQ	0.005	-0.046	***	0.003	-0.031	***	0.008	-0.041	***
AFE	0.225	0.293	***	0.243	0.260	***	0.231	0.285	***
PMAFE	-0.026	0.009	***	-0.026	0.012	***	-0.026	0.010	***
Log(market cap)	16.231	12.933	***	15.873	13.304	***	16.225	13.010	***
Log(trading volume)	13.932	11.683	***	14.216	11.298	***	13.900	11.621	***
Log(ownership)	15.515	11.717	***	15.153	12.111	***	15.544	11.649	***

Table 2: Analyst Earnings Forecast Accuracy

This table presents OLS regression results for analyst earnings forecast accuracy for the full sample. The dependent variable is the proportional mean absolute forecast error *PMAFE* (multiplied by 100). The primary variables of interest are *High* and *Low*. *High* is a dummy variable which takes the value of 1 if the firm's market capitalization (or trading volume, institutional ownership) is in the top quartile of all firms the analyst covers in that year, zero otherwise. *Low* is a dummy variable which is an indicator variable equal to one if the firm's market capitalization (or trading volume, institutional ownership) is in the lower quartile of all firms the analyst covers in that year, zero otherwise. See Appendix A for a description of control variables. In parentheses are t-statistics based on heteroskedastic-consistent standard errors clustered at the firm and analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively. Panel B presents analyst fixed effect regression results, Panel C presents firm fixed effect regression results, and Panel D presents analyst-firm pair fixed effect regression results.

Panel A: OLS regression results

Variables	(1) Market cap	(2) Trading volume	(3) Ownership
High	-2.383***	-1.712***	-2.029***
	(6.74)	(5.38)	(5.96)
Low	1.905***	1.511***	1.791***
	(6.39)	(5.13)	(6.02)
DGExp	-0.242***	-0.238***	-0.242***
	(3.17)	(3.11)	(3.16)
DFExp	-0.635***	-0.642***	-0.637***
	(6.73)	(6.80)	(6.75)
DAge	0.509***	0.509***	0.509***
	(84.16)	(84.14)	(84.14)
DPortsize	0.133**	0.133**	0.133**
	(2.01)	(2.01)	(2.02)
DSIC2	0.710***	0.711***	0.705***
	(4.44)	(4.44)	(4.41)
DTop10	-2.522***	-2.478***	-2.512***
	(5.07)	(4.98)	(5.05)
All-star	-4.325***	-4.169***	-4.292***
	(7.25)	(7.00)	(7.18)
Size	0.452***	0.399***	0.443***
	(3.05)	(2.72)	(3.01)
Log(trading volume)	-0.341***	-0.078	-0.389***
	(3.02)	(0.59)	(3.47)
Institutional holding	-0.236	(0.551)	0.686
	(0.45)	(1.05)	(1.26)
BM	0.262	0.579*	0.345
	(0.86)	(1.92)	(1.14)
Past Ret	-0.374*	-0.414*	-0.366*
	(1.74)	(1.93)	(1.70)
No. of Analysts	-0.075***	-0.071***	-0.071***
	(3.02)	(2.85)	(2.86)
# of observations	529,427	529,427	529,427
R^2	0.188	0.188	0.188

Panel B – Analyst fixed effect results

Variables	(1) Market cap	(2) Trading volume	(3) Ownership
High	-1.582***	-1.371***	-1.392***
	(4.29)	(3.74)	(3.85)
Low	1.536***	1.579***	1.624***
	(4.65)	(4.53)	(4.82)
Controls (from Panel A)	Y	Y	Y
Analyst FE	Y	Y	Y
# of observations	529,427	529,427	529,427
R^2	0.234	0.234	0.234

Panel C – Firm fixed effect results

Variables	(1) Market cap	(2) Trading volume	(3) Ownership
High	-2.083***	-1.989***	-1.811***
	(4.46)	(4.23)	(3.86)
Low	1.848***	2.120***	1.834***
	(4.29)	(4.81)	(4.37)
Controls (from Panel A)	Y	Y	Y
Firm FE	Y	Y	Y
# of observations	529,427	529,427	529,427
R^2	0.189	0.189	0.189

Panel D – Analyst-firm pair fixed effect results

Variables	(1) Market cap	(2) Trading volume	(3) Ownership
High	-2.060***	-1.545**	-2.056***
	(2.93)	(2.32)	(3.02)
Low	1.866***	1.338**	1.597**
	(2.94)	(2.10)	(2.57)
Controls (from Panel A)	Y	Y	Y
Analyst-firm FE	Y	Y	Y
# of observations	529,427	529,427	529,427
R^2	0.550	0.550	0.550

Table 3: Analyst Forecast Accuracy: Absolute Forecast Error

The dependent variable is the absolute forecast error (AFE, multiplied by 100) rather than the proportional mean forecast error as in Table 2. The explanatory variables of interest are *High* and *Low*. *High* is a dummy variable which takes the value of 1 if the firm's market capitalization (or trading volume, institutional ownership) is in the top quartile of all firms the analyst covers in that year, zero otherwise. *Low* is a dummy variable which is an indicator variable equal to one if the firm's market capitalization (or trading volume, institutional ownership) is in the lower quartile of all firms the analyst covers in that year, zero otherwise. See Appendix A for a description of control variables. In parentheses are t-statistics based on heteroskedastic-consistent standard errors clustered at the firm and analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
Variables	Market cap	Trading volume	Ownership
High	-0.229***	-0.272***	-0.226***
	(3.44)	(3.87)	(3.52)
Low	0.342***	0.369***	0.315***
	(4.75)	(5.19)	(4.62)
GExp	-0.025**	-0.025**	-0.025**
	(2.20)	(2.18)	(2.19)
FExp	-0.080***	-0.081***	-0.081***
	(6.11)	(6.11)	(6.12)
Age	0.064***	0.064***	0.064***
	(53.98)	(53.96)	(53.97)
Portsize	0.015	0.015	0.015
	(1.26)	(1.26)	(1.27)
SIC2	0.085***	0.087***	0.085***
	(2.96)	(3.01)	(2.94)
Top10	-0.380***	-0.377***	-0.378***
	(5.14)	(5.11)	(5.11)
All-star	-0.674***	-0.675***	-0.672***
	(6.67)	(6.68)	(6.64)
Firm-year FE	Y	Y	Y
# of observations	529,427	529,427	529,427
R^2	0.798	0.798	0.799

Table 4: Busy Analysts vs. Non-busy Analysts

This table presents results from OLS regressions of earnings forecast accuracy for "busy" and "non-busy" analysts, where "busy" analysts are defined as those whose portfolio size in a given year is greater than the sample median. The dependent variable is the proportional mean absolute forecast error (PMAFE) defined as the difference between the absolute forecast errors for analyst i for firm j and the mean absolute forecast error at year t scaled by the mean absolute forecast error for firm j at year t. *High* is a dummy variable which takes the value of 1 if the firm's market capitalization (or trading volume, institutional ownership) is in the top quartile of all firms the analyst covers in that year, zero otherwise. *Low* is a dummy variable which is an indicator variable equal to one if the firm's market capitalization (or trading volume, institutional ownership) is in the lower quartile of all firms the analyst covers in that year, zero otherwise. See Appendix A for a description of control variables. In parentheses are t-statistics based on heteroskedastic-consistent standard errors clustered at the firm and analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: "Busy" analysts

	(1)	(2)	(3)
Variables	Market cap	Trading volume	Ownership
High	-2.848***	-1.945***	-2.506***
	(6.06)	(4.59)	(5.52)
Low	2.920***	1.747***	2.715***
	(7.22)	(4.47)	(6.85)
Controls (from Table 2)	Y	Y	Y
# of observations	349,933	349,933	349,933
R-squared	0.165	0.165	0.165

Panel B: "Non-busy" analysts

	(1)	(2)	(3)
Variables	Market cap	Trading volume	Ownership
High	-1.112**	-0.905	-0.562
	(2.05)	(1.62)	(1.03)
Low	0.819*	1.115**	0.898*
	(1.67)	(2.27)	(1.76)
Controls (from Table 2)	Y	Y	Y
# of observations	179,494	179,494	179,494
R-squared	0.229	0.230	0.230

Table 5: Stock Market Reactions to Forecast Revision

This table reports the market reaction to analysts' revisions of earnings forecasts. The dependent variable is the cumulative 3-day market adjusted return (multiplied by 100) around the announcement of forecast revision by analyst i for firm j at year t. *High* is a dummy variable which takes the value of 1 if the firm's market capitalization (column (1), trading volume (2) or institutional ownership (3) is in the top quartile of all firms the analyst covers in that year, zero otherwise. *Low* is a dummy variable which is an indicator variable equal to one if the firm's market capitalization, trading volume or institutional ownership is in the lower quartile of all firms the analyst covers in that year, zero otherwise. Forecast revision (FR) is the ratio of the difference between the new forecast and the old forecast to the absolute value of the old forecast. See Appendix A for a description of control variables. Analyst data are from I/B/E/S from 1983 to 2012, stock price data are from CRSP, and firm characteristics are obtained from Compustat. Year fixed effects are included. In parentheses are t-statistics based on heteroskedastic-consistent standard errors clustered at the firm level and analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
Variables	Market cap	Trading volume	Ownership
High*FR	0.007*	0.006*	0.004
	(1.89)	(1.72)	(1.01)
Low*FR	-0.008***	-0.006**	-0.010***
	(2.77)	(2.04)	(3.47)
FR	0.082***	0.082***	0.083***
	(31.68)	(31.78)	(32.58)
High	0.049	0.011	0.028
	(1.37)	(0.27)	(0.75)
Low	-0.072	-0.058	-0.061
	(1.61)	(1.47)	(1.48)
Controls from Table 2	Y	Y	Y
Year FE	Y	Y	Y
R-squared	0.150	0.150	0.150
# of observations	350,488	350,488	350,488

Table 6: Stock Market Reactions to Recommendation Updates

This table reports the market reaction to analysts' recommendation updates. The dependent variable is the cumulative 3-day market adjusted return (multiplied by 100) around the announcement of recommendation update by analyst i for firm j at year t. *High* is a dummy variable which takes the value of 1 if the firm's market capitalization (column (1), trading volume (2), or institutional ownership (3) is in the top quartile of all firms the analyst covers in that year, zero otherwise. *Low* is a dummy variable which is an indicator variable equal to one if the firm's market capitalization, trading volume or institutional ownership is in the lower quartile of all firms the analyst covers in that year, zero otherwise. Panel A reports analysis for recommendation downgrade and Panel B reports analysis for recommendation upgrade. Year fixed effects are included. See Appendix A for a description of control variables. In parentheses are t-statistics based on heteroskedastic-consistent standard errors clustered at the firm and analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Downgrades

Variables	(1) Market cap	(2) Trading volume	(3) Ownership
High	-0.548***	-0.501***	-0.583***
	(5.76)	(5.21)	(5.87)
Low	0.333***	0.324***	0.372***
	(3.08)	(3.02)	(3.35)
Gexp	-0.036**	-0.033**	-0.037***
	(2.58)	(2.30)	(2.62)
Fexp	0.066***	0.061***	0.066***
	(4.19)	(3.88)	(4.19)
Portsize	0.009	0.009	0.009
	(1.28)	(1.36)	(1.34)
SIC2	0.082***	0.073***	0.079***
	(3.99)	(3.59)	(3.89)
Top10	-0.859***	-0.809***	-0.871***
	(8.88)	(8.28)	(9.03)
All-star	-0.341**	-0.281*	-0.345***
	(2.32)	(1.93)	(2.36)
Lag recommendation	-0.145***	-0.121**	-0.146***
	(2.67)	(2.23)	(2.70)
Size	1.532***	1.433***	1.526***
	(27.88)	(28.67)	(27.97)
Log(trading volume)	-0.902***	-0.966***	-0.905***
	(18.13)	(17.00)	(18.18)
Institutional holding	-0.543***	-0.521**	-0.319
	(2.64)	(2.53)	(1.51)
BM	2.052***	2.096***	2.062***
	(13.36)	(13.53)	(13.41)
Past Ret	3.943***	3.956***	3.943***
	(21.92)	(21.99)	(21.96)
No. of Analysts	0.020***	0.020***	0.020***
	(3.15)	(3.23)	(3.20)
Year FE	Y	Y	Y
R-squared	0.0889	0.0885	0.0891
# of observations	75,552	75,552	75,552

Panel B: Upgrades

Variables	(1) Market cap	(2) Trading volume	(3) Ownership
High	0.152**	0.174**	0.167**
	(2.13)	(2.38)	(2.27)
Low	-0.131	-0.162*	-0.105
	(1.52)	(1.85)	(1.16)
Gexp	0.023**	0.023**	0.023**
	(2.26)	(2.22)	(2.28)
Fexp	-0.019	-0.019	-0.019
	(1.41)	(1.37)	(1.42)
Portsize	-0.016***	-0.016***	-0.016***
	(3.99)	(3.91)	(4.00)
SIC2	-0.015	-0.013	-0.016
	(1.01)	(0.89)	(1.03)
Top10	0.828***	0.823***	0.832***
	(11.65)	(11.63)	(11.72)
All-star	0.601***	0.592***	0.604***
	(5.75)	(5.67)	(5.78)
Lag recommendation	-0.335***	-0.337***	-0.332***
	(7.81)	(7.91)	(7.78)
Size	-0.794***	-0.792***	-0.802***
	(20.92)	(22.89)	(21.67)
Log(trading volume)	0.373***	0.398***	0.373***
	(9.74)	(9.21)	(9.72)
Institutional holding	-0.062	-0.085	-0.067
	(0.36)	(0.49)	(0.38)
BM	-0.244**	-0.231**	-0.237**
	(2.38)	(2.24)	(2.30)
Past Ret	2.231***	2.229***	2.234***
	(16.08)	(16.06)	(16.10)
No. of Analysts	-0.014***	-0.015***	-0.015***
	(2.98)	(3.01)	(2.96)
Year FE	Y	Y	Y
R-squared	0.0546	0.0546	0.0546
# of observations	63,874	63,874	63,874

Table 7: Bid-ask spread and stock illiquidity

This table reports the analysis of the impact of analysts' effort allocation on a firm's bid-ask spread and stock illiquidity. The dependent variable is bid-ask spread in Panel A and Amihud illiquidity measure in Panel B. *%High* is the ratio of the number of analysts ranking the firm high in their portfolio to the total number of analysts covering the firm in a year, and *%Low* is the ratio of the number of analysts ranking the firm low in their portfolio to the total number of analysts covering the firm in a year. See Appendix A for a description of control variables. Year and firm fixed effects are included. In parentheses are t-statistics based on heteroskedastic-consistent standard errors clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Bid-ask spread

	(1)	(2)	(3)
Variables	Market cap	Trading volume	Ownership
% high	-0.118***	-0.169***	-0.120***
	(4.10)	(5.69)	(4.20)
% low	0.039*	0.036*	0.030
	(1.87)	(1.75)	(1.39)
No. of Analysts	-0.003*	-0.003**	-0.003*
	(1.87)	(1.97)	(1.83)
Size	-1.332***	-1.247***	-1.305***
	(12.93)	(12.39)	(12.71)
$Size^2$	0.051***	0.048***	0.050***
	(13.93)	(13.37)	(13.72)
Log(trading volume)	-0.242***	-0.259***	-0.243***
	(3.87)	(4.02)	(3.87)
$Log(trading\ volume)^2$	0.005**	0.007***	0.005**
	(2.04)	(2.70)	(2.04)
Institutional holding	-0.197	-0.185	-0.185
	(1.61)	(1.52)	(1.47)
$Institutional\ holding^2$	0.255**	0.237**	0.260**
	(2.50)	(2.33)	(2.52)
BM	0.062	0.062	0.06
	(1.59)	(1.59)	(1.53)
Leverage	0.223***	0.226***	0.222***
	(3.94)	(4.00)	(3.93)
Log(price)	-0.346***	-0.343**	-0.348***
	(14.85)	(15.16)	(14.80)
Past Ret	-0.067***	-0.066***	-0.067***
	(9.32)	(9.19)	(9.31)
ROA	0.042	0.051	0.045
	(0.66)	(0.78)	(0.70)
Volatility	5.373***	5.233***	5.388***
	(7.36)	(7.17)	(7.38)
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
# of observations	64,011	64,011	64,011
R-squared	0.813	0.813	0.813

Panel B: Amihud illiquidity

Variables	(1) Market cap	(2) Trading volume	(3) Ownership
% high	-0.0112*** (2.81)	-0.0137*** (3.28)	-0.0109*** (2.72)
% low	0.0063 (1.27)	0.0086* (1.79)	0.0087* (1.81)
No. of Analysts	-0.0011*** (4.36)	-0.0011*** (4.41)	-0.0011*** (4.35)
Controls (Table 7, Panel A)	Y	Y	Y
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
# of observations	64,011	64,011	64,011
R-squared	0.758	0.758	0.758

Table 8: Implied costs of equity capital

This table reports the analysis of the impact of analysts' effort allocation on a firm's implied cost of capital. The dependent variable is the implied cost of capital (multiplied by 100) in Gebhardt, Lee, and Swaminathan (2001). *%High* is the ratio of the number of analysts ranking the firm high in their portfolio to the total number of analysts covering the firm in a year, and *%Low* is the ratio of the number of analysts ranking the firm low in their portfolio to the total number of analysts covering the firm in a year. See Appendix A for a description of control variables. Year and firm fixed effects are included. In parentheses are t-statistics based on heteroskedastic-consistent standard errors clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Variables	(1) Market cap	(2) Trading volume	(3) Ownership
% high	-0.259**	-0.241**	-0.243**
	(2.29)	(2.01)	(2.11)
% low	0.193**	0.142*	0.108
	(2.34)	(1.78)	(1.22)
No. of Analysts	-0.009*	-0.009*	-0.009*
	(1.67)	(1.69)	(1.70)
Size	-0.099	-0.113	-0.223
	(0.25)	(0.30)	(0.57)
$Size^2$	0.008	0.006	0.012
	(0.60)	(0.47)	(0.86)
Log(trading volume)	-0.082	-0.116	-0.085
	(0.38)	(0.54)	(0.39)
$Log(trading\ volume)^2$	0.003	0.003	0.003
	(0.29)	(0.39)	(0.29)
Institutional holding	-0.322	-0.340	-0.156
	(0.68)	(0.72)	(0.33)
$Institutional\ holding^2$	0.225	0.236	0.165
	(0.57)	(0.60)	(0.42)
MAE of forecasts	-0.052	-0.050	-0.051
	(0.36)	(0.35)	(0.36)
Earnings variability	0.075	0.075	0.075
	(0.92)	(0.91)	(0.91)
Dispersion of analyst forecasts	0.182*	0.181*	0.183*
	(1.89)	(1.90)	(1.90)
BM	1.766***	1.678***	1.764***
	(8.75)	(8.05)	(8.73)
Leverage	1.621***	1.672***	1.681***
	(5.35)	(4.59)	(4.60)
Past Ret	-0.084*	-0.079*	-0.083*
	(1.86)	(1.76)	(1.85)
Long-term growth	0.009***	0.009***	0.009***
	(3.23)	(3.15)	(3.22)
Beta	0.019	0.019	0.019
	(0.41)	(0.40)	(0.40)
Volatility	4.404*	4.277	4.310*
	(1.68)	(1.63)	(1.65)
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
# of observations	34,219	34,219	34,219
R-squared	0.716	0.716	0.716

Table 9: Coverage termination and information asymmetry

This table reports the average differences in difference-in-difference (DiD) for firm-level information environment measures between *High* and *Low* groups. We compute the effect of coverage terminations on changes in 3- and 6-month bid-ask spreads (Panel A) and Amihud's illiquidity measures (Panel B). For each treatment firm, we first follow Kelly and Ljungqvist (2012) and Daniel, Grinblatt, Titman, and Wermers (1997) to construct a control group. For each treatment stock, we choose up to five stocks that are closest in terms of the relevant pre-event information asymmetry measure. We then employ a difference-in-difference (DiD) approach to compare the change in the information environment of control firms to treatment firms. We further split the affected firms into *High* and *Low* groups based on the firms' rankings (high or low) in the analysts' portfolios in the year before the brokerage house closures and mergers and report the mean differences in DiD for firm-level information environment measures between *High* and *Low* groups. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	Difference in DiD between the High and Low groups		
High and low based on	Market cap	Trading volume	Ownership
Panel A: bid-ask spread			
3 month window	0.137***	0.125**	0.136***
6 month window	0.120**	0.102*	0.118**
Panel B: Amihud illiquidity measure			
3 month window	0.011*	0.007	0.012**
6 month window	0.018**	0.009	0.017**

Table 10: Analysts' effort allocation and labor market outcomes

This table presents logistic regression results for the effect of analysts' effort allocation on their labor market outcomes. The dependent variable is a dummy variable that is equal to 1 if an analyst is named an all-star analyst (Panel A) or promoted (Panel B) in a given year. All control variables are lagged by one year. See Appendix A for a description of control variables. Year fixed effects are included. In parentheses are t-statistics based on heteroskedastic-consistent standard errors clustered at the firm and analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: All-star analysis

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
High and Low based on:	Market cap	Trading volume	Ownership	Market cap	Trading volume	Ownership
Diff(High-low) in DFREQ	0.079***	0.078***	0.086***			
	(3.91)	(3.61)	(4.30)			
Diff(High-low) in PMAFE				-0.107**	-0.117***	-0.136***
				(2.42)	(2.64)	(3.05)
GExp	0.009	0.009	0.01	0.008	0.008	0.009
	(1.14)	(1.07)	(1.27)	(1.04)	(1.01)	(1.14)
Portsize	0.017***	0.017***	0.016***	0.017***	0.017***	0.016***
	(4.95)	(4.93)	(4.61)	(4.86)	(4.89)	(4.53)
SIC2	-0.023*	-0.023	-0.025*	-0.023	-0.023	-0.025*
	(1.65)	(1.62)	(1.78)	(1.62)	(1.64)	(1.79)
Brokerage size	0.035***	0.035***	0.035***	0.035***	0.035***	0.035***
	(23.44)	(23.42)	(23.50)	(23.50)	(23.52)	(23.56)
Average PMAFE	-0.744***	-0.739***	-0.743***	-0.714***	-0.722***	-0.705***
	(8.63)	(8.58)	(8.57)	(8.14)	(8.28)	(7.94)
Average DFREQ	0.352***	0.352***	0.349***	0.376***	0.375***	0.375***
	(13.10)	(13.06)	(12.70)	(14.27)	(14.27)	(13.96)
Average firm size	0.297***	0.299***	0.290***	0.299***	0.297***	0.290***
	(11.12)	(11.21)	(10.79)	(11.18)	(11.15)	(10.82)
Lag (All-star)	5.509***	5.511***	5.491***	5.520***	5.521***	5.506***
	(70.86)	(70.89)	(70.79)	(71.06)	(71.09)	(70.95)
Year FE	Y	Y	Y	Y	Y	Y
Pseudo R^2	0.678	0.678	0.677	0.678	0.678	0.677
# of observations	46,494	46,494	45,558	46,464	46,460	45,525

Panel B: Move-up analysis

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
High and Low based on:	Market cap	Trading volume	Ownership	Market cap	Trading volume	Ownership
Diff(High-low) in DFREQ	0.206**	0.232**	0.187**			
	(2.24)	(2.47)	(2.05)			
Diff(High-low) in PMAFE				-0.477**	-0.242	-0.408**
				(2.41)	(1.13)	(2.04)
GExp	-0.058***	-0.060***	-0.062***	-0.056***	-0.056***	-0.059***
	(2.72)	(2.82)	(2.83)	(2.61)	(2.64)	(2.71)
Portsize	0.003	0.003	0.005	0.003	0.002	0.005
	(0.31)	(0.37)	(0.56)	(0.33)	(0.23)	(0.53)
SIC2	-0.154***	-0.154***	-0.149***	-0.155***	-0.153***	-0.149***
	(4.27)	(4.26)	(4.14)	(4.31)	(4.25)	(4.13)
Brokerage size	0.042***	0.041***	0.043***	0.042***	0.042***	0.043***
	(8.22)	(8.15)	(8.33)	(8.22)	(8.27)	(8.37)
Average PMAFE	-0.818*	-0.787*	-0.903**	-0.721*	-0.799*	-0.954**
	(1.94)	(1.89)	(2.13)	(1.70)	(1.91)	(2.20)
Average DFREQ	-0.075	-0.098	-0.088	-0.048	-0.047	-0.049
	(-0.86)	(1.10)	(0.98)	(0.56)	(0.56)	(0.56)
Average firm size	0.135**	0.137**	0.127**	0.134**	0.141**	0.129**
	(2.41)	(2.46)	(2.22)	(2.39)	(2.54)	(2.29)
Year FE	Y	Y	Y	Y	Y	Y
Pseudo R^2	0.092	0.094	0.095	0.093	0.092	0.094
# of observations	14,654	14,655	14,413	14,638	14,630	14,387

Digital currencies, decentralized ledgers, and the future of central banking

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Abstract

Central banking in an age of digital currencies is a fast-developing topic in monetary economics. Algorithmic digital currencies such as bitcoin appear to be viable competitors to central bank fiat currency, and their presence in the marketplace may pressure central banks to pursue tighter monetary policy. More interestingly, the blockchain technology behind digital currencies has the potential to improve central banks' payment and clearing operations, and possibly to serve as a platform from which central banks might launch their own digital currencies. A sovereign digital currency could have profound implications for the banking system, narrowing the relationship between citizens and central banks and removing the need for the public to keep deposits in fractional reserve commercial banks. Debates over the wisdom of these policies have led to a revival of interest in classical monetary economics.

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Digital currencies, decentralized ledgers, and the future of central banking

I. Introduction

Digital currencies were created to compete with central banks.

Nakamoto's (2008) design of bitcoin, as a "Peer to Peer Electronic Cash System," was intended to allow network members to transfer value directly between each other without any role for a trusted third party, such as a central bank. Few people noticed the launch of bitcoin in early 2009, but its creator, still unknown today, had a clear political agenda. The first block of bitcoins was accompanied by the encoded text, "The Times 03/Jan/2009 Chancellor on brink of second bailout for banks" (Elliott and Duncan, 2009). Appearing near the lowest depths of the global financial crisis, this headline from *The Times* provided an implicit commentary on the fragility of the world banking system and the inability of central banks to do anything about it. Bitcoin's anonymous creators symbolically hard-coded this message into the "genesis block" of their main innovation, the blockchain. They could hardly have expected that within five years, their blockchain and its shared ledger would be viewed as major breakthroughs in financial record-keeping, with central banks, stock exchanges, and numerous other financial markets beginning to co-opt the disruptive technology in order to modernize their own operations.

This chapter evaluates the challenges and opportunities for central banks in a world that appears to have been irreversibly changed by the arrival of algorithmic digital currencies. The world economy had been moving away from hard currency in favor of electronic payment systems for many years before the arrival of bitcoin. Such an innovation was not unexpected, with prominent economists of past generations such as John Nash (2002) and Milton Friedman speaking openly of the opportunities for an algorithmic currency, issued according to a mathematically fixed policy rule, to usurp the role of central banks and discretionary monetary

policy.[1] Yet bitcoin represented a radical departure from past schemes, with a novel focus on decentralized governance and record-keeping that placed control of money in the hands of its users, rather than a committee of elected politicians or a circle of enlightened experts. The equations underlying bitcoin stipulated a predetermined and transparent rate of monetary growth, pre-empting the use of discretionary monetary policy that might debase the currency in response to an economic slump.

At the time of this writing, bitcoin faces a significant governance issue, as its community of users has been unable to reach consensus about how to scale its network to accommodate rapid growth in transaction volume. Ironically, the lack of political leadership that seemed so important in the design of bitcoin is an obstacle in settling on a strategy for the currency to grow. Even as the bitcoin network struggles with delays and bottlenecks, blockchains and distributed ledger innovations have been incorporated by hundreds of knock-off imitator digital currencies. These innovations have also inspired financiers, regulators, and academics to reconsider the first principles of central banking, including whether central banks should reinvent their national currencies in algorithmic form, residing on national blockchains and shared ledgers overseen by the very institutions that bitcoin's creators wished to do away with.

Central banking in an age of digital currencies is a fast-developing topic in monetary economics. Algorithmic digital currencies such as bitcoin appear to be viable competitors to central bank fiat currency, and their presence in the marketplace may pressure central banks to pursue tighter monetary policy. However, the technology behind digital currencies may be co-opted by central banks themselves, giving them more power and greater control over monetary policy than ever before. This chapter provides a brief introduction to these topics, with the caveat that the field is changing so quickly that new issues and opportunities seem likely to re-shape the research agenda frequently. Section II provides a brief overview of the structure of bitcoin and alternative digital currencies. Section III considers how central banks have reacted to competition from alternative currencies, outside the official national monetary base. Section IV discusses implications of the possibility that central banks may issue their own digital currencies

[1] See Babbage (2011), which provides a concise introduction to the structure of bitcoin and begins by recounting Friedman's oft-repeated calls for replacing the U.S. Federal Reserve System with an automated rule for money creation. In a videotaped 1999 interview that has been widely shared on the Internet, Friedman seemed to anticipate the arrival of bitcoin ten years later when he stated, "I think that the Internet is going to be one of the major forces for reducing the role of government . . . The one thing that's missing, but that will soon be developed, is a reliable e-cash, a method whereby on the Internet you can transfer funds from A to B, without A knowing B or B knowing A."

with blockchain and distributed ledger architecture. Section V provides an overview of operational benefits that may accrue to central banks from incorporating the new technology into their processing systems, even if they choose not to issue digital currency. Section VI concludes the chapter.

II. Emergence of digital currencies

Digital currencies that circulate today confound some members of the public who question the value of an asset that exists only in computer memory. However, the idea of virtual money is not new, as electronic payment systems have steadily grown with advances in computer memory and communications technology, inexorably supplanting hard currency and paper checks in advanced economies. The distinguishing features of digital currencies really come from their independence from any political authority or commercial sponsor as well as their decentralized governance and record-keeping.

Various forms of electronic money have circulated for decades. Twenty years ago, both the Office of the U.S. Comptroller of the Currency (1996) and the Bank for International Settlements (1996) published reports noting the proliferation of "electronic cash" stored on "smart" debit cards that consumers could use at a point of sale. These devices differed in two important ways from the digital currencies circulating today: they were always denominated in units of a sovereign currency, such as the U.S. dollar, and their stored value was created via a transfer of value from a third party, typically a credit card issuer such as MasterCard or Visa. Early concerns about the growth of electronic cash focused on computer security issues and the solvency of the third party guarantors.

Online fantasy games provided a platform for issuing virtual currencies beginning in the late 1980s, and today many regard these as predecessors of bitcoin and other autonomous digital currencies. These massively multiplayer online role-playing games, or MMORPGs, have internal economies in which players earn rewards in the fantasy currency and spend them to acquire in-game powers or objects from other players. Some of these currency markets have become deep enough that they have migrated to external platforms, where they trade on a speculative basis against real-world currencies (Kim, 2015). Promoters of these games need to consider issues such as seignorage and inflation of the monetary base much like a central bank would.

To some observers, the first private digital currency to establish itself as a medium of exchange in the real economy was M-Pesa, a currency denominated in mobile phone minutes that was launched in Kenya by Safaricom in 2007. M-Pesa could be acquired by anyone with a mobile phone and could be transferred over great distances at extremely low cost. Within two years, it had been used by more than half the population of Kenya (Jack and Suri, 2011). Kaminska (2015) observes that M-Pesa appears to have succeeded because Safaricom, which is 40% owned by the multinational giant Vodaphone, is trusted by the public more than the Kenyan banking system, but she argues that M-Pesa really resembles a money transmission service more than a standalone currency, since its sponsor collateralizes units of M-Pesa with Kenyan hard currency deposits in escrow accounts. The reach of M-Pesa does not appear to have extended beyond the Kenyan economy, although parallel mobile phone based currency systems have been introduced in other developing nations.

Bitcoin, proposed in an Internet posting[2] by Nakamoto (2008) and introduced into circulation in 2009, probably has a more clear-cut claim to being the first successful private digital currency, as it is used in countries all around the world and is not tied to any established banking system as is the case with M-Pesa. Bitcoins are circulated over an open computer network that can be joined by anyone with an Internet connection. Users of the network store bitcoins in computer memory banks colloquially known as digital wallets, and transfers occur via an encryption system described in Babbage (2011) and numerous other sources. Bitcoins can be acquired in the stream of commerce (by exchanging goods and services for bitcoins) or as a reward for participating in "mining," the activity by which users update the network's "blockchain," or archive of previous bitcoin transactions. Bitcoins paid out as mining fees represent the seigniorage of new currency, which occurs at a fixed rate that periodically ratchets downward until it is scheduled to asymptotically approach no new money creation in 2140.

Bitcoin features a number of innovations in security, seigniorage, and transparency that appear to have contributed to its success. Its archival blockchain links together all previous transfers of a given unit of currency as a method of authentication. The blockchain is known as a "shared ledger" or "distributed ledger," because it is available to all members of the network, any one of whom can see all previous transactions into or out of other digital wallets. Perhaps most

[2] The Nakamoto (2008) white paper was posted via a link provided to www.bitcoin.org/bitcoin.pdf distributed to The Cryptography Mailing List at www.metzdown.com. The original post, including introductory comments by the author, can be viewed at www.mail-archive.com/cryptography@metzdowd.com/msg09959.html.

importantly, the process of reaching "consensus" to validate transactions on a bitcoin network requires no trusted third party, such as a central bank, credit card issuer, or mobile phone company, to play the role of authenticator. Instead, authentication relies upon an algorithmic proof-of-work process that enables users to trust one another with very high levels of confidence, removing the need for sponsor to play the role of enforcer or gatekeeper on the network. This feature reduces the central bank to a set of equations in the bitcoin economy.

Bitcoin's success has spawned hundreds of imitator digital currencies, which are generally distinguished from one another by differences in their protocols for mining and proof of work. Although bitcoin continues to have by far the largest market capitalization, successful competitor digital currencies have included litecoin, ripple, and most recently, the ether currency that ciculates on the Ethereum platform.[3]

III. Central banks and competition from digital currencies

When an autonomous digital currency circulates in an economy, it competes with the official currency issued by the country's central bank. Competition between official currency and private money is nothing new, and in various societies alternative money has included commodities like gold and silver as well as other goods that have served as stores of value and media of exchange. However, in most countries the local currency faces its greatest competition from foreign governments' currencies, especially the U.S. dollar. For a central bank, the challenges posed by a digital currency are basically the same as those posed by the presence of a competing foreign currency.

For an economy, competition among currencies causes suppliers to drive price and quality to an appropriate equilibrium that reflects utility (Hayek, 1976). Historically, most of these suppliers have been central banks, although there are numerous and well-documented examples of non-central bank currency used both idiosyncratically and generally (Radford, 1945). One benefit from competition between different monies is the stability produced by the flexibility of contracting parties to choose settlement terms. Private creditors and debtors, if given a free choice, will tend to use the currency that is neutral as between them. Debtors would not want to contract in currencies that would appreciate after contracting, and creditors would

[3] More than 700 digital currencies have been launched since the inception of bitcoin, and a list with current market values is maintained at http://coinmarketcap.com/all/views/all/.

not want to contract in currencies that would depreciate. Thus, from the point of view of consumers of money, having competitors in the provision of money is a check on the unilateral behavior of the supplier. Put into concrete terms, digital currencies could offer a country struggling with a mismanaged money supply a way of creating stability.

Argentina provides an instructive recent example of how digital currencies, like foreign currencies, have the ability to provide a check against a central bank's policy rules that are detrimental to a country. According to the World Bank, Argentina has experienced double-digit inflation every year except one since 2002.[4] Such a situation wreaks havoc on a country's economy by adding unwanted risk to capital allocation decisions. Before the 2015 election of President Mauricio Macri, *The New York Times* reported on the use of bitcoin in evading the country's currency controls amid an atmosphere of financial instability (Popper, 2015). When the Argentine peso and the country's central bank were unable to provide individuals with the qualities they demanded of their money, they were relatively free to switch to other options, which included not only digital currencies but also the U.S. dollar and other foreign currencies. A country which risks its participation in global financial markets if its currency is too unstable will be more likely to tolerate the use of black and grey market options.[5] Prior to becoming president, Macri served as mayor of Buenos Aires, where he helped organize a bitcoin forum. After being inaugurated, one of his first actions was to lift the country's currency controls.

A slightly different approach was adopted by Ecuador, which officially banned bitcoin in 2014, but introduced its own digital currency project called Sistema de Dinero Electrónico (electronic money system) (Rosenfeld, 2015). Modeled on private providers of mobile money, the system gives individuals access to mobile credit accounts denominated in currency approved by the central bank. Ecuador's official currency is the U.S. dollar, which it adopted after years of monetary instability. As articulated by the Ecuadorian government, the new digital system is not designed to replace the dollar, but to save money on replacing deteriorating physical bills. Some, however, have seen the project as a move towards de-dollarization and an attempt by the government to assert more control over the economy (White, 2014).[6] Certainly the banning of

[4] http://data.worldbank.org/indicator/NY.GDP.DEFL.KD.ZG/countries/AR?display=default.

[5] Iran provides another recent example. See Raskin (2012).

[6] As White writes, "In sum, there is no plausibly efficient or honorable reason for the Ecuadoran government to go into the business of providing an exclusive medium for mobile payments. Consequently it is hard to make any sense

bitcoin and other digital currencies demonstrates that the advantages of competition are not what the Banco Central del Ecuador envisioned in establishing the new system.

With the above benefits in mind, we now turn to the costs of competing digital currencies, which primarily consist in undermining a central bank's ability to conduct monetary policy as a monopolist. In a world where central banks are forced to compete with other central banks and private actors, supply and demand alone will drive which money is used as the generally accepted medium of exchange. However, central banks operate under regimes that have enacted legal tender laws whose function is to compel acceptance of their notes.[7] Such laws do not require parties to contract in the currency of the central bank, but they deny legal recourse to a party who refuses to accept the legal tender of the country as payment for debts contracted in some other medium of exchange. This gives rise to Gresham's Law, namely that bad money drives out the good.[8] At the same exchange rate, a debtor is less likely, *ceterus paribus*, to pay in appreciated currency if he has the option to pay in depreciated currency.

Legal tender laws therefore confer a monopoly privilege on the government, allowing it to operate its printing press. Without such laws, central banks would not be nearly as powerful. If consumers were allowed to refuse acceptance of central bank currency for public and private debts, a regime of free banking would exist and the central bank would be forced to operate monetary policy in accord with the demands of its consumers and not according to political or policy goals untethered from the market. Whether the central bank's monopoly power is desirable is beyond the scope of this chapter and is part of an enduring "rules vs. discretion" debate in macroeconomics.

The history of American monetary policy provides an important example. Until the 1861-65 U.S. Civil War, currency in the United States was issued by private banks, including the First Bank of the United States, which, though chartered by Congress was still a private institution. In order to fund the Civil War without raising taxes, Congress passed the Legal Tender Act in 1862, which authorized the issuance of $150 million in United States notes, which

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of the project other than as fiscal maneuver that paves the way toward official de-dollarization. I gather that President Correa does not like the way that dollarization limits his government's power to manage the economy."

[7] *See, e.g.*, 31 U.S.C §5103 (United States); Coinage Act 1971 §2 (United Kingdom); Reserve Bank Act 1959 §36(1) (Australia); Bank of Israel Law 1954 §30 (Israel).

[8] Mundell (1998) states that "The correct expression of Gresham's Law law is: 'cheap money drives out dear, if they exchange for the same price.' That proposition is neither trivial nor obvious."

were declared to be "lawful money and legal tender in payment of all debts, public and private, within the United States, except duties on imports and interest on the public debt." This legislation was politically controversial and was at first declared unconstitutional by the U.S. Supreme Court. Writing for the Court on behalf of a 4-3 majority in *Hepburn* v. *Griswold*, Chief Justice Salmon P. Chase held that forcing parties to accept depreciated currency violated the Constitution's prohibition against governmental taking of property without due process of law. The Chief Justice found no distinction between the Legal Tender Act "and an act compelling all citizens to accept, in satisfaction of all contracts for money, half or three-quarters or any other proportion less than the whole of the value actually due, according to their terms. It is difficult to conceive what act would take private property without process of law if such an act would not."[9]

The *Hepburn* decision was reversed the next year in a pair of 5-4 decisions that were supported by two new Justices who, coincidentally, were appointed by President Grant on the same day that *Hepburn* was decided.[10] Together these two decisions are known as the Legal Tender Cases, and few in the American legal scene today advocate their reversal.[11] The U.S. has reached a political consensus that the federal government should not operate without a legal safety net that privileges its currency.

These events in 19th century United States history provide an interesting context for understanding the 2014 political debate in Iceland. That country confronted an alternative to its króna in the form of a private, autonomous digital currency called auroracoin that was targeted squarely at the Icelandic market. Introduced by the pseudonymous Baldur Friggjar Óðinsson, auroracoin entered circulation in March 2014 by way of an "airdrop" in which 50% of auroracoins were distributed evenly to holders of Iceland's Kennitala national identification.

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[9] *Hepburn* v. *Griswold*, 75 U.S. 603 (1870). Ironically, Chase had served as President Lincoln's Secretary of the Treasury and had played a role in enacting the Legal Tender Act in 1862.

[10] *Knox* v. *Lee* and *Parker* v. *Davis*, 79 U.S. 457 (1871).

[11] See Bork (1987) who at his Supreme Court confirmation hearings testified, "I cite to you the legal tender cases. Scholarship suggests - these are extreme examples, admittedly - scholarship suggests that the framers intended to prohibit paper money. Any judge who today thought he would go back to the original intent really ought to be accompanied by a guardian rather than be sitting on a bench." But see Epstein (2014), who writes, "As a matter of constitutional principle, therefore, Legal Tender laws should fall by the wayside, thereby preserving both the rule of law and the stability of private expectations…One way to counteract this risk [of arbitrary power to inflate or deflate] is to let the government print whatever (cheap) currency it will, but to discipline its behavior by allowing other banks to issue their own currency (whether or not backed by gold) in competition with the federal government."

These events occurred when Iceland was operating under strict capital controls in the aftermath of the global financial crisis, which had decimated the country's banking system. The introduction of auroracoin prompted the government to hold a parliamentary meeting of the Economic Affairs and Trade Committee. Frosti Sigurjónsson, chairman of the committee, wrote, "There is evidence however that this is a case of [a money] scam and illegal," but the government ultimately took no action against it (Cawrey, 2014). By all accounts, auroracoin has been a failure and has not supplanted the Icelandic króna in any meaningful way.

Along with legal tender laws, governments can use licensing requirements for money transmission to regulate indirectly the threat from competing currencies. These laws make it easier for governments to combat tax evasion and money laundering, which have been widely reported uses of digital currencies such as bitcoin.

Countries have taken different attitudes towards digital currencies, ranging from equivocating or hostile to *laissez-faire* and encouraging. Often an overlap exists between these attitudes and how the country treats foreign currencies generally. For instance, in China the government imposes capital controls, combined with active market intervention by the central bank, to affect the value of the renminbi, demonstrating a policy choice that disfavors private actors setting the values of foreign exchange rates. Similarly, the country's attitude towards bitcoin and other digital currencies also ties the hands of private actors. Although it is legal for individuals to own bitcoin in China, banks and financial institutions are prohibited from doing so. In April of 2014, the People's Bank of China ordered commercial banks and trading companies to shut down accounts that dealt in bitcoin. In addition to concern about the financial well-being of their citizenry, the Chinese government may see bitcoin and other digital currencies as a threat to the country's capital controls, given the ease of transmitting bitcoin across international borders.

The United Kingdom, on the other hand, allows the private use of bitcoin as well as the opening of businesses that transact in the currency. Many officials in the United States government have expressed a similar attitude of benign neglect toward digital currencies (Raskin, 2013).[12] Although anti-money laundering laws apply in both countries, neither has

[12] While the U.S. has tolerated the circulation of private digital currencies and other instruments such as the Ithaca Hour (which takes its value from the price of an hour of labor), the government's forebearance does not extend to private coinage incorporating precious metals. The United States in 2009 prosecuted the issuer of Liberty Dollars, a

attempted to ban bitcoin or prevent its proliferation. Indeed, Andrew Haldane, the Bank of England's Chief Economist and a contributor to this volume, has suggested that digital currencies might be a solution to the supposed zero lower bound problem of monetary policy, as we discuss in Section IV below. The U.S. Library of Congress provides a comprehensive analysis of bitcoin's treatment in various jurisdictions.[13]

IV. Should central banks issue their own digital currencies?

Although bitcoin and other digital currencies were created to bypass the control of central banks, the possibility of a central bank withdrawing its bills and notes from circulation and replacing them with its own digital currency has become an appealing topic of debate among monetary economists. This would result in omnipotent uber-banks such as the U.S. Federal Reserve co-opting the very technology that was created to compete against them.

Koning (2014), in a blog post titled "Fedcoin," has advanced the most trenchant and widely discussed proposal for a central bank digital currency, although his work draws on a number of earlier, similar proposals by others. The Fedcoin ideas have been taken up and discussed by two top officials of the Bank of England, Haldane (2015) and Broadbent (2016), in recent public speeches, leading to some speculation that the U.K. might be the first country to launch a national digital currency. If a digital pound did enter the marketplace, it would almost certainly have to circulate alongside traditional coins and banknotes, at least for a time, to accommodate citizens who were uncomfortable with modern technology as well as those who were unable to afford ordinary consumer devices such as mobile phones.

Under the Fedcoin proposal, citizens and businesses would be permitted to open accounts at the central bank itself, rather than depositing their funds in commercial banks as is done today. Central banks historically have not taken deposits from the public, because the sheer volume of required record-keeping and customer contact would be overwhelming (Winkler, 2015). Digital technology overcomes these concerns, since cloud-based servers and storage could easily accommodate very large volumes of financial transactions, and bank branches and ATMs would not have to be maintained if currency could be accessed via mobile phones and other hand-held

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private currency pegged to the market prices of gold and silver. Liberty Dollars had shapes and denominations similar to the official U.S. coinage but featured portraits of Congressman Ron Paul, a political libertarian.

[13] See http://www.loc.gov/law/help/bitcoin-survey/

electronics. Central bank digital accounts could initially be funded by permitting depositors to convert existing currency, presumably at a 1-to-1 rate, and the new digital currency would reside on a blockchain operated by the central bank. When depositors wished to spend their digital currency, they would transfer it over the blockchain to the account of a counterparty, with the central bank coding each transaction into its blockchain. Rather than being updated by miners in competition with one another, the blockchain would instead be overseen by a trusted third party – the central bank – which would have the exclusive right to add or modify entries. In addition, a central bank's blockchain would almost certainly be kept hidden, at least to an extent, in order to preserve the privacy of citizens and the competitive secrets of businesses. Because of these two differences, a central bank's blockchain would be markedly different than the open, shared ledger that is characteristic of digital currencies that operate by consensus of the network members and do not rely on a powerful gatekeeper. It has led some to question whether a central bank blockchain would be a blockchain at all. Such centralization would also represent a single point of failure that could make the entire financial system vulnerable to hacking or sabotage.

By concentrating deposits in the central bank, Fedcoin schemes would implicitly end the practice of fractional reserve banking, thereby "narrowing" the banking system so that depositors dealt directly with the central bank rather than with intermediary private banks. In many ways, Fedcoin represents a revival of the 1933 "Chicago Plan," a widely discussed academic proposal to end fractional reserve banking in order to restore public confidence during the Great Depression (Fisher, 1936).

Monetary policy would become much easier for the central bank to implement under a digital currency system. The bank could commit to an algorithmic rate of money creation and control it precisely via interest on customer deposits. In principle, this interest rate could be negative. Such a policy could be modified by contingent smart contracts that could change the rate of money creation if the economy followed certain future paths. Alternatively, the central bank could retain discretion to adjust the money supply on a tactical basis as part of a stabilization policy. In either case, the concept of open market operations would by superseded by direct manipulation of customer balances, which could be targeted finely toward certain geographical regions or distinct demographic or economic clienteles of depositors. Broadly speaking, this narrowing of the banking system to a direct relationship between citizens and the

central bank would represent financial socialism. The implications of this innovation would be vast, and below we sketch some of its potential benefits and costs.

Allowing private accounts at the central bank would solve many problems inherent in the current fractional reserve banking system. The central bank would not be vulnerable to bank runs, and governments could exit the business of providing deposit insurance and occasional bailouts as the lender of last resort to inadequately funded commercial banks. Commercial banks would no longer have to engage in "maturity transformation," under which they raise funds from short-term demand deposits and lend them out in long-term mortgages and other loans. Risk-shifting and other moral hazard problems on the part of banks, which now receive free deposit insurance from the government, might be eliminated.

In macroeconomics, the main advantages to a central bank of having its own digital currency would come from giving the government more control and understanding of the financial system. Such control would permit better intervention in response to the business cycle while also ensuring better individual compliance with tax collection and anti-money laundering statutes.

As articulated by Haldane (2015), a central bank digital currency could solve the "zero lower bound" problem by permitting the central bank to reduce interest rates below zero as a strategy to encourage spending and investment. When money circulates in the form of bills and notes, negative interest rates can be difficult to implement because citizens can hoard hard currency, obtaining an interest rate of zero, and refuse to deposit it into banks which would confiscate some fraction of it under a negative interest rate regime. Haldane notes that for much of the 20th century, relatively high real interest rates around the world made the zero lower bound problem all but irrelevant. However, a sustained drop in real interest rates in recent years has made the problem potentially important again. This has occurred for a variety of reasons, including the economic slump during the global financial crisis and changing demographic patterns that affect savings patterns in advanced economies.

If the main innovation of digital currency is to permit the central bank to force interest rates below zero, the public might come to resent the technology or even prevent its introduction. In 2013, the "bail-in" recapitalization of banks in Cyprus proved politically controversial and difficult to implement, after the government proposed that banks increase their equity by reducing the balances in certain customer accounts. A negative interest payment by a bank to its

depositors would mean much the same thing, and citizens might have difficulty seeing the broad public benefits of an interest rate policy that led the government to erase some of their cash from computer memory. The Cypriot Financial Crisis fueled a massive increase in the price of bitcoin, seeing the currency rise to its current all-time high of $1216.73 per bitcoin.

If a central bank digital currency did narrow the banking system by transferring the deposit-taking function away from commercial banks and into the hands of the central bank, the dangers to the commercial banking sector could be severe. Commercial banks would lose access to their main source of funds and would either have to cut back on lending or raise new capital by issuing securities to investors. The new financing would probably be far more costly and less stable than demand deposits. As a result, commercial banks might greatly reduce their lending activity to both businesses and private citizens, such as for mortgage loans or commercial lines of credit. It is not clear how the economy might compensate to offset the effects of this likely credit contraction. Perhaps, however, the abolition of mandatory fractional reserve banking would smooth out the business cycle if done through private reforms. See von Mises (1912).

A related problem would likely arise in the regulatory sphere. A central bank that took deposits from the public would end up competing head to head with commercial banks, even as it served as the regulatory overseer of the same institutions.

Such an expansion of state-established banking would not occur without criticism. A central bank controlling and tracking a national digital currency would have immense power to observe and potentially to control an individual's finances. The government could determine how much currency each individual owned and on what and where he spent his money, without the need for any independent judiciary to subpoena the information. Many people prefer to hold hard currency for precisely this reason. If governments issued digital currency, a political clientele would very likely emerge out of concern that digital currency would create a dangerous temptation for abuse. Additionally, although the cost of creating physical currency is not a total check on the government's ability to devalue a currency, without having to print dollars or mint coins, a central bank would be able to hyperinflate in a costless manner simply by adding more zeros to accounts.

Though free banking, like a free economy, is more difficult to control and understand than a centrally planned economy, modern economics has come to the conclusion that through

the channeling of incentives, well-defined property rights, and profit calculation, such disorganization produces a more robust and productive system.

V. Central bank operations using blockchains

Central banks may never elect to narrow the banking system and issue digital currency along the lines of the Fedcoin model. However, like other financial institutions central banks may see great appeal in the blockchain technology that lies at the foundation of bitcoin and other algorithmic currencies, and central banks may choose to adapt blockchains for use in their payments processing and transaction clearing functions. Even though the original goal of digital currency blockchains was to facilitate peer-to-peer value transfers that could bypass the interbank clearing process, the technology may ironically find its widest use in allowing central banks to move money more reliably and more cheaply between their depositors. The central bank currency would be a settlement currency, akin to the function served by gold in the past.

Banks perform these bookkeeping and settlement tasks not only for themselves, but also on behalf of commercial banks. Although blockchain technology remains in its infancy, estimates of its potential savings in processing and bookkeeping costs often fall in the range of 50% to 80%. For a central bank processing enormous volumes of transactions,[14] the possible size of these savings is substantial.

When central banks oversee payment and settlement functions on behalf of the entire financial system, they seek to provide a system that is both safe and efficient in order to create a high level of public confidence in the health of the banking system. See Bank for International Settlements (2005). Central banks process transactions on behalf of businesses, consumers, banks, and international counterparts, and even small gains in efficiency can save vast amounts of money. Despite the potential to achieve efficiencies through economies of scale, certain segments of the money transfer market such as international remittances remain extraordinarily costly for users. According to the World Bank, at the end of 2015 the average cost of an

[14] As an example, The U.S. Federal Reserve's FedWire electronic transfer service has handled an average daily volume of $3 trillion since November 2013, and the Fed operates several other payment and clearing services such as the Automated Clearinghouse (ACH) system. Fedwire statistics are available at https://www.frbservices.org/operations/fedwire/fedwire_funds_services_statistics.html.

international money transfer was 7.37% worldwide, and it was only modestly lower, at 6.89%, for sending funds overseas from one of the G8 countries.[15] Such transfers typically take several days to complete due to many layers of checking and verification in the clearing process.[16] In addition, fraud and theft remain problems, even when the parties involved are government central banks.[17] While the international money transfer market involves numerous intermediaries in addition to central banks, blockchain technology could make many of them unnecessary. It would have the beneficial side effect of allowing central banks to monitor the behavior of their depositors more directly, helping to defeat problems such as money laundering and tax evasion.

VI. Conclusions

Digital currencies present central banks with challenges and opportunities. In some economies, bitcoin has emerged as viable competition for fiat currencies during periods when the central bank is perceived as weak or untrustworthy, although to date these cases remain limited to troubled economies with capital controls. More interestingly, the blockchain technology behind digital currencies has the potential to improve central banks' payment and clearing operations, and possibly to serve as a platform from which central banks might launch their own digital currencies. A sovereign digital currency could have profound implications for the banking system, narrowing the relationship between citizens and central banks and removing the need for the public to keep deposits in fractional reserve commercial banks. This could lead to a serious de-funding of the commercial banking sector and have spillover effects into credit creation and monetary policy. Debates over the wisdom of these policies have led to a revival of interest in classical monetary economics. Competition among fiat currency and private digital currency evokes the 19th century "free banking" era, while the possibility for central banks to issue digital currency recalls the 1930s Chicago Plan for narrowing the financial system by eliminating fractional reserve banking.

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[15] See https://remittanceprices.worldbank.org/sites/default/files/rpw_report_december_2015.pdf.

[16] Perhaps, however, both the monetary and time cost of international remittance is a designed feature of the system to ensure compliance with national policies designed to combat ills like terrorism and sex trafficking.

[17] In a widely reported recent case, the government of Bangladesh lost $81 million in March 2016 when thieves operating through Philippine banks obtained access codes that enabled them to purloin the funds from Bangladesh's account at the Federal Reserve Bank of New York (Whaley and Gough, 2016).

As a disruptive new technology, digital currency forces governments and central banks to choose between banning, tolerating, or co-opting its innovations. In most mature economies, central banks have taken the middle course, with a few openly examining the possibility of incorporating sovereign digital currencies into their operations. With so much still to be learned about the possibilities of digital currencies and blockchains, a central bank digital currency still appears to be a radical proposition that carries significant risks for the rest of the financial system. Moreover, a mandatory central bank digital currency with the protection of legal tender laws would stand athwart the vision of competition, decentralization, and openness that the creators of modern digital currencies envisioned.

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