THREE ESSAYS ON INVESTMENTS AND CORPORATE FINANCE

by

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ABSTRACT

This dissertation consists of three essays on investments and corporate finance. The first essay is an investment article focused on factors affecting market makers in the trading of securities, the second essay is a corporate finance article which empirically tests theories of what factors motivate executives to innovate, while the third essay is a corporate finance article which empirically tests theories of why returns are higher in firms with high organization capital investments.

For the first essay, I evaluate the shift in the duration of legal insider trading and asymmetric information after Sarbanes Oxley, and find that market makers can identify asymmetric trading via the PIN measure and abnormal volumes and adjust spreads accordingly. This study is the first to consider the duration and accuracy of asymmetric trading and their effects on bid ask spreads.

The second essay considers executive incentives to innovate based on firm governance and compensation policies. Basically it seeks to empirically test the theoretical predictions of Manso (2011). Manso theorizes that the individual choice of management to innovate is motivated by a firm "tolerance for early failure", as innovations often struggle along their development paths. Ultimately, I find empirical support for many of the predictions of Manso.

The third essay addresses how the threat of talented employee departure from firms affects firm risk. Eisfeldt and Papanikoloau (2013) introduced the idea that the threat of the loss of "key talent" may increase risk for firms with high levels of organization capital (SG&A stock

/ assets). However, they do not provide direct evidence that this risk increase is due to this employment threat, and other literature has suggested that SG&A risk is from management inability or unwillingness to reduce costs. I add to this debate by testing the movement of inventors between firms, and find strong support for the theories of Eisfeldt and Papanikolaou (2013).

DEDICATION

This dissertation is dedicated to my parents, Ray and Betty Via, and to my fiancée Chimge Budgaa. The loving support my parents have given me has been a constant source of encouragement, inspiration, and motivation in my life. I am forever thankful for all they have done for me and I hope to make them proud. My goal in life is to honor them by striving to be successful in all that I do and to do the right things. In addition, I am so thankful to Chimge Budgaa for being patient with me throughout the trials of the dissertation process, and for supporting me in so many ways to accomplish this dream.

LIST OF ABBREVIATIONS AND SYMBOLS

AIM	Dummy variable equal to 1 if the insider trade passes all four asymmetric information filters; 0 otherwise.
Cash	Total cash of the firm (in $M). I take log(x) for the regressions. (Source: Compustat)
Capratio	Capital Expenditure Ratio, which equals (capital expenditure / total assets). I take log(1+x) for the regressions. (Source: Compustat)
Cites / R&D Stock	Total executive patent citations / R&D stock. The ratio of all adjusted future patent citations by top five executive firm-year patent filings divided by the stock of R&D for the current and prior 4 years (R&D stock straight line depreciated at 15% per year by the perpetual inventory method). Patent citations are adjusted using the adjustment factor of Hall, Jaffe, and Trajtenberg (2001)). I take log(1+x) for the regressions. (Source: Compustat, Hall, Jaffe, and Trajtenberg (2001), Lai, D'Amore, and Fleming (2013) patent dataverse, Sampat (2011) Harvard patent file).
Compplan	Provision of the Protection subindex of the G index that provides a compensation plan to participants to accelerate bonus payments or cash out options in the event of a change in control.
Delay	Subindex constructed by Gompers, Ishii, and Metrick (2003) of 4 provisions of the G Index used as tactics for delaying hostile bidders.
Delta	Sensitivity of an individual's firm option portfolio only to a change in the price of the firm stock. I take log(1+x) for the regressions. (Source: Core and Guay (2002), Clementi and Cooley (2010))
Dirind	Provision of the Protection subindex of the G index that indicates whether a firm has a clause in their bylaws, charter, or both that indemnifies officers and directors from certain legal expenses/judgments incurred from lawsuits pertaining to their conduct.
Dirindc	Provision of the Protection subindex of the G index that indicates whether a firm has specific contracts indemnifying individual officers and directors

from certain legal expenses/judgments incurred from lawsuits pertaining to their conduct.

Dirliab	Provision of the Protection subindex of the G index that indicates whether a firm has charter amendments to limit officer and director personal liability (to the extent provided by state incorporation laws) for breaches of the duty of care.
E Index	"Entrenchment" index of Bebchuk, Cohen, and Ferrell (2009) composed of 6 provisions of the G index that the authors find can lead to entrenchment of management and a reduction in firm value.
Employees	Log of (1 + number of employees working for the firm). (Source: Compustat)
Employment Ratio	Ratio of the selling, general, and administrative expenses for a firm divided by total assets, divided by the average firm selling, general, and administrative expenses for a firm divided by total assets for the two-digit SIC industry. SGA Ratio = [(SGA/total assets) / (SGA average for the 2-digit SIC industry / Total assets average for the 2-digit SIC industry)]. I exclude the firm's SG&A/total assets ratio when calculating the industry ratio in the denominator.
Enfstate	Indicator variable equal to 0 for the following not enforcing non-compete laws: Michigan, Alaska, California, Connecticut, Minnesota, Montana, North Dakota, Nevada, Oklahoma, Washington; 0 otherwise. (Source: Marx, Strumsky, and Fleming (2009)).
Exec Pat	Binary variable equal to 1 for firms recording at least one patent filed by a top executive (as indicated by Execucomp) during the year, zero otherwise. (Source: Execucomp; NBER Patent Data file of Hall, Jaffe, and Trajtenberg (2001); Sampat (2011) Harvard patent file; Lai, D'Amore, and Fleming (2013) patent dataverse; Kogan, Papanikolaou, Seru, and Stoffman (2012) patent data).
Exec Pat Ct	Count variable of the number of patents filed by the all top executives (as recorded by Execucomp) for a firm during the year, zero otherwise. (Source: Execucomp; NBER Patent Data file of Hall, Jaffe, and Trajtenberg (2001); Sampat (2011) Harvard patent file; Lai, D'Amore, and Fleming (2013) patent dataverse; Kogan, Papanikolaou, Seru, and Stoffman (2012) patent data).
Firm Age	Number of years since the IPO date of the firm. (Source: SDC Platinum)
Firmpatct	Log of (1 + number of patents per firm year). The total number of patents filed by the firm during the calendar year. (Source: Marx Strumsky, and

	Fleming (2009), NBER patent data project of Hall, Jaffe, and Trajtenberg (2001)).
Firmspec	Log transformation of firm specificity. The number of internal citations (from future firm patents) divided by the total citations received. (Source: Marx Strumsky, and Fleming (2009), NBER patent data project of Hall, Jaffe, and Trajtenberg (2001)).
Garm	Categorical variable ranging from 0 to 9 based on the state presence of noncompete law provisions, with a higher score indicating tougher non-compete laws. For this paper, I use a modified Garmaise index (which subtracts 9 from the original index) to allow for easier interpretation of interaction terms, so that a higher score indicates weaker non-compete laws, and higher "outside option" risk (Source: Garmaise (2011))
G Index	"Governance" index of Gompers, Ishii, and Metrick (2003) composed of the incidences of 24 governance rules. A higher score indicates a reduction in shareholder strength.
Gindexadj	"Governance" index of Gompers, Ishii, and Metrick (2003) composed of the incidences of 24 governance rules, minus the three protection subindex provisions of Dirind, Dirindc, and Dirliab.
Goldpar	Provision of the Protection subindex of the G index that provides compensation to top executives when a termination occurs not due to a change in control following a takeover.
Herf	Herfindahl index measure of the size of the firm in relation to its industry using the Hoberg and Phillips (2010) fixed industry Herfindahl index measure, calculated from 1996-2008 data. I use the 400 industry series. I take log(x) for the regressions. (Source: Hoberg and Phillips Data Library).
IAROA	Industry Adjusted Return on Assets=annual firm market return / total assets. (Source: Wintocki, Linck, and Netter (2012), CRSP, Compustat)
Innovind	Dummy variable equal to 1 for firms above the 50th percentile for the rank of innovativeness, zero otherwise. (Source: Hirshliefer, Low, and Teoh (2012))
Insider	Dollar value of the insider trade (in 1000s).
Inst Own C	Total number of institutional owners of a stock. I take log(x) for the regressions. (Source: Thomson Reuters)

Inst Own F	Fraction of institutional owners / total owners of a firm's stock, as per Aghion, Van Reenen, and Zingales (2009), Becker-Blease (2011), and Hirshleifer, Low, and Teoh (2012). (Source: Thomson Reuters)
Invidindconc	Inventor industry concentration of patents across technology classes. Herfindahl type measure of the degree of specialization of an inventor. (Source: Marx Strumsky, and Fleming (2009), Hirshleifer, Hsu, and Li (2013), NBER patent data project of Hall, Jaffe, and Trajtenberg (2001)).
Ipt	Log of (1 + inventor patent total). Total number of prior patents for the inventor. (Source: Marx Strumsky, and Fleming (2009), NBER patent data project of Hall, Jaffe, and Trajtenberg (2001)).
Liab Index	Index of the three Gompers, Ishii, and Metrick (2003) governance protection subindex provisions of Dirind, Dirindc, and Dirliab.
LT Comp	Long Term Compensation Ratio. [(Black-Scholes value of option awards) + (Restricted stock) + (Long term incentive compensation)] / (salary + bonus + other annual + restricted stock grants + LTIP payouts + all other + value of option grants). I take the log transformation (log(x/1-x)) for the regressions. (Source: Execucomp).
M/B Ratio	Market value / Book value of a firm. I take log(x) for the regressions. (Source : Compustat)
Mktcap	Market capitalization of the firm. I take log(x) for the regressions. (Source: CRSP)
Momentum	Prior 12-month return for a firm. (Source: Jegadeesh and Titman (1993), CRSP)
Mom1yr	Rank of the prior 12-month return of a firm against the prior 12-month return of NYSE, Nasdaq, and AMEX firms. (Source: Jegadeesh and Titman (1993), CRSP)
NoBind Ratio	Log transformation of the ratio of total compensation divided by forms of compensation that tend to "bind" employees to a firm, defined as follows: (salary+bonus+other annual+restricted stock grants+LTIP payouts+all other+Black Scholes value of option grants+value of options exercised) / (Black Scholes value of option grants+restricted stock grants+LTIP payouts). (Source: Execucomp).
Nonauto	Indicator variable equal to 0 for firms located in between 4-digit SIC code 3700 and 3799, 1 otherwise.

NYSE	Dummy variable equal to 1 for firm trading on the New York Stock Exchange; 0 otherwise.
O Index	"Other" index of Bebchuk, Cohen, and Ferrell (2009) composed of the remaining 18 provisions of the G index that the authors find do not have a significant impact on firm value.
O/K	Log of organization capital. Selling, general, and administrative (SG&A) stock / total assets, adjusted to 2012 dollars using the CPI index, discounted using the perpetual inventory method with a 15% discount rate, as follows: SG&A stock = SG&At + (.85)(SG&At-1) + (.7)(SG&At-2) + (.55)(SG&At-3) + (.4)(SG&At-4). (Source: Compustat)
Other	Subindex constructed by Gompers, Ishii, and Metrick (2003) of 6 provisions of the G Index composed of other miscellaneous takeover defenses.
Outflow	Net number of inventors leaving a firm in the prior 5 years. (Source: NBER patent data project of Hall, Jaffe, and Trajtenberg (2001), the patent dataverse of Lai, D'Amore, and Fleming (2011), and the Kogan, Papanikolaou, Seru, and Stoffman (2012) patent data).
Postevent	Ch.3: Indicator variable equal to 1 in the year after an executive files a patent, 0 in the year before an executive files a patent (Note: This excludes the patent filing event year).
Postevent	Ch. 4 Michigan Experiment: Indicator variable equal to 1 in the year 1990, 0 in the year 1984.
Postevent	Ch. 4 Headquarter Moves: Dummy variable equal to 1 for the 3rd year after a headquarter move, 0 for the 3rd year before a headquarter move. (Source: 10-K searches)
PPS	Pay performance sensitivity. Sensitivity of an individual's firm stock and option portfolio to a change in the price of the firm stock. I take log(1+x) for the regressions. (Source: Core and Guay (2002), Clementi and Cooley (2010)).
Price	Stock price level of the firm.
Protection	Subindex constructed by Gompers, Ishii, and Metrick (2003) of 6 provisions of the G Index used to provide officers and directors compensation after a termination, or to protect them against job related liability.
Reprice Event	Annual binary variable equal to 1 for each year a firm records at least one option repricing event between 1992 and 2012, zero otherwise. (Source: Execucomp)

Reprice Firm	Binary variable equal to 1 for firms recording at least one option repricing event anytime between 1992 and 2012, zero otherwise. (Source: Execucomp)
R&D / Assets	R&D / Assets. The ratio of annual research and development expenses to assets. Similar to Hirshleifer, Low, and Teoh (2012), if R&D is missing for a year, I record the value of R&D spending as zero. However, I add the additional filter that a firm must have recorded at least one R&D expense between 1996-2006, or R&D is left as missing. I take log(1+x) for the regressions. (Source: Compustat)
Ret	Percent return for the stock (including dividends).
Ret1yrE	One-year firm returns net of equal-weighted market returns. (Source: CRSP)
Ret1yrV	One-year firm returns net of value-weighted market returns. (Source: CRSP)
Revenue	Sales revenue of the firm (in $M). I take log(x) for the regressions. (Source: Compustat)
ROA	Return on Assets=annual firm market return / total assets. (Source: CRSP, Compustat)
SG&A Ratio	Ratio of the selling, general, and administrative expenses for a firm divided by total assets, divided by the average firm selling, general, and administrative expenses for a firm divided by total assets for the two-digit SIC industry. SGA Ratio = [(SGA/total assets) / (SGA average for the 2-digit SIC industry / Total assets average for the 2-digit SIC industry)]. I exclude the firm's SG&A/total assets ratio when calculating the industry ratio in the denominator.
Spread	Size of the bid-ask spread.
Staff Exp Ratio	Ratio of the selling, general, and administrative expenses for a firm divided by total assets, divided by the average firm selling, general, and administrative expenses for a firm divided by total assets for the two-digit SIC industry. SGA Ratio = [(SGA/total assets) / (SGA average for the 2-digit SIC industry / Total assets average for the 2-digit SIC industry)]. I exclude the firm's SG&A/total assets ratio when calculating the industry ratio in the denominator.
State	Subindex constructed by Gompers, Ishii, and Metrick (2003) of 6 provisions of the G Index regarding state laws.

Severance	Provision of the Protection subindex of the G index that provides cash and non-cash compensation to top executives when a termination occurs due to the event of a change in control following a takeover.
Size	Log of (1 + market capitalization of the firm). (Source: CRSP)
Total Comp	Log of total compensation, defined as follows: (salary+bonus+other annual+restricted stock grants+LTIP payouts+all other+Black Scholes value of option grants+value of options exercised). (Source: Execucomp).
Treatment	Ch.3: Indicator variable equal to 1 for firms experiencing an executive patent filing event, 0 for firms not experiencing an executive patent filing event (Source: Execucomp and Lai,D'Amore, and Fleming (2013) patent dataverse).
Treatment	Ch. 4 Michigan Experiment: Indicator variable equal to 1 for firms headquartered in Michigan, 0 for firms headquartered outside of Michigan. (Source: Compustat)
Treatment	Ch. 4 Headquarter Moves: Dummy variable equal to 1 for firms moving to a state with non-compete laws 2 points stricter on the Garmaise index, 0 for firms moving to a state with non-compete laws 2 points less strict on the Garmaise index. (Source: Garmaise (2011), 10-K searches)
Tslp	Time since last patent. Total number of years since the last patent filing for the inventor. (Source: Marx, Strumsky, and Fleming (2009), NBER patent data project of Hall, Jaffe, and Trajtenberg (2001)).
Vega	Sensitivity of an individual's firm option portfolio only to a change in the volatility of the firm stock. I take log(1+x) for the regressions. (Source: Core and Guay (2002), Clementi and Cooley (2010))
Velocity	(Number of inventors leaving a firm in the prior 5 years) + (Number of inventors joining a firm in the prior 5 years). (Source: NBER patent data project of Hall, Jaffe, and Trajtenberg (2001), the patent dataverse of Lai, D'Amore, and Fleming (2011), and the Kogan, Papanikolaou, Seru, and Stoffman (2012) patent data).
Vol	Volume of shares traded (in 1000s).
Voting	Subindex constructed by Gompers, Ishii, and Metrick (2003) of 6 provisions of the G Index used to establish shareholder voting rights in elections or charter/bylaw amendments. Two provisions (secret ballot and cumulative vote) are negative if they occur.

1-Year CAPM	1-year value weighted market return net of 1-year risk free rate (from U.S. Treasuries). (Source: Ken French's website).
3-Year CAPM	3-year value weighted market return net of 3-year risk free rate (from U.S. Treasuries). (Source: Ken French's website).
1-Year Rets	1-year firm returns including dividends, net of the risk-free rate (1-year Treasury bills). (Source: CRSP)
3-Year Rets	3-year firm returns including dividends, net of the risk-free rate (geometric return of the past three (1-year returns minus 1- year Treasury bills)). (Source: CRSP)

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CHAPTER 1

INTRODUCTION

This dissertation consists of three essays on investments and corporate finance. For the investment essay, the dissertation research seeks to contribute to a more thorough understanding of the impact of market makers upon the financial markets. For the two essays on corporate finance, the dissertation seeks to find empirical evidence supporting theoretical research on what motivates managers to innovate, and how the threat of talented employee departure from firms affects firm risk.

The first essay investigates the impact of the duration and accuracy of asymmetric trades on market making. Prior studies evaluating the effect of asymmetric information upon bid ask spreads have typically focused on the impact of discrete one-day events. However, a longer sustained duration of asymmetric trading may have a stronger impact on the bid ask spreads of a firm than a specific one-day event. In addition, market makers might notice a statistically significant loss in their deals in a certain stock if the accuracy of the asymmetric information of the informed traders is stronger. This study evaluates the shift in the duration of legal insider trading asymmetric information after Sarbanes Oxley, and finds that market makers can identify asymmetric trading via the PIN measure and abnormal volumes and adjust spreads accordingly. Accuracy also reduces spreads for insider sales, lending support to a hypothesis that certainty of short-term price trends will allow the market maker to adjust their bid/ask prices and inventory levels to maintain profits. This study is the first to consider the duration and accuracy of asymmetric trading and their effects on bid ask spreads.

The second essay considers executive incentives to innovate based on firm governance and compensation policies. Manso (2011) theorizes that the individual choice of management to innovate is motivated by a firm "tolerance for early failure", as innovations often struggle along their development paths; however, empirical proof is difficult to obtain because individual executive contribution toward firm innovation is difficult to measure. In response, I develop a unique dataset of 1,355 firm-year patent filings by members of management between 1996 and 2006 as a proxy for their individual innovative contributions and a firm culture of innovation. Using this data, in contrast to Manso I find modest evidence that personal executive innovation efforts are higher in firms with strong shareholder rights. Because of recent literature suggesting governance research is subject to autocorrelation bias (Wintoki, Linck, and Netter (2012)), I use logit/probit models, a negative binomial model, a dynamic OLS model, and an Arellano Bond (1991) difference GMM dynamic panel model to find that the 3 liability protection measures of the "protection" subindex of Gompers, Ishii, and Metrick (2003) increase executive patenting, which indirectly supports Manso, although I also find evidence opposing Manso for golden parachutes. I also find a relationship between executive patenting and option repricing, long term compensation policies, and option structure. Finally, I find that firms with innovative executives face higher short-term risk, also supporting the Manso (2011) predictions.

The third essay studies the effect of organization capital on firm risk in light of the "outside option" of skilled employees to leave the firm. Eisfeldt and Papanikoloau (2013) introduced the idea that the threat of the loss of "key talent" may increase risk for firms with high levels of organization capital (SG&A stock / assets). However, they do not provide direct evidence that this risk increase is due to this employment threat, and other literature has suggested that SG&A risk is from management inability or unwillingness to reduce costs. In this paper, I follow 22,021 inventor moves between firms from 1976-2006, and find that 1) inventor movement away from a firm and 2) overall increases in inventor moves both increase firm risk for high organization capital firms. I test this against other measures of compensation structure and non-compete laws and find that the results still hold. For robustness, I use three instrumental variables to proxy for the wage differential between the firm and its industry, and find that when organization capital increases due to a rise in industry wages or employment, firm risk goes up. In addition, I test an exogenous repeal of non-compete ban laws in Michigan in 1985, and find that firm risk goes down for Michigan firms after the repeal. Finally, I test the movement of firm headquarters between states with differing non-compete laws as per Garmaise (2011), and find that firms moving to high non-compete strength states face lower risks.

CHAPTER 2[1]

DOES THE DURATION AND ACCURACY OF ASYMMETRIC TRADING MATTER TO MARKET MAKERS?

2.1 Introduction

Do market makers immediately recoup their losses to informed traders by widening the bid ask spread? If not, how do they determine the sources of their losses, and how do they adjust spreads to recoup these longer term losses? Previous studies have focused on discrete events and their effect on the bid ask spread. However, several studies have found that discrete trading events by informed traders can go unnoticed by the market makers, leaving them in a quandary as to how to determine where their losses are arising from, and how properly to adjust their spreads to compensate for the damage. This study suggests that discrete events can be lost amongst the many variables affecting the market makers profits, but that a longer duration of intense informed trading in a stock might allow a market maker to determine a statistically significant occurrence of asymmetric information, and adjust their spreads accordingly in that stock without spreading the blame (and the damage of a larger spread) to a wider class of stocks in which that firm is located.

The change in the reporting delay of legal insider trades after the Sarbanes Oxley Act of 2002[2] provides a perfect laboratory for testing such a shift in the duration of asymmetric

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[1] A working paper version of this chapter exists and is being circulated.
[2] Section 403(a) of the Sarbanes Oxley Act of 2002 amended several aspects of the insider reporting requirements of Section 16(a) of the Securities Exchange Act of 1934.

information. Due to the long reporting delay (up to 40 days) prior to Sarbanes Oxley (SOX) between the actual insider trade and the report of the trade to the SEC, the potential existed for asymmetric information to trickle out only very slowly in a stock. Sarbanes Oxley reduced the long reporting delay to 2 business day, allowing the insider trade and the informed trades upon public response to the public reporting of the insider trade to be concentrated in a much shorter period, allowing for better detection (and spread compensation from that firm alone) for the market maker. In addition, market makers might notice a statistically significant loss in their deals in a certain stock if the accuracy of the asymmetric information is stronger. In other words, if the informed trader realizes a larger profit off of their signal, they apparently have better information. This study is the first to consider the duration and accuracy of asymmetric trading and its effect on bid ask spreads.

This study becomes especially timely at present because of two legislative acts in recent years: 1) The "Volcker Rule" of the "Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010" and 2) the "Small Cap Liquidity Reform Act of 2013" which is under consideration. The Volcker Rule bans proprietary trading by banks, which some have speculated could potentially affect market making activities. While the SEC current exempts market makers from the requirement[3], the debate is ongoing and additional research in this area will help future regulators properly initiate policy adjustments.

In addition, the "Small Cap Liquidity Reform Act of 2013" which was introduced on November 12, 2013, is intended to improve liquidity in small stocks. Instead of allowing penny decimalization, it would require a tick size of $0.05 or $0.10 in an attempt to encourage market makers to become more active in these types of stocks. Although the change would likely

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[3] "Remarks on the Volcker Rule's Market Making Exemption". John Ramsay, Acting Director, Division of Trading and Markets, SEC. February 4, 2014. http://www.sec.gov/News/Speech/Detail/Speech/1370541128316#.U5YJ-3JdW4Q

initially start as only a pilot program to study its effects, any relevant research before the change is initiated would help regulators to update and adjust its implementation, or even decide whether or not the bill is worthwhile at all in its current form.

A. Legislative Motivation for Sarbanes Oxley Section 403

In the Capital University Law Review in 2004, Stanislav Dolgopolov discusses the legislative motivations of the harm of insider trading on market makers that were in play before Sarbanes Oxley was enacted. He references that in 1984 the SEC gave the following response on insider trading and adverse selection:

> "Insider trading may also inflict significant economic injury on exchange specialists or market makers [that] provide market liquidity by standing ready to buy or sell for their own accounts in conditions of excess buying or selling demand. This liquidity creates … an orderly market which is advantageous to all investors. But exchange specialists and market makers cannot protect themselves from inside traders. Their market making obligations sometimes force them to trade securities with insiders at prices not reflecting the value of the inside information, and, as a result, they may incur losses great enough to cause them to go out of business."[4]

In addition, he notes that a motivation for Regulation Fair Disclosure (Reg FD) in 2000 was the adverse selection literature:

> "Economic theory and empirical studies have shown that stock market transaction costs increase when certain traders may be aware of material, undisclosed information. A reduction in these costs should make investors more willing to commit their capital."[5]

These ideas helped lead to the introduction of Section 403(a) of the Sarbanes Oxley Act of 2002. This section went into effect on August 29, 2002, reducing the reporting delay of insider trades

[4] From "Memorandum of the Securities and Exchange Commission in Support of the Insider Trading Sanctions Act of 1984".
[5] From "Selective Disclosure and Insider Trading, Exchange Act Release (August 15, 2000).

from the tenth of the month after the trade (up to 40 days from the time of the trade) to only two business days.

B. Insider Trades vs. Informed Trades; Duration vs. Accuracy

In this paper, asymmetric information refers both to the superior information of company insiders and superior information of outside traders who properly interpret insider trades as informed. Legal insider trading[6] refers to transactions by directors, officers, and large shareholders who own 10% or more of a firm's shares[7]. This insider trading can refer to both informed trades (acting on either private information or superior knowledge) and uninformed trades (insiders transacting shares simply for liquidity purposes, portfolio rebalancing, etc.). On the broader level I define for this paper, informed trading refers not only to the previously mentioned subset of SEC-filed insider transactions by those with superior information, but also to traders reacting to market-wide or "public" information (Dolgopolov (2004)) as proxied by the public disclosure of the insider trades (as required by the SEC) to outside traders who can properly identify informed insider trades.

First, the informed trading by insiders is proxied in this paper by calculating four additional filters of insider trades, to show how highly accurate insider trades can indeed earn higher positive returns for insiders.. These signals are defined here as asymmetric information measures (AIM), and are added conditionally to the requirement of an insider trade. Second, I use the implementation of Sarbanes Oxley 2002 and its reduction in insider trade reporting time from up to 40 days down to only 48 hours to show how a fresh signal of highly accurate insider

[6] This can also include illegal insider trading on the basis of leaked private information before the public becomes aware (however, this type is not considered in this study).
[7] As defined by the Securities and Exchange Act of 1934.

trades can be interpreted by knowledgeable traders, thus encouraging them to trade in the direction of the signal.

Accuracy

Accuracy in this paper refers to how much information content is contained in an insider trade. In other words, trades that contain all four AIM filters would be highly informed, and thus would be considered highly accurate. Other insider trades that do not pass through any of the AIM filters would be assumed to be uninformed, and thus not very accurate in terms of giving an information signal.

Duration

Duration refers to the length of time of intense informed trading a market maker would face. An insider with a large buy or sell order may require a significant amount of time to complete their trade in a stock. For example, if an insider owns a large percentage of firm stock and wants to sell quickly in a stock with low liquidity, it may take several days or weeks to complete the trade. This was not a problem before SOX, as insiders had up to 40 days to report their trades, and thus they could easily complete their trades before attracting the interest of any outside traders. However, after Sarbanes Oxley the insider is required to complete their trade in 2 business days, meaning that large trades will not likely be completed before the trade is reported to the public, attracting potential front-running by outside traders. This would mean that insiders would need to complete their trading very quickly to avoid losses due to front-running, which would lead to a steady and sustained duration of the insider trade. Thus, duration of insider trades becomes stronger for insider trades after the passage of SOX. Prior to Sarbanes Oxley, it is possible that the insider and the broker would ease their informed trades into the market, so that the market maker would not see an intense period of informed trading against them. In addition, the information signal would be so delayed, it is possible that informed outside traders would not react very strongly to seeing that an informed insider had traded, since the signal would likely not be very recent. However, after Sarbanes Oxley, the insider and their broker would need to quickly execute their trades in the market, having a more serious impact on the market makers they deal with. In addition, with this signal less than 48 hours old, informed outside traders would likely react strongly to this information signal, and also put intense pressure against the market makers. Thus, market makers after Sarbanes Oxley would see an intense duration of informed trading affecting their offsetting inventory position, both from insiders quickly seeking to complete their trades, and informed outsiders strongly reacting to this fresh signal from the informed insiders.

C. Bid Ask Spreads: Market Maker Loss Hypothesis vs. Certainty Hypothesis

Market makers assist market performance by providing liquidity and immediacy of trading in exchange for a profit derived from the bid-ask spread. Many exchanges have designated market makers deemed "specialists" who are contracted to perform this function in a specific stock as long as they provide a certain minimal amount of liquidity to traders in the stock. While not necessary for a market to function, they provide stability and consistency in trading by smoothing variation in price and spread levels.

Market makers face potential harm from informed traders simply by the nature of their business: to provide a market for a security, they take the opposite side of a transaction desired by a trader. This creates an inventory of stock for the market maker that they then seek to dispose of at the opposite end of the bid-ask spread. The profit that they earn is the spread itself. For example, if trader A buys 100 shares at an ask price of $31.00, the market maker assumes a net short position of 100 shares at $31.00. Assuming the price does not move on the stock, the market maker then closes this short position by "buying back" 100 shares from trader B, who wishes to sell 100 shares at an ask price of $30.00. Thus, the market maker earns $1.00 per share off of this round trip transaction. The $1.00 per share earned in this example might be more or less depending on the particular transaction, but averages this amount when dealing with uninformed traders.

However, suppose trader A was an informed trader. The market maker would still assume a net short position of 100 shares at $31.00, but given the information that trader A possessed, it is likely that the stock would move up during the interval between trader A's trade and trader B's trade. So in this case, perhaps the market maker disposes of his/her inventory at $30.20, thus reducing their profit by 20%. This would of course be harmful to the market maker, and potentially to their very existence as a provider of market liquidity.

In this paper, I propose two hypotheses of how market makers deal with informed traders. The first is the "Market Maker Loss Hypothesis", which is the traditional view among many academics that market makers lose to informed traders, as described in the example above. However, the second hypothesis presents an opposite outcome, which I call the "Certainty Hypothesis". In this case, market makers are able to correctly determine short term trade direction based off of these signals by informed traders, and adjust bid prices, ask prices, and spreads to obtain the profit necessary for their survival. Thus, liquidity can be increased and spreads actually reduced when market makers can correctly infer short term trade direction.

In the following paragraphs, I present a more extensive literature review of prior studies that debate what I deem as the Market Maker Loss Hypothesis. It has been well established in the academic literature that asymmetric information should lead to higher bid ask spreads. Dolgopolov (2004) sums this up by stating "Because providers of liquidity, unable to distinguish among types of traders, are always "losing" on trades with better-informed counterparties, they must charge everyone a higher bid-ask spread to compensate for their losses and still enter into some "adverse" transactions."

However, if market makers cannot effectively determine in which stocks informed trading is occurring, they may simply increase spreads on a permanent basis in that stock, or increase spreads on an entire class of stocks to recoup their losses. Glosten and Milgrom (1985) mention that market makers may increase spreads in small companies because of a larger probability of insider trading. In fact, they state that the adverse selection model might explain "the small firm effect and the ignored firm effect[8]". Their paper helped spawn a stream of literature seeking to decompose the spread and to discover, among other things, what portion of the bid ask spread resulted from asymmetric information. In fact, Easley, Kiefer, O'Hara, and Paperman (1996) wrote their seminal paper on the PIN (probability of informed trading) measure in response to the problem of higher spreads on smaller, less frequently traded stocks. Although a few studies cite only a small degree of asymmetric information in the spread (Weston (2000), De Winne and Platten (2003)), most studies find a significant portion of the spread can be attributed to asymmetric information (Huang and Stoll (1997), Madhavan, Richardson, and Roomans (1997), Coughenor and Deli (2002). The two latter studies find that asymmetric information may even be the single largest component of the spread. In fact, Silva and Chavez (2002) find that the adverse selection component among 29 corporations on the Mexico Stock Exchange (MSE) amounts to 95% of the spread.

[8] Firms with little market coverage. Brennan, Jegadeesh, and Swaminathan (1993) argue that stocks with a greater number of financial analysts adjust more quickly to information events than "neglected" stocks.

Some studies suggest that the asymmetric information risk to market makers extends over only a few minutes. Saar and Yu (2002)[9] state the following:

> "Market makers are concerned with order imbalances over very short horizons (often less than an hour), and these need not correspond to the creation of new information about the firm or the trading by investors with special knowledge about the firm."

However, if all losses were recouped that quickly, there would be no need to increase spreads before important firm events. Foster and Viswanathan (1991) and Lee, Mucklow, and Ready (1993) find a significant increase in spreads prior to important company announcements[10]. If a market maker suspects greater uncertainty in a stock's near-term future price movement, they may increase the spread to compensate for a higher inventory risk, even if no asymmetric trading has yet occurred. This could happen on rumors of a takeover, a firm announcing that they have "substantial impending news", or prior to an earnings announcement. If the market makers could quickly recoup any losses by simply increasing their bid ask spreads after the asymmetric trades, there would be no need to increase their spreads prior to the firm-specific event. However, because of the fact that insiders and informed traders will guard their knowledge carefully, revealing only to close associates their relevant trading information, the majority of the time the market maker will not know if asymmetric information is about to occur or currently occurring. Typically they will only know far ex-post, when they review their trades in a particular firm and find a statistically significant level of losses in their trading. For example, Chakravarty and McConnell (1997) examined insider trading in Carnation prior to its acquisition by Nestle in 1984. Ivan Boesky illegally purchased 1.7 million shares in the company in the three-month period prior to the acquisition. Although stock prices rose off the purchases, bid ask spreads hardly changed.

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[9] Found in Dolgopolov (2004) pp. 110-111.
[10] Chung Charoenwong (1998).

Not being able to pinpoint when or to what extent this asymmetric information is taking place, market makers may seek to permanently increase the bid ask spread in that stock. Kini and Mian (1995) hint at this, as they find no statistically significant relationship between spreads and insider trading, and suggest that insiders may increase bid-ask spreads only over time to compensate for their losses. This has the resulting adverse market microstructure effect of reducing overall liquidity and price discovery in the stock. The higher transaction costs from the increased bid ask spread will deter traders, at the margin, from buying or selling the stock, even if they feel the price is overvalued or undervalued. This means that the price will drift above and below its true value within the range of these transaction costs that traders would have to hurdle to realize a profit from their assessment of an improper valuation.

In addition, if the market maker can't pinpoint losses to particular events in a stock, they may simply try to determine if the asymmetric information (and ensuing losses) are simply attributable to a certain class of stocks, either by size or industry, for example. After all, a market maker dealing in a wide variety of stocks can diversify away the losses in one stock, but if losses are occurring in an entire class of stocks, diversification may be impossible. Thus it is of utmost importance for a market maker to determine trading losses in a non-diversifiable class of stocks, and increase the spread accordingly to compensate for the risk.

As for the Certainty Hypothesis, I lay out the case for studying this outcome in the Methodology section below.

D. Background on Insider Trades and Their Effect on Abnormal Returns

Insider trading abnormal returns has been the primary focus of most prior papers studying the effect of insider trades. It is important to understand the effect of *abnormal* positive or negative returns by insider trades, because this leads to additional informed trading after the insider trade (which contributes to the asymmetric trading affecting the market maker). Previous studies by Lorie and Niederhoffer (1968), Pratt and Devere (1970), Jaffe (1974), Finnerty (1976), and Seyhun (1988,1992,1998), Rozeff and Zaman (1988), Lin and Howe (1990), Jeng, Metrick, and Zeckhauser (1999), and Lakonishok and Lee (2001) have shown that insiders earn profits of 3% - 30% during holding periods between three months and three years.

Lakonishok and Lee (2001) further evaluate the production of abnormal returns by insider trades, focusing on an extreme short term horizon and an intermediate term horizon. They find that there is at least some insider trading in more than 50% of stocks in a given year. Insider sales amount to 1.3% of company market capitalization, while insider purchases amount to 0.6% of company market capitalization. In contrast to previous studies, they do not find any abnormal return close to the time of insider trades, but do find a positive correlation with returns over longer time periods such as 12 months. Firms with extensive insider purchases during the prior six months were found to outperform companies with extensive insider sales by 7.8% over the next 12 months. Even after controlling for size and book-to-market effects (Fama and French 1993), the spread in returns was still 4.8%.

E. Insider Trading and Short-Term Abnormal Returns

To properly determine if the shift in insider trade reporting time as established by Sarbanes Oxley had an effect on trading profits, it is first necessary to confirm that insider trading indeed affects returns in the short-term. Short-term insider trading is defined in this paper as periods of up to 1½ months (approximately 32 trading days). Seyhun (1986) also discusses short-term insider trading returns, and looks at not only the next 1-5 days after an insider trade is placed, but also at the next several months. However, to gain an understanding of the effect of short-term insider trading, it is helpful to look at extreme short-term time frames like 1-5 days. Lakonishok and Lee (2001) evaluate this extreme short-term holding period and find statistically significant returns, but with magnitudes that are small and relatively meaningless. They find a 5-day return for officer insider transactions of 0.13% for purchases, and -0.23% for sales, giving a difference of only 0.36% (and less of a difference for large shareholders and others). Seyhun (1986) and Pascutti (1996) find similar results when considering these extreme short-term holding periods. Brochet (2012) is the latest to look at extreme short term returns. He examines returns from insider trading post Sarbanes Oxley, and finds short term returns increase post-SOX in the days just after an insider purchase, but little change occurs in the returns post-SOX for insider sales.

However, Seyhun (1986), in contrast to Lakonishok and Lee (2001), finds a statistically significant cumulative abnormal return of significant magnitude when evaluating returns at a slightly longer time frame of 100 days. Purchases exhibit a 3.0% return, while sales exhibit a -1.7% return, which would equate to a difference of 4.7% between the two portfolios. But it is important to note that these returns are not significant after subtracting trading costs.

F. Reasons For Informed Trader (non-Insider) Profit Potential After Insider Trades

The reason for informed trader (non-insider)[11] profit potential after insider trades is based on how accurate the insider trades are themselves, and how quickly this information reaches the market. So informed traders can earn higher profits by better understanding the reasons why insiders make timely trades, and why they have such an informational advantage. Seyhun (1992) breaks this informational advantage into two competing hypotheses: (i) the cash flow hypothesis, and (ii) the fads hypothesis. First, the cash flow hypothesis states that corporate insiders can predict the future cash flows in their own firms before other market participants. This viewpoint

[11] Insiders are also generally considered informed traders, but this section refers to public traders who are responding in an informed way to the insider trading signal.

is strongly supported by Lakonishok and Lee (2001), who quote an article in Individual Investor (Feb. 1998, p. 54) which states "Company executives and directors know their business more intimately than any Wall Street analyst ever would. They know when a new product is flying out the door, when inventories are piling up, whether profit margins are expanding or whether production costs are rising…You always hear about the smart money. Generally, that is the smart money."

Second, the fads hypothesis states that stock prices can and will deviate away from fundamental values. Insiders, highly knowledgeable of their firm, will realize that their current price is different from fundamentals, and will trade (buy or sell) accordingly. Aggregate insider trading across firms could even indicate if the mispricing is market wide. If a current fad pushes stock prices too high, prices will subsequently decline when the fundamentals eventually become more influential. Thus, informed traders can improve their profit potential after the insider trade (and introduced a higher level of asymmetric trading) by better understanding the reasons behind each trade (leading to the AIM measures).

G. Information Content of Purchases Versus Sales

In studying the asymmetric trading effect of insider trades on market makers, it is also important to understand if there is a difference between the effect of insider purchases and insider sales. Lakonishok and Lee (2001) find that insider sales are not as significant a predictor of a firm's stock price movement as insider purchases, which yield significant positive abnormal returns. For small, low book / market stocks, the abnormal returns for the following 12 months, based on aggregate purchases in the prior six months, amount to 7.2% (while aggregate sales have a negligible effect). Although insider sales are less significant, they find that insider sales for small, high book / market stocks yield an abnormal return of -3.7% for the following six months (while aggregate purchases have a negligible effect). This contributes strongly to the idea that insider trading is a contributor to price momentum, although it indicates that insider trades may not be the first contributor to the momentum effect (because for these stocks, price had already moved strongly in the direction of the insiders' transactions prior to their trade). Seyhun (1998) also finds that insider purchases earn a higher profit than insider sales, and that insider purchases for small stocks have a higher information content than insider sales for small stocks.

The rest of the paper is organized as follows. Section 2.2 describes the data sets used in the analysis. Section 2.3 describes the five primary methods used to test for asymmetric information. Section 2.4 provides the results of the event studies, panel regressions, and additional analysis. Section 2.5 performs robustness checks. Section 2.6 concludes. Section 2.7 Appendix A includes relevant tables and figures. Section 2.8 Appendix B contains secondary confirming tables and figures.

2.2 Data and Descriptive Statistics

The data that is used in this paper is derived from three sources. First, insider trades are obtained from Thompson Reuters Table 1 (to obtain Form 4 data) for the period 1993-2009. Insider trade data becomes available in 1986, but is rather scarce before 1993, so no data is used before this period. Variables used include transaction date (trandate), company identifier (cusip – 1st six digits), identification number of insider (personid), type of insider filing form (formtype), adjusted transaction price (tprice_adj), adjusted shares (shares_adj), position title (rolecode1), transaction code (trancode), and cleansing level (cleanse). Thompson Reuters uses a proprietary process to cleanse the data and verify its accuracy from external sources. Only the top 3 cleanse indicators out of the 9 levels listed are kept in this study: R, which identifies records that passed all data cleansing checks for reasonableness; H, which makes updates, but with high confidence; and L, in which one or more data cleansing updates were undertaken, but complete verification was unavailable from secondary sources (see Thompson Reuters for more details). In addition, formtype is set to 4 to capture only Form 4 data.

Second, monthly stock data is provided by the Center for Research in Security Prices (CRSP) for the period 1993-2009. The variables used include three company identifiers (permno, tic(ticker), cusip – 1st six digits), date, exchange code (exchcd), share code (shrcd), return (ret), stock price (prc), shares outstanding (shrout), bid price (bid), ask price (ask), and the bid-ask spread (spread). Observations are excluded if they are not in the NYSE, AMEX, and Nasdaq (exchcd=1,2,3), or if the data is not common stock (shrcd=10,11). Data for the spread variable is supplemented by calculating the difference between ask price and bid price if spread is not available. Daily stock data is also obtained from the Center for Research in Security Prices for January 1 – March 31 for both 2002 and 2005[12]. The variables used include a company identifier (permno), date, bid price (bid), ask price (ask), and return (ret).

Finally, intraday data is obtained the from the Trade and Quote (TAQ) database for the NYSE, AMEX, and Nasdaq exchanges. The data is obtained from January 1 – March 31 for both 2002 and 2005, for a select sample[13] filtered by market capitalization. Firms are kept if they meet the following conditions: market capitalization >$100 million and <$200 million on January 1, 2002, and market capitalization >$100 million on March 31, 2005. Quote variables include the following: symbol, quote date (date), quote time (time), bid price (bid), offer price (ofr), bid size in number of round lots (bidsiz), offer size in number of round lots (ofrsiz), and

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[12] No exclusion is done for exchange code or share code within this data, as it is merged with insider trading events previously filtered for exchange and share code as indicated for monthly CRSP data above. So filtering is done by default.

[13] Although a larger sample could have been used, I argue that the large number of intraday observations provides a reasonable analysis of the effects of informed trading on the market maker pre- and post- SOX.

quote condition (mode). Trade variables include the following: symbol, transaction date (date), trade time (time), actual trade price per share (price), correction indicator (corr), sale condition (cond), number of shares traded (size).

Data sets are matched by permno, 6-digit cusip, or ticker(symbol), in this order. Ex: If permno is not available for a data set, then matching is done with the first six digits of the cusip. And if neither permno or cusip is available, matching is done with ticker (symbol).

It is important to note that the SEC required all exchanges to switch from fractional price quotes to decimal quotes by April 9,2001, which could bias studies of bid-ask spreads extending before and after this period. Thus, while the sample period extends from 1993-2009 overall, I only consider the period after April 9, 2001 when evaluating bid-ask spreads, to avoid any biases due to decimalization which could result.

2.3 Methodology

The introduction of the Sarbanes Oxley legislation created a perfect laboratory for studying the effects of changes in the duration of asymmetric information on stock spreads. In order to determine how SOX changed these parameters, five methods are developed in this paper. First, a method to determine the change in asymmetric information duration after Sarbanes Oxley, in terms of the timeframe around the insider trading event, is determined from a paper by Aktas, de Bodt, and Van Oppens (2008). Second, a method is developed for determining high accuracy of asymmetric information versus low accuracy of asymmetric information. Third, event studies are utilized for the analysis of stock returns, volume, and bid-ask spreads around the insider trade. Fourth, the PIN measure of Easley, Kiefer, O'Hara, and Paperman (1996) is used as a confirming asymmetric information signal to the event studies.

Finally, cross sectional panel regressions of the bid ask spread, controlled by well-established spread predictors, are calculated for all four periods listed in Figure 1.

A. Asymmetric Information Duration Changes Introduced by Sarbanes Oxley

The dramatic reduction in the reporting time of insider trades after Sarbanes Oxley went into effect on August 29, 2002, reducing reporting delays for insider trades from up to 40 days down to only two business days. The goal of this change was to reduce the harm to market makers and investors from the preliminary leakage of information pertaining to the insider trade before the public had a chance to act on the information. The challenge is to know which period of time around the insider trading event window to study to evaluate the effects of a possible reduction in asymmetric information. Aktas, de Bodt, and Van Oppens (2008) find that the average reporting delay by insiders of their trades to the SEC is 22 days (15 trading days) for the period 1995-1999, whereas after Sarbanes Oxley in 2002 the insider trade reporting time is well defined since it occurs in such a quick period of time (two business days). Also, to gain a clear picture of all movements around the event, a sufficient event window length must be analyzed. Since it is well known in the literature that acquisition targets experience significant price increases up to 20 trading days (approximately 1 month) before the announcement (Agrawal and Nasser (2012), Keown and Pinkerton (1981)), this study evaluates 32 trading days (1½ months) before and after the event. In addition, the event study abnormal return is divided into 4 periods:

Period 1: -32, -2 days
Period 2: -1, +3 days
Period 3: +4, +15 days
Period 4: +16,+32 days

Although after SOX insider trades are reported within two business days, period 3 does not begin until day 4 to allow a lag in the effect of the insider trade reporting (if the trade is reported on day +2 after hours, the effect of the trade might not be felt until the market open on day +3). Figure 1 provides a further explanation of the hypotheses surrounding these four windows, and is presented after the following section.

B. Screening for Information Content by Accuracy of Asymmetric Information (AIM Measures)

This paper theorizes that if asymmetric trading occurs more quickly by shortening the reporting time of insider trades, allowing market makers to more easily detect asymmetric trades and increase spreads, then an increase in the accuracy of insider trades should also aid detection and increase spreads. In addition to the signal from the insider trade itself, four additional screening methods are used which more than double the information content of the insider trading signals (as seen by stock returns). This paper defines these screens as Asymmetric Information Measures (AIM). These methods are as follows:

AIM 1) Only consider insider trades from top officers and directors[14].
AIM 2) No conflicts from other insider trades in the last 3 months for that firm.
AIM 3) Eliminate routine trades in favor of opportunistic trades only.
AIM 4) Include active trades (which are trades placed in the direction of the trend) over passive trades.

It is also important to note that these screens are applied conditionally in the order above – in other words, after certain trades are eliminated using AIM1, the new smaller dataset is then screened for AIM2, and so on.

In addition to allowing insiders to more easily detect asymmetric trades and increase the bid ask spread accordingly in the short term, a conditional filter including all the AIM measures

[14] Top officers and directors, as defined in this paper, contain the following variables in rolecode 1: AV, CEO, CFO, CI, CO, CT, EVP, O, OB, OP, OS, OT, OX, P, S, SVP, VP. This list differs slightly from Seyhun (1998).

(AIM=1 in the tables) might actually increase the certainty of stock price direction in the near term, thus reducing volatility and reducing bid ask spreads. So while bid ask spreads may increase in period 2 based on the high accuracy of the insider trade, they may be lower than normal by period 4 when AIM=1 is applied. This possible support for Certainty Hypothesis is examined later in the results section.

It is important to understand the construction of the AIM measures, to be able to more fully interpret their effect, so following are the details of each of the four AIM measures. First, an improvement in the information content of insider trades can be obtained by following the insider trades of only the most informed insiders. In other words, a top executive with 30 years of experience with the firm, and knowledge of the latest inventory levels, new product sales, etc., from all the divisions of the firm, would likely be able to make a better decision with regards to buying or selling firm stock than a lower level executive with less firm experience and less firm information. Seyhun (1998) finds that top executives do indeed make better insider trading decisions than lower level executives. In addition, trades are filtered to only include transactions by these executives > $10,000 and < $5 million.

Second, the elimination of trades that show conflicts with trades by other insiders in the previous three months also improves the information content of the insider trade signal, as first determined by Seyhun (1998). In other words, if an insider sells a quantity of stock, but another insider bought stock within the last three months, then the latest trade would be considered a conflicting trade, and would be screened out of the analysis if considering only non-conflicting trades. This screen takes on additional significance by the use of conditional filtering: conflicting trades are examined only after the AIM 1 screen takes place, so the conflicting trades in the AIM 2 step would be by highly knowledgeable officers and directors only.

Third, keeping only opportunistic trades and eliminating routine trades further improves the information signal. Cohen, Malloy, and Pomorski (2012) find that traders that place an insider trade in the same calendar month for 3+ consecutive years (defined as routine trades) earn a much lower abnormal return than other insider traders (trades defined as opportunistic). They find that opportunistic trades outperform routine trades by 82 basis points per month, with routine trades earning essentially zero abnormal returns.

Finally, Seyhun (1998) introduces a screening process that more accurately parses out the information content of an insider trade by dividing trades into active or passive trades. Seyhun (1998) considers active transactions as forward-looking transactions that open new trades, while passive transactions are backward-looking, and simply close previous positions. To determine which trades are active, Seyhun proxies the decisions of insiders by assuming that a sale after a large stock price increase simply closes a previous position at a profit, while a purchase after a large stock price decline simply opens a previously closed position. Both of these trades are considered passive. Because passive trades are backward-looking, they do not contain much information content as to the future level of the stock price. However, a purchase after a large stock price increase would not represent a value buy for the insider, thus can only be explained by new information that indicates the stock is going to continue to increase. The same applies to a sale after a large stock price decrease. The trade would likely not indicate a profit to the insider, thus would indicate that the insider has new negative information on the stock, and is trying to avoid a larger loss in profit. So screening for only active trades can improve the information content of insider trades. Seyhun (1998) finds stronger and more significant returns for active trades versus considering all insider trades.

One caveat of the active versus passive trade approach is a correlation by construction with stock price momentum. In the momentum study of Jegadeesh and Titman (1993), the authors found positive serial autocorrelation in stock price returns, based on a 3-12 month portfolio formation period, and a 3-12 month portfolio holding period. The results showed that a long minus short investment strategy based on going long a portfolio with positive returns in the recent past, and going short a portfolio with negative returns in the recent past, would produce positive and significant results. A followup study by Jegadeesh and Titman (2001) showed that this phenomenon has not gone away. In fact, over 300 momentum papers have been written in the past 17 years, with over 150 in the past 5 years alone, showing the resilience of this anomaly. Thus a higher return from active trades may simply reflect the momentum effect on the stock price, and not improved information content in the insider trade. For this reason, this paper also controls for momentum effects when analyzing short term returns before and after Sarbanes Oxley.

Figure 1 displays the time frames that affect asymmetric information before and after Sarbanes Oxley as predicted by this study. The impact of SOX and the level of AIM measures are discussed for all four time periods listed in the event window.

C. Event Studies for Analysis of Stock Returns, Volume, and Bid-Ask Spreads

Event studies[15] are designed around the insider trade to capture abnormal levels of stock returns, volume, and bid-ask spreads. These abnormal levels are defined as the prediction error $PE_{i,t}$ for security *i* on day *t*, ranging from 32 days before the insider trade to 32 days after the insider trade. Let

[15] Because event studies may not have a normal distribution, Patell Z, Portfolio Time-Series (CDA) t, and Generalized Sign Z test statistics are reported as per Henderson (1990).

$$PE_{i,t} = \left(X_{i,t} - E(X_{it})\right) \quad (1)$$

where X is defined as either return, volume, or bid-ask spread. Market wide levels of X are found in the following market model equation

$$X_{i,t} = \alpha_i + \beta_i x_{m,t} + \varepsilon_{it} \text{ where } t = -252, -33 \quad (2)$$

$$PE_{i,t} = \left(X_{i,t} - \left(\alpha_i + \beta_i x_{m,t}\right)\right) \text{where } t = -32, +32 \quad (3)$$

where $X_{i,t}$ is the event study variable of concern for security i on day t, and $x_{m,t}$ is the variable of concern to an equal weighted portfolio of NYSE, NASDAQ, and AMEX stocks on day t. The parameters α and β are estimated using the pre-event daily values ranging from -252 trading days to -33 trading days.

Three separate event studies are performed. First, event studies are conducted for purchases and sales covering the period 1993 – 2009 for stock returns to establish a baseline estimate of the effectiveness of the AIM measures. Second, event studies are also calculated for insider purchase and sale volume in 2001 and 2003 to cover the immediate period before and after Sarbanes Oxley compliance was required, beginning on August 29, 2002. In order to avoid biases resulting from compliance problems around this date, the year 2002 is left out of this event study. Finally, event studies for insider purchases and sales are performed for the period from January 1 – March 31 of 2002 and 2005 for bid ask spreads. These time frames are chosen to compare with PIN measure estimates from available TAQ data.

D. PIN Measure Development and Calculation

Asymmetric information around the event is also evaluated by calculating the PIN measure of Easley, Kiefer, O'Hara, and Paperman (1996) and Easley, Kiefer, and O'Hara (1997), defined here as the EKO model. The PIN measure is a way to identify trading on the basis of private information when that information is not readily available, thus serving as a good proxy of unknown asymmetric trading (and also confirming the results in the event studies). It determines insider trading on the basis of imbalances between the number of buy and sell orders. EKO is a Bayesian learning model in which the market maker draws inferences about the presence and type of informed trading based on the order flow observed. From this information, the market maker can calculate the probability of informed trading (PIN).

The basic structure of the EKO model is a tree diagram[16]. Private information events occur with probability α, whereas the lack of events occurs with probability (1-α). Upon occurrence, this private information contains bad news with probability δ, or good news with probability (1-δ). Trade orders arrive sequentially to the market according to Poisson processes. Orders from uninformed traders (buyers-b, sellers-s) arrive randomly at the rate ε every trading day. Orders from informed traders arrive randomly at the arrival rate μ only on good and bad news days. All of the arrival processes are assumed to be independent, and their parameters well known to all trader types and market makers. The market maker sets buy and sell prices at each point in time based on their current information set.

Three patterns of trade orders result: 1) No news day – model predicts a roughly equal number of buyer or seller initiated trades. 2) Bad news day – a large imbalance exists in order flow, with seller initiated trades dominating. 3) Good news day – a large imbalance exists in order flow, with buyer initiated trades dominating. Even though the market maker does not know which pattern will develop that day, the market maker knows the probability of each, and the order flow that would result. They thus use the observed number of buys and sells to update

[16] See Easley, Kiefer, O'Hara (1997) and Brown, Hillegeist, and Lo (2004) for the actual game tree diagram and a detailed explanation of the PIN measure and EKO models. An example tree diagram from Brown, Hillegeist, and Lo (2004) is in Appendix B.

their beliefs via Bayes Rule throughout the day. At the beginning of the day, this probability of informed trading is as follows:

$$PIN = \frac{\alpha\mu}{\alpha\mu + \varepsilon_b + \varepsilon_s} \tag{4}$$

The numerator is the expected number of orders from privately informed investors, while the denominator is the expected probability that the first trade of the day is based on private information; thus the PIN measure represents the fraction of trades expected that will be information based.

The likelihood function induced by the EKO model is determined by some combination of the pattern of trade orders (no news, bad news, good news) with weighting reflected by their probability of occurrence. The likelihood for a particular trading day is given by:

$$L(B,S|\theta) = (1-\alpha)e^{-\varepsilon_b}\frac{\varepsilon_b^B}{B!}e^{-\varepsilon_s}\frac{\varepsilon_s^S}{S!} + \alpha\delta e^{-\varepsilon_b}\frac{\varepsilon_b^B}{B!}e^{-(\mu+\varepsilon_s)}\frac{(\mu+\varepsilon_s)^S}{S!}$$

$$+\alpha(1-\delta)e^{-(\mu+\varepsilon_b)}\frac{(\mu+\varepsilon_b)^B}{B!}e^{-\varepsilon_s}\frac{\varepsilon_s^S}{S!} \tag{5}$$

The daily numbers of buy and sell orders are sufficient statistics for the calculation above; however, considering the order flow over an increasing number of days increases the precision of the estimate of the parameter vector θ. Abnormal buy or sell volume is considered information based and identifies μ. The number of days of abnormal buy or sell volume identifies α and δ, respectively. The maximum likelihood estimates for each firm's parameter vector θ over a specific time period allows the calculation of firm-specific or period-specific PINs via equation (1).

To estimate the PIN parameter vector θ, the daily numbers of buy and sell orders over each estimation period for each firm is necessary. This data is obtained from the Trades and

Quotes (TAQ) database. Each trade is classified as buyer or seller initiated using the Lee and Ready (1991) algorithm. This algorithm classifies trades that take place above the current midpoint of the bid ask spread as buy orders, while those below the bid ask spread are classified as sell orders. For trades occurring right at the midpoint, a "tick test" is used to classify the trade, based on the most recent transaction price. A five second lag on reported quote times is used to adjust for differences in reporting times between trades and quotes on the NYSE, NASDAQ, and AMEX[17]. Following Hasbrouck (1988), all trades occurring within 5 seconds of each other are classified as a single trade.

E. Cross Sectional Panel Analysis of Bid Ask Spreads

Finally, cross sectional panel regressions[18] are calculated using as control variables predictors of the bid ask spread as referenced in Chung Charoenwong (1998). These regressions are done for both purchases and sales, and for each of the four time periods listed in Figure 1. In addition, model fit is improved by including a one-day lag of the daily spread as a control variable. Growth versus value firms (as defined by P/E ratios) are also evaluated.

2.4 Results

A. Event study results / Tests of AIM effectiveness

Table 2.1 shows descriptive statistics for all common stock insider trades for the NYSE, Nasdaq, and AMEX between January 1 – March 31 for 2002 and 2005. There are a total of 473 insider purchases for 2002 and 540 insider purchases for 2005, with 1292 insider sales for 2002 and 1580 insider sales for 2005. Insider and volume are both in thousands, while market capitalization is in millions.

[17] Ellis et al. (2002) recommends that quote times not be adjusted for the AMEX and Nasdaq. However, that recommendation is not followed in this study, as we adhere to the original classification method.
[18] Regression also controls for fixed effects by grouped by firm.

Panel A of Figure 2 shows market adjusted cumulative abnormal returns around the event date for insider purchases during the period 1993-2009. The event window extends -1 to +10 trading days before and after the event. "ALL" represents the baseline case, with all insider purchases included, while the AIM filters are included conditionally as defined in the methodology section. Although not shown, ALL – AIM3 exhibit declining cumulative returns (at an increasing rate) approaching the event date, with increasing cumulative returns (at a declining rate) after the event date. This confirms earlier studies indicating the same phenomenon for insider trading cumulative abnormal returns for purchases (Seyhun (1986), Lakonishok and Lee (2001)).

Panel A[19] shows market adjusted cumulative abnormal returns for insider purchases from the event day to 10 days after the event day (NOTE: Figure starts at t = -1 to show the return from the close of trading on the day before the event date, to the close of trading on the event date) for 1993 to 2009. Because of the large range of data, the concave shape of the functions is remarkably consistent throughout this 10 day period. These figures confirm the hypothesis that including these filters conditionally should improve the asymmetric information signal progressively as each filter is added.

Panel B[20] of Figure 2 shows market adjusted cumulative abnormal returns around the event date for insider sales during the period 1993-2009. The event window extends -1 to +10 trading days before and after the event. "ALL" represents the baseline case, with all insider sales included, while the AIM filters are included conditionally as defined in the methodology section.

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[19] AIM4 is excluded from Figure 2 Panel A, as its results are shown in Table II. As a note, cumulative abnormal returns actually increase before the event date when applying AIM4 as an additional filter; however, this is mostly a function of the momentum component of this filter. Note in Table II that the overall shape of the function is similar to the other AIM filters, except that the function is rotated 30 – 45 degrees counterclockwise.

[20] AIM4 is excluded from Figure 2 Panel B, as its results are shown in Table II. The momentum component of AIM4 causes the same rotation in the shape of the function as witnessed in the case of purchases. The overall shape of the function is similar to the other AIM filters, except that the function is rotated 30 – 45 degrees clockwise.

Although not shown, ALL – AIM3 experience increasing cumulative returns (at an increasing rate) approaching the event date, with slightly decreasing cumulative returns (at a steady rate) after the event date. This confirms earlier studies indicating a very weak effect for insider sales on future abnormal returns (Seyhun (1986), Lakonishok and Lee (2001)). It is not clearly proven that including these filters conditionally should improve the asymmetric information signal progressively as each filter is added. AIM1, AIM2, and AIM3 all show no improvements to asymmetric information, since they seem to parallel the ALL filter.

One interesting feature is noted when comparing Panel B with Panel A, and that is the actual returns on the event day. Insider purchases show a feature typical with event study cumulative abnormal returns, with a classic V-shape of abnormal returns declining before the event date, then increasing afterwards. Typically, the event causes a change in the signal on the event day, with returns expanding in the direction suggested by the event after the event day. However, insider sales show a curious lag in this phenomenon. The event day for insider sales shows no obvious change in abnormal returns from the period previous to the event day. Only on the day after the event does the signal seem to change. One would expect abnormal returns to decline on the event day for insider sales, at the very least from the market impact of the insider sale itself. Aktas, De Bodt, and Van Oppens (2008) propose four explanations for this phenomenon, but cannot establish a definitive cause. In addition to these theories, it is also possible that insider sales are executed only after previously arranged block trades (with market makers specializing in block trades) to prevent the adverse market impact effects of a sale[21]. A possible, but much less likely hypothesis is that sales are finalized in the thinly traded after-hours market; thus, they might not show up until the next day (reporting microstructure).

[21] In contrast, insiders might actually prefer a market impact from their trades for insider purchases, hoping to promote some follow-through price momentum.

Table 2.2 represents event study returns before and after Sarbanes Oxley for periods 1-4, as specified in Figure 1. The period before Sarbanes Oxley represents January 1, 2001 through December 31, 2001, while the period after Sarbanes Oxley represents January 1, 2003 through December 31, 2003; both periods include all insider trading events on the NYSE, NASDAQ, and AMEX. This period is chosen for a reason, to measure market reactions symmetrically around the implementation of Sarbanes Oxley for insider trades on August 29, 2002, assuming that insider trades may have been reported with some degree of inaccuracy in the months before and after the rule was implemented. Market adjusted and Fama French / Momentum adjusted returns are reported for AIM=0 and AIM=1, and for both purchases and sales. Panel A of Table 2.2 shows market adjusted and Fama French / momentum adjusted returns for insider purchases before Sarbanes Oxley for the four periods listed in Figure 1, and trading days -1 through +3 around the event date. Fama French and momentum factors are included for two important reasons. First, the method of Seyhun (1998) for calculating active trades incorporates the price trend, which would by definition improve the results above that expected by the insider trades themselves by incorporating the well established phenomenon of price momentum as defined by Jegadeesh and Titman (1993,2001). Second, since insiders are shown to be contrarian investors, it is important to control for the Fama French (1993) 3-factor model to ensure the insider trade is not merely a function of CAPM, size, and book-to-market. Market adjusted returns are higher in periods 3 and 4 for the high asymmetric information case (AIM=1), with AIM=1 returns totaling 7.71%, while AIM=0 returns are only 5.58%. Returns on the event day are much higher for AIM=1, totaling 0.82%, while AIM=0 event day returns are only 0.32%. AIM=1 outperformance is also persistent in the 31 trading days preceding the event in period 1. Interestingly though, this outperformance is not seen in the days 1-3 immediately after the event, in which AIM=0 actually slightly outperforms. Despite this dominance in AIM=1 returns, it is important to note the significant momentum effect when applying AIM measure #4. This is controlled for in the Fama French / momentum adjusted returns in Panel A. While the AIM=1 returns are still greater in period 1, they are roughly the same as AIM=0 in periods 3 and 4, with AIM=1 returning 4.94% while AIM=0 returns 4.96%. Instead of these AIM=1 insiders possessing a high degree of inside information or being better able to interpret firm-specific results, they may simply be taking advantage of the well-documented momentum effect in stock returns (Jegadeesh and Titman 1993). However, note that event day returns are still much higher for AIM=1 even after controlling for Fama French / Momentum factors, with AIM=1 returns of 0.71% on the event day, versus only 0.37% for AIM=0.

Panel B of Table 2.2 shows returns from insider purchases in 2003 (after Sarbanes Oxley). For AIM=0, market adjusted returns are higher in period 2 than before Sarbanes Oxley, indicating the effect of the expedited reporting time of the insider trades to within two business days of the actual insider trade. Market adjusted returns in the three days after the event total 1.18% after Sarbanes Oxley, versus only 0.95% before SOX. For AIM=1 the same effect occurs but to a much greater extreme, with market adjusted returns in the three days after the event day, and before Sarbanes Oxley, of 0.67%, versus 3.58% in the same period after Sarbanes Oxley.

It is also important to note the effect on returns in periods 3 and 4 for both AIM=0 and AIM=1. Before Sarbanes Oxley, both AIM levels experienced higher returns in period 4 than period 3. This, of course, is consistent with Aktas, De Bodt, Van Oppens (2008) which show a mean insider trade reporting delay of 22 days (15 trading days) from the time of the actual insider trade in the pre-SOX period of 1995 to 1999. The signal from the insider trade is only slowly incorporated into stock prices before Sarbanes Oxley because the insider trade is reported to the public after a prolonged delay. However, AIM=0 market adjusted returns in period 4 after SOX are lower, with a -0.97% return; for AIM=1 the difference is much more pronounced, with market adjusted returns over five times higher (5.20% versus 0.98%) in period 3 than period 4 after SOX. This is consistent with the fact that after Sarbanes Oxley, insider trades must be reported to the public within two business days.

As a robustness confirmation, Fama French / momentum effects yield similar results to the market adjusted returns for periods 3 and 4. AIM=0 returns in period 4 after SOX are much lower, with a -1.15% return after SOX versus a 2.58% return before SOX; for AIM=1 the difference is even larger, with post-SOX returns of 4.16% in period 3 versus -0.55% in period 4. In addition, returns in the three days after the event increase for both AIM levels after SOX. So even after controlling for the effects of the Fama French factors and momentum (important due to the momentum effects of AIM level 4), there is still a major shift of returns from period 4 to period 3 after SOX for purchases.

For insider sales, the same shift of returns from period 4 to period 3 in the post-SOX era occurs, but to a lesser extent. This may be in part due to the weaker effect of insider sales on future stock performance, as has been well documented (Seyhun (1986), Lakonishok and Lee (2001)). Panel C of Table 2.2 shows market adjusted and Fama French/ momentum adjusted returns for insider sales before Sarbanes Oxley for the four periods listed in Figure 1, and trading days -1 through +3 around the event date. As in the case of insider purchases, market adjusted returns are more pronounced (and lower, since insider sales predict lower future returns) in periods 3 and 4 for the high asymmetric information case (AIM=1), with AIM=1 returns totaling a huge -14.57% decline, while AIM=0 returns decline by only -5.32%.

As discussed for Figure 2, returns on the event day for insider sales differ from the case of insider purchases. Instead of declining (as would be expected, either from the market impact of the actual insider sale itself, or from informed traders privy to the knowledge of the sale placing their sell orders), market adjusted returns actually increase on the insider sale date, with a magnitude very similar to the magnitude on days preceding the sale. This phenomenon can be seen both before and after Sarbanes Oxley, and for both AIM=0 and AIM=1 levels. It is also robust to controls for the Fama French / momentum factors.

In addition, in contrast to the insider purchases, insider sales show a rather muted decline in the three days after the event day both before and after SOX, and for both AIM=0 and AIM=1. There seems to be no increase in selling activity in this three day period after Sarbanes Oxley, as compared to the same period before SOX. However, it appears that the quicker reporting time mandated from Sarbanes Oxley has simply shifted insider selling information to be leaked and acted upon before the event date. The highly positive market adjusted returns in period 1 before Sarbanes Oxley are reduced for both the AIM=0 and AIM=1 cases after Sarbanes Oxley. AIM=0 returns drop by 2.29%, while AIM=1 returns drop by 0.66%.

To confirm these trends, for robustness Fama French / momentum adjusted returns confirm the shift of insider selling from period 4 to period 3 after Sarbanes Oxley, just as in the case of purchases. However, it is more difficult to confirm the idea that insider selling has also shifted to period 1 before the event (as suggested by market adjusted returns), since Fama French / momentum adjust returns are higher for period 1 in the post-SOX era.

Figure 3 shows the risk and market adjusted log transformed average volume for insider purchases and insider sales in 2001 and 2003. This transformation is accomplished in a two-step process. First, volume is transformed to natural log scale and is adjusted to market volume.

Second, log abnormal volume for each trading day is adjusted to risk by subtracting out the average log abnormal volume and dividing by the standard deviation of log abnormal volume in the entire 64 trading day event period[22], as follows:

$$MRAV_{it} = \frac{x_{it} - \mu_i}{\sigma_i} \qquad 6)$$

where MRAV is the market and risk adjusted volume, x is the log abnormal volume, μ is the average log abnormal volume, and σ is the standard deviation of log abnormal volume. Firm is represented by i, while t ranges from -32 to +32 trading days.

Panel A of Figure 3 shows the MRAV for the 32 trading days (1½ months) before and after the event day for insider purchases and insider sales in 2001 and 2003. In general, volume increases exponentially toward the event date starting about 15 trading days before the event day, and declines in a symmetrical pattern for 15 days after the event day. However, one will notice that volume tends to be larger before the event than after the event for sales, with the opposite trend (larger volume after the event than before) for insider purchases.

To understand this phenomenon more clearly, I examine purchases and sales independently for both 2001 and 2003 in Panels B and C. Consistent with the shift in returns from period 3 to period 4 as shown in Table 2.2, MRAV volume increases in the 15 trading days after an insider purchase in 2003, compared to volume in 2001. This is consistent with the Sarbanes Oxley legislation initiated in 2002 that shifts the reporting period for an insider trade from a mean of 15 trading days (Aktas, De Bodt, and Van Oppens (2008)), to a maximum of 2 business days. The positive information signal of the insider purchase leads informed traders to initiate purchasing volume of their own, which takes about 15 trading days to achieve full advantage of the signal, as shown in both Figure 2 and Figure 3 Panel A.

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[22] This is similar to the Sharpe ratio adjustment for risk.

However, Panel C of Figure 3 shows a more concerning result for insider sale MRAV volume before and after Sarbanes Oxley. Insider sale MRAV volume in 2001 is already suspiciously high in the period before the event (as compared to a very symmetric volume trend around insider purchases in 2001). However, MRAV volume in 2003 increases in the period before the event in a similar amount to the reduction in MRAV volume after the event. One hypothesis is that insiders with information are motivated to leak the information of the insider sale earlier after Sarbanes Oxley than before Sarbanes Oxley, because they recognize that the sale signal will become public much more quickly, and their associates may not be able to profit from the signal unless they receive the inside information at an earlier date. This hypothesis would suggest that, at least in the case of insider sales, Sarbanes Oxley did not reduce illegal asymmetric information, but simply shifted it to an earlier period of time.

Table III shows the average bid ask spread and Chung Charoenwong (1998) average standardized abnormal spread for January 1, 2002 – March 31, 2002 and January 1, 2005 – March 31, 2005. The spreads are calculated for all insider purchases and sales on the NYSE, Nasdaq, and AMEX for these time periods, and are equal-weighted by firm. The Chung Charoenwong (1998) abnormal spread (SAS, the standardized abnormal spread) is calculated as follows:

$$SAS_{i,t} = \frac{Spread_{i,t} - \mu_i}{\sigma_i} \qquad 7)$$

where μ_i and σ_i represent the sample mean and standard deviation, respectively, of the spread of stock i during the entire estimation period (-10 to +15 days around the event date). Panel A of Table 2.3 shows that, in general, spreads for insider purchases are higher than spreads for insider sales. Since these spreads are not market adjusted, this could simply be a function of the general state of a firm prior to an insider purchase or sale. If the firm is in a state of increased risk due to bad news (a scenario correlated with insider sales), then stock volatility would be expected to increase, which would increase the likelihood of a larger bid-ask spread (Copeland and Galai (1988), Stoll (1989), Chung Charoenwong (1998)). Also, Panel A shows that average spreads are higher for both purchases and sales, before and after Sarbanes Oxley, for AIM=0 versus AIM=1. At first, intuition would suggest that this is the opposite of what should be expected. Since AIM=1 equates better asymmetric information, it would seem that the market makers would lose to the informed traders more significantly in this case, and the market makers would increase the bid-ask spread to compensate for their heavier losses. However, I present two hypotheses to explain this phenomenon. First, one hypothesis is that AIM=1 increases certainty in future stock direction, and thus less volatility is created in the short term, which as previously explained reduces the bid ask spread. For purchases, the "stars are aligned" more clearly for AIM=1, and the stock moves up with more certainty and less volatility in the short term. For sales, the "stars are aligned" more clearly for AIM=1 again, and the stock moves down with more certainty and less volatility in the short term. Second, an alternate hypothesis is that the AIM4 filter creates a volume-based bias in this case. Trading volume has been shown in previous studies to be inversely related to bid-ask spreads (McInish and Wood (1992), Chung Charoenwong (1998)). Since AIM4 includes a heavy momentum component, and momentum has been shown to increase trading volume in a stock (Jegadeesh and Titman (1993,2001)), it may simply be that volume is higher for the AIM=1 case, causing a resultant lower bid-ask spread.

However, Table 2.3 Panel A shows that the average bid-ask spread reveals an inconsistent picture of the changes occurring around the event day[23]. There are no clear trends

[23] For a simple comparison, Appendix B includes Figure 4, which measures the change in raw spreads in event time for both purchases and sales, without any controls.

when comparing purchases versus sales, AIM=1 versus AIM=0, or pre-SOX versus post-SOX. Many factors could cause this ambiguity, as these spreads are not adjusted for market spreads, volume levels could significantly affect the results, and volatility could play the biggest role in skewing results. In fact, many studies suggest bid-ask spreads do not reveal any information pertaining to asymmetric information. For this reason, I also control for volatility risk and market spread using the Chung Charoenwong (1998) standardized abnormal spread (henceforth called CC spreads). Since the CC spread controls for volatility risk and market spread, CC abnormal returns should mostly reflect volume levels and asymmetric information risk. Indeed, volume clearly reduces the CC spread around the event day, as shown in Panel A of Table 2.3, consistent with findings previously discussed in this paper. The CC spread is lower in the (-1,3) range than in the event periods before and afterwards in all cases except pre-SOX purchases for AIM=1, which might be skewed by the lower number of observations (162-389 observations). One caveat is that Panel B of Table 2.3 has trouble confirming this trend, as the event day shows no noticeable change in CC spreads from the days immediately before and after the event day. However, this supports the idea that market makers need some time to readjust their spreads, so don't necessarily pick up high volume or high asymmetric information days immediately.

Interestingly, Panel B of Table 2.3 does confirm another previous finding in the paper. Post-SOX sales for AIM=0 in 2005 show a declining trend in bid-ask spreads until the day after the event date, when they experience spreads 20% below the average spreads before and after that date (spread = 0.1385), with CC spreads also reaching their lowest level on the day after the event date. This confirms findings in both 2001 and 2003 for insider sale abnormal returns (Table 2.2 Panels C and D) in that there seems to be a one-day delayed reaction to the stock price after insider sales. Figure 4[24] is listed in the appendix, providing some possible clarity to these spread trends.

B. Pin Measure Parameters around Sarbanes Oxley

Table 2.4 evaluates asymmetric information around the event by calculating the PIN measure of (Easley, Kiefer, O'Hara, and Paperman (1996), Easley, Kiefer, and O'Hara (1997)), defined here as the EKO model. The table shows the PIN measure and its four components for January 1, 2002 to March 31, 2002, and for January 1, 2005 to March 31, 2005. These time periods are chosen specifically because they represent periods of relative calm in the markets[25] for the small cap sample chosen for this TAQ data. Period 1 represents trading range (-10,-2), period 2 represents trading range (-1,3), and period 3 represents trading range (4,10). All stocks in the NYSE, NASDAQ, and AMEX that have a market capitalization between $100 million and $200 million in 2002 are included in the sample. To ensure consistency in the parameters, only firms that still exist in 2005 with a market cap greater than $100 million are included in the final sample. Although this may appear to skew results by eliminating low performing stocks, especially for insider sales, it is important to note that market-wide stock prices rose significantly between 2002 and 2005, so the bias should be negligible. In addition, because firms trading below a $100 million market cap are often thinly traded, it is difficult to obtain accurate PIN measure parameters in this range, so prudence favors a lower bound on market capitalization.

[24] Figure 4 plots average spread trends for purchases and sales over a trading period starting 10 days before the event and ending 15 days after the event. Panels A and B show that, in both cases, average spreads trend down from before the event to after the event. Volume could be one factor, as it lowers spreads in the immediate vicinity of the event. However, although Figure 4 would tend to confirm this for sales, Figure 4 also shows that purchase volume is actually higher after the event, contradicting this notion. It is most likely that the insider trade, and asymmetric informed trading around the insider trade, reduce uncertainty regarding the future direction of stock price movement, and thus lower volatility risk for the market maker (as posited by the "certainty hypothesis").

[25] See Appendix B Figure 6 for market performance during the first 3 months of 2002 and 2005 for small cap stocks.

The delta measure of Panel A of Table 2.4 shows the probability that the information from trades in that period is bad news. As expected, the delta measure is higher in periods 1, 2, and 3 for the insider sale than they are during the same periods for an insider purchase. Interestingly, for both insider purchases and insider sales, the delta measure becomes more accurate after the insider trade is made, and after it becomes known publicly. The difference between the purchases average (3rd column from the end) and the sales average (2nd and last column from the end) is .025 in period 1, but is 0.155 after the event in period 3. This supports the Certainty Hypothesis as suggested in the previous discussion of bid-ask spreads, in which it is posited that because traders and market makers are more certain of the short term direction of a stock, bid ask spreads are reduced as volatility drops in the stock.

The parameters μ and ε represent the arrival rates of informed traders and uninformed traders, respectively. Except for AIM=0 purchases in 2002, parameter μ is lower in period 1 than in the period 3, as the informed traders have generally placed all their trades before the period 3. In addition, it is important to note that epsilon increases significantly from 2002 to 2005, for both purchases and sales. This suggests a distinct improvement in liquidity for all stocks in this sample in 2005, as uninformed traders increase the amount of their trades, and provides greater means for informed traders to hide their trades. However, an alternate hypothesis would suggest that informed traders instead got better at hiding their trades as uninformed trades in 2005.

Panel B of Table 2.4 details the PIN measure around the event date. Because this is a small sample, the measure is rather noisy from day-to-day. However, the purchases average and sales average show in general a higher pin on the event day. Also, note that for insider sales, trading days -1 and 0 show a higher pin than trading days 1,2, and 3, as informed traders place their trades early to take advantage of the insider trading signal.

C. Cross Sectional Panel Regression of Bid Ask Spreads

Table 2.5 shows a cross sectional panel regression[26] of insider purchases and sales for January 1, 2002 to March 31, 2002, and January 1, 2005 to March 31, 2005, including the NYSE, Nasdaq, and AMEX stocks. These time periods are chosen because they match the PIN measure time periods covered in Table 2.4 and also represent insider trades before and after Sarbanes Oxley. Four periods are evaluated, with period 1 - 4 including trading days (-32,-2), (-1,3), (4,15), and (16,32), respectively. The dependent variable is the bid ask spread. The independent variables of interest are SOX, AIM, and the interaction variable (SOX x AIM), and control variables are used based on previously documented predictors of the bid ask spread, as discussed in Chung and Charoenwong (1998). The following regression model is estimated:

$$Spread_i = \propto_0 + \propto_1 MktSpread_i + \propto_2 SOX_i + \propto_3 AIM_i + \propto_4 (SOX\ x\ AIM)_i$$

$$+ \propto_5 Ltsize_i + \propto_6 Lvol_i + \propto_7 Lprice_i + \propto_8 NYSE_i + \propto_9 Lmktcap_i$$

$$+ \propto_{10} Lspread_i + \varepsilon_i \qquad (6)$$

where SOX is a dummy variable equal to 1 if after August 29,2002, AIM is a variable equal to 1 if all four AIM filters are included, (SOX x AIM) an interaction term between the two primary variables, LTSIZE is the log of the dollar amount of the insider trade on the event date (t=0). The other control variables, as follows, use the value for that date, in the range (-32,32) trading days. MKTSPREAD is the average market spread on that date. LVOL is the log dollar volume on that date. PRICE is the stock price on that date. NYSE is a dummy variable equal to 1 if the

[26] Regression also controls for fixed effects grouped by firm.

stock is traded on the NYSE. LMKTCAP is the log of market capitalization representing the market dollar value of the firm on that date. LAGSPREAD represents the lagged spread on the previous trading day.

Panel A of Table 2.5 shows a fixed effects panel regression of purchases in the first three months of both 2002 and 2005. All the control variables except for trade size are significant in at least one of the four time periods measured around the event, so the controls show at least some relevance in the model[27]. There seems to be a structural change in the markets after Sarbanes Oxley that allows a lower overall spread level to exist that is not controlled by the variables listed in this regression, as shown by the period 1 negative and significant SOX variable. It is highly interesting to note that the SOX coefficient becomes more negative and more highly significant in period 3, indicating the effect of releasing information more quickly to the markets tends to lower spreads during the time these insider trades are first revealed to the public. However, while revealing insider trades in a timely manner to the public appears to lower spreads, AIM is not significant in any time period for purchases. Thus no support is seen from AIM here for Certainty Hypothesis or Market Maker Loss Hypothesis.

Because of the high statistical significance of the lagged spread variable, Model 2 is shown without this variable for clarity. This does not change the results of the key variables appreciably: SOX shifts to become more negative and significant in each time period, but its trend stays the same. AIM remains insignificant in all time periods. The adjusted R^2 is much higher in Model 1, so Model 1 is still preferable to the other models.

Model 3 simply looks at the key variables of SOX and AIM, while considering an interaction dummy variable of (SOX x AIM). LAGSPREAD is used as an additional control because of its high significance. (SOX x AIM) is insignificant in all time periods.

[27] Several variables are not significant for purchases, but are significant for sales.

Panel B of Table 2.5 shows a fixed effects panel regression of sales in the first three months of both 2002 and 2005. Model 1 of Panel B, similar to Panel A, shows that all control variables are significant in at least one of the four periods, except for trade size. The apparent structural change in the markets after Sarbanes Oxley allowing a lower overall spread level to exist is seen again, as in Panel A. And note that like Panel A the coefficients trend upward from period 1 – period 4, supporting the hypothesis that market makers are better able to detect this asymmetric information after Sarbanes Oxley and adjust their spreads up accordingly. This somewhat contradicts Panel A. Also, AIM is negative and highly significant in periods 3 and 4. This provides support for the Certainty Hypothesis presented earlier in this paper.

Model 2 does not change the results of the key variables appreciably. As in Panel A, SOX is negative and significant in each time period, but its trend stays the same. AIM is negative and highly significant in periods 3 and 4, as in Model 1.

Model 3 simply looks at the key variables of SOX and AIM, while considering an interaction dummy variable of (SOX x AIM). LAGSPREAD is used as an additional control because of its high significance. SOX and AIM both individually retain their significance just like in Models 1 and 2. However, (SOX x AIM) is insignificant in all time periods.

I also evaluate value versus growth stocks, as growth stocks are often considered to possess more idiosyncratic information, and thus may have a stronger effect on both insider trading accuracy and its effect on market makers and spreads. Table 2.6 evaluates a fixed effects panel regression similar to Table 2.5, separating into value firms and growth firms. Value firms are classified as having a P/E ratio below the mean for the time period being evaluated, with growth firms being classified as having a P/E ratio above the mean for that period. Purchases and sales are again analyzed in the first three months of both 2002 and 2005. All the control variables are significant in at least one of the four time periods measured around the event (including trade size this time, at least in the case of sales), so the controls show at least some relevance. It is important to note, however, that NYSE stocks are very sparse in the value portfolio, so are not included in the regression for value stocks. Only model 1 from Table 2.5 is used in Table 2.6, as it appears most reliable in this analysis[28].

In both panels A and B, it appears the structural shift lowering spreads after Sarbanes Oxley only occurred for growth stocks. The coefficient of SOX is negative and highly significant for all four time periods for growth stocks in the case of both purchases and sales, thus lending strong support to the Certainty Hypothesis. AIM is reduced in the period after the insider trade for purchases and sales for growth stocks, lending some support to the Certainty Hypothesis. However, the interaction term (SOX x AIM) shows an increase for growth stock purchases, so is somewhat contradictory with the individual results of SOX and AIM. However, no significance occurs at any period for the value stocks for the SOX, AIM, or (SOX x AIM) variables.

2.5 Robustness Checks

In order to test interactions between AIM and SOX, the interaction variable (SOX x AIM) was included in Models 1 and 2 of Panels A and B of Table 2.5, and no significance was noted in any of the four time periods, so this interaction was rejected as having an impact on any of the models. However, weak support for the Market Maker Loss Hypothesis resulted from this term in Table 2.6, but was contradicted by the individual results for SOX and AIM. Although the time period of 2002 and 2005 was chosen to match the PIN measure calculations using TAQ

[28] Although model 3 shows a higher adjusted R^2, model 1 gives a better representation of proven control variables, so it likely to provide a more accurate determination of AIM and SOX significance. However, since Table V shows similar significance between models 1 and 3 for the primary variables, this is not an issue warranting concern.

data from 2002 and 2005, for robustness these regressions were also run for 2001 and 2003, to more closely capture the effects of changes around the Sarbanes Oxley Section 403 implementation on August 29, 2002. No significant differences were noted for SOX or AIM using this alternate period.

2.6 Conclusions

Overall, I find strong support for the "Certainty Hypothesis" that highly accurate insider trades occurring for an extended period of intense trading actually reduce spreads by allowing market makers to more correctly establish bid and ask prices in order to earn their required profit margins. The 2002 Sarbanes Oxley legislation of Section 403(a) reduced the reporting time delay after insider trades from up to 40 days (the 10^{th} day of the following month) down to only 2 business days, which allows for a natural experiment to study the effects of informed trade duration.

Event study market adjusted returns around the insider trading date show a dramatic shift from period 4 (days 16 to 32 after the event) to period 3 (days 4 to 15 after the event) after Sarbanes Oxley. In addition, returns after filtering for the four AIM measures show a higher level than insider returns without any filtering, implying that a higher accuracy of asymmetric information does indeed lead to higher returns. Average market and risk adjusted volumes (MRAV) increase in the 15 post-event days after Sarbanes Oxley for insider purchases, as would be expected given the earlier reporting date for the insider trade post-SOX. However, MRAVs present a shift for insider sales in the period after Sarbanes Oxley to occur at a higher level before the event date, and a lower level after the event date, suggesting higher spreads due to illegal asymmetric information before the event as information leakage on the insider sale shifts to an earlier period.

Time series event studies show the Chung Charoenwong (1998) abnormal spreads are lower around the event date (period -1 to +3) than they are in earlier or later periods. However, the average spread and the Chung Charoenwong (1998) spreads show little change from the time before SOX to the time after SOX. These time series based event study spreads are only adjusted for market spread levels, so it is likely that better controls might confirm an effect.

The PIN measure is higher around the event date, confirming this measure for insider trades. In addition, the probability of bad news (δ) is higher for the period after the event for sales both before and after Sarbanes Oxley, which could show why AIM is negative and significant in affecting spreads both before and after SOX, supporting the Certainty Hypothesis by suggesting that the detection of a bad event could have been found using the PIN measure even before SOX. However, the other parameters of the PIN measure show little effect, and the PIN measure itself is only weakly confirming. Further analysis might strengthen the signal provided by the TAQ data.

A cross sectional panel regression of the bid ask spread shows that after controlling for predictors of the bid-ask spread, the hypothesized post-SOX reduction in bid ask spreads after the event is confirmed. In addition, this happens in the case of both value and growth firms. The AIM measures appear to play no part in *increasing* spreads in periods 2 or 3 by increasing detection by market makers; however, for insider sales the AIM measures appear to play a significant part in *reducing* spreads in periods 3 and 4, possibly by confirming the Certainty Hypothesis that highly accurate insider information confirms short term trade direction, reducing volatility and bid ask spreads.

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2.7. Appendix A: Tables

Table 2.1

Descriptive Statistics

This table presents descriptive statistics for NYSE, AMEX, and NASDAQ common stocks experiencing insider trades between January 1 and March 31 in both 2002 and 2005. The level of each variable is as of the event date. INSIDER is the dollar value of the insider trade (in 1000s), VOLUME represents the number of shares traded (in 1000s), RETURN equals the percent return, SPREAD is the level of the bid-ask spread, PRICE is the stock price level, and MKTCAP is the market capitalization (in 1M). N represents the total number of insider trading events in this period.

Panel A: Insider purchases before SOX (2002)

				Percentile			
	N	Mean	S.D.	5%	25%	75%	95%
INSIDER	473	88.6754	264.5659	10.6800	15.3000	52.8400	319.7250
VOL	473	247.7775	1501.8784	0.0000	5.1500	89.5350	749.5640
RET	473	0.7055	7.2871	-7.4871	-1.3954	1.9418	11.0236
SPREAD	473	0.2137	0.2443	0.0200	0.0500	0.2900	0.7000
PRICE	473	11.0250	12.2186	0.9500	2.8400	15.7500	31.1300
MKTCAP	473	861.2231	4030.4849	9.4188	26.4602	124.8153	3731.3850
NYSE	473	0.0698					
AIM	473	0.0550					

Panel B: Insider purchases after SOX (2002)

				Percentile			
	N	Mean	S.D.	5%	25%	75%	95%
INSIDER	540	108.9225	269.7196	11.3219	17.0370	90.3199	388.3365
VOL	540	218.7435	652.7737	0.9165	5.8845	94.1370	1483.9000
RET	540	0.2750	3.2286	-3.9374	-1.0648	1.2334	4.4395
SPREAD	540	0.1937	0.4791	0.0100	0.0300	0.1700	0.7300
PRICE	540	19.0518	13.4482	1.8450	8.7225	25.9400	40.6000
MKTCAP	540	1578.2932	8468.0150	24.5823	74.9211	202.0216	4475.5258
NYSE	540	0.1259					
AIM	540	0.0315					

Panel C: Insider sales before SOX (2002)

				Percentile			
	N	Mean	S.D.	5%	25%	75%	95%
INSIDER	1292	-218.9850	519.9861	-975.0000	-159.9473	-25.0000	-12.3000
VOL	1292	541.4676	1713.6966	2.8000	25.3830	309.1000	2705.1000
RET	1292	-0.0117	5.8497	-6.8965	-1.5414	1.5070	6.2753
SPREAD	1292	0.2062	0.7332	0.0100	0.0400	0.2500	0.5800
PRICE	1292	19.9953	30.3627	1.2100	6.7950	25.1200	56.0200
MKTCAP	1292	4155.2685	15462.0503	18.3701	65.5036	429.7982	18615.6354
NYSE	1292	0.1471					
AIM	1292	0.1540					

Panel D: Insider sales after SOX (2002)

				Percentile			
	N	Mean	S.D.	5%	25%	75%	95%
INSIDER	1580	-271.5098	562.1587	-1335.4339	-219.1750	-25.3473	-11.8182
VOL	1580	530.5393	1285.3860	2.4765	16.2100	378.9100	2780.2500
RET	1580	0.1487	3.4944	-4.4253	-1.1263	1.2614	4.3646
SPREAD	1580	0.1458	0.4066	0.0100	0.0300	0.1400	0.4800
PRICE	1580	31.7778	68.8506	3.5000	12.7550	34.6900	76.3550
MKTCAP	1580	3933.7110	12628.2272	30.5781	87.0824	1246.5410	20841.4022
NYSE	1580	0.3462					
AIM	1580	0.0880					

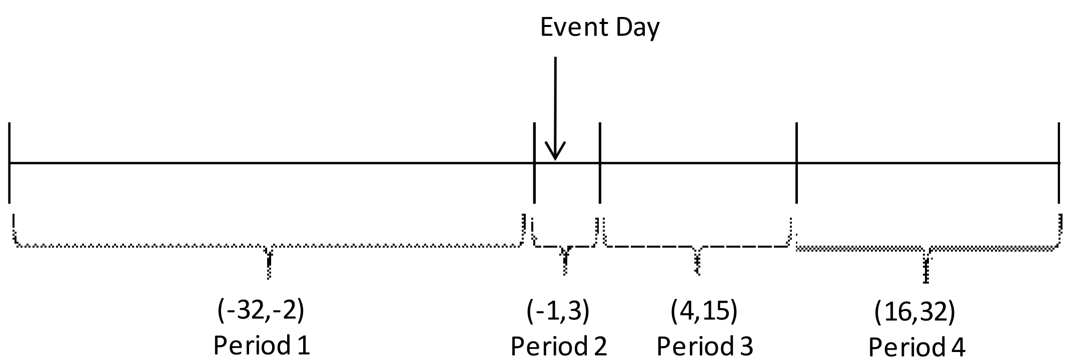
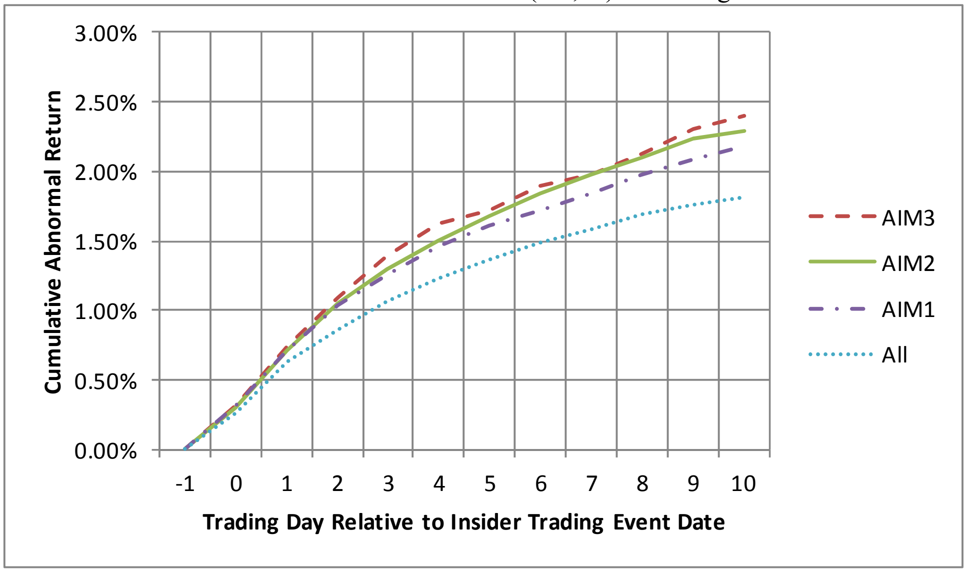


Figure 2.1. Asymmetric information around insider trades – the effect of Sarbanes Oxley
This figure shows the four time periods evaluated in this study around the event window (-32,32) of insider purchases and sales. The periods are classified as follows:

Period 1:	(-32,-2) trading days
Period 2:	(-1,3) trading days
Period 3:	(4,15) trading days
Period 4:	(16,32) trading days

Period 3 begins at day 4 to allow the reporting time post-SOX of two business days to fully incorporate into stock prices before considering the reduction in asymmetric information in period 3. Period 2 covers the insider trade event window itself, while periods 1 and 4 are used mainly as controls to capture any other trends occurring during the broader event window.

Panel A: 1993-2009 Insider Purchases for Period (-32,32) Excluding AIM 4



Panel B: 1993-2009 Insider Sales for Period (-32,32) Excluding AIM 4

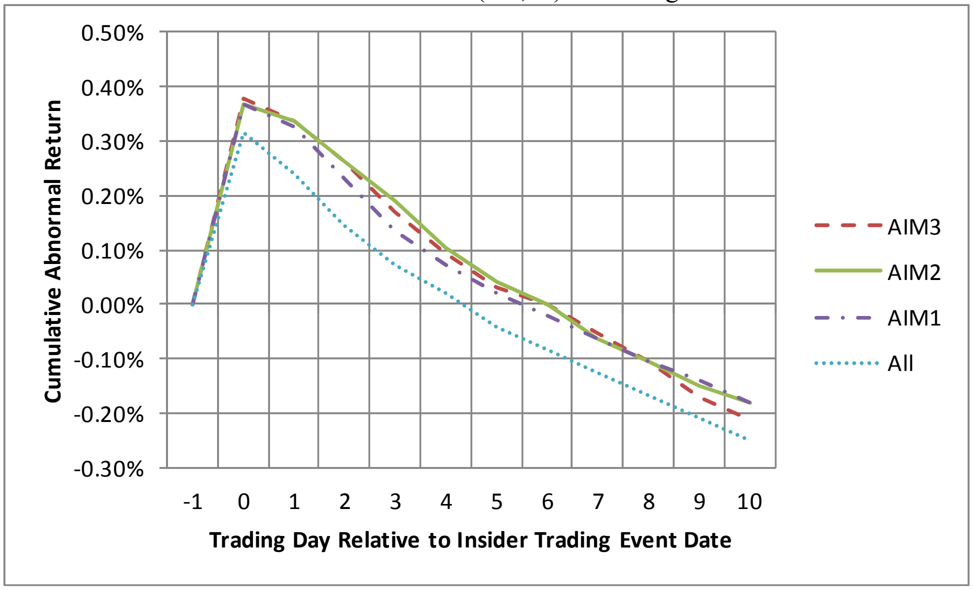


Figure 2.2. Event study results for the AIM criteria for 1993-2009
This figure shows cumulative abnormal returns for insider purchases and sales from 1993-2009. "All" represents all insider trades, while AIM1 – AIM3 represent conditional filters. AIM4 is excluded from Figure 2 in order to allow a better evaluation of these less dominant AIM measures.

Table 2.2

Event Study Returns Before and After Sarbanes Oxley

This table shows market adjusted and Fama French/momentum adjusted returns before and after Sarbanes Oxley for purchases and sales. The period before Sarbanes Oxley is January 1 - December 31, 2001, while the period after Sarbanes Oxley is January 1 - December 31, 2003. Data covers all common stocks in the NYSE, Nasdaq, and AMEX having insider trades. Days represents trading days in relation to the event date. Returns are either market adjusted, or adjusted to the Fama French 3-factors (size, book-to-market, CAPM) and momentum. AIM represents a measure of the accuracy of asymmetric information, with AIM=0 representing all insider trades, and AIM=1 filtering insider trades for 1) officers and directors only, 2) no conflicting trades in prior 3 months, 3) opportunistic trades only, and 4) active trades only. *,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A: Returns Before Sarbanes Oxley - Purchases

	Market Adjusted Returns						Fama French/Momentum Adj Returns					
	AIM=0			AIM=1			AIM=0			AIM=1		
Days	Mean Cumulative Abnormal Return	Portfolio Time-Series (CDA) t	Generalized Sign Z	Mean Cumulative Abnormal Return	Portfolio Time-Series (CDA) t	Generalized Sign Z	Mean Cumulative Abnormal Return	Portfolio Time-Series (CDA) t	Generalized Sign Z	Mean Cumulative Abnormal Return	Portfolio Time-Series (CDA) t	Generalized Sign Z
(-32,-2)	-3.47%	-5.387***	-10.282***	5.54%	3.100***	4.705***	-4.15%	-7.336***	-15.604***	1.76%	1.019	1.197
(-1,3)	1.13%	4.374***	10.125***	1.84%	2.557**	5.279***	1.20%	5.283***	11.930***	1.67%	2.408**	5.439***
(-1)	-0.15%	-1.26	-2.053*	0.34%	1.054	2.479**	-0.10%	-0.945	-0.501	0.33%	1.052	2.132*
(0)	0.32%	2.781**	8.532***	0.82%	2.569**	4.274***	0.37%	3.634***	9.192***	0.71%	2.279*	3.857***
(1)	0.42%	3.616***	4.600***	0.32%	0.984	-0.465	0.38%	3.784***	5.822***	0.32%	1.031	-0.097
(2)	0.36%	3.147***	4.293***	0.17%	0.538	1.258	0.36%	3.532***	4.801***	0.11%	0.366	0.479
(3)	0.17%	1.495$	1.704*	0.18%	0.573	-1.906*	0.18%	1.807*	5.216***	0.20%	0.659	1.627$
(4,15)	2.63%	6.560***	17.217***	3.52%	3.163***	5.136***	2.38%	6.769***	15.424***	2.89%	2.685**	3.785***
(16,32)	2.95%	6.182***	20.167***	4.19%	3.164***	4.202***	2.58%	6.146***	18.522***	2.05%	1.601$	2.635**

Panel B: Returns After Sarbanes Oxley - Purchases

	Market Adjusted Returns						Fama French/Momentum Adj Returns					
	AIM=0			AIM=1			AIM=0			AIM=1		
Days	Mean Cumulative Abnormal Return	Portfolio Time-Series (CDA) t	Generalized Sign Z	Mean Cumulative Abnormal Return	Portfolio Time-Series (CDA) t	Generalized Sign Z	Mean Cumulative Abnormal Return	Portfolio Time-Series (CDA) t	Generalized Sign Z	Mean Cumulative Abnormal Return	Portfolio Time-Series (CDA) t	Generalized Sign Z
(-32,-2)	-0.28%	-0.409	-2.121*	3.78%	1.610$	0.852	0.48%	0.733	-0.421	0.77%	0.349	-1.044
(-1,3)	1.72%	6.160***	19.571***	5.94%	6.295***	6.741***	1.78%	6.774***	21.937***	5.17%	5.849***	7.274***
(-1)	0.12%	0.947	3.925***	1.07%	2.540**	4.311***	0.15%	1.255	1.919*	0.95%	2.409**	2.695**
(0)	0.41%	3.274***	6.351***	1.29%	3.058**	3.750***	0.46%	3.928***	8.738***	1.28%	3.235***	1.386$
(1)	0.40%	3.234***	11.218***	1.01%	2.394**	2.628**	0.42%	3.577***	12.542***	0.84%	2.117*	1.760*
(2)	0.38%	3.081**	10.536***	1.58%	3.736***	5.339***	0.36%	3.050**	9.167***	1.31%	3.311***	5.686***
(3)	0.40%	3.239***	15.521***	0.99%	2.348**	7.208***	0.39%	3.339***	14.639***	0.79%	2.007*	5.779***
(4,15)	1.30%	3.007**	12.043***	5.20%	3.557***	4.124***	1.42%	3.480***	13.588***	4.16%	3.037**	4.938***
(16,32)	-0.97%	-1.881*	-8.600***	0.98%	0.562	-1.578$	-1.15%	-2.377**	-11.007***	-0.55%	-0.339	-3.100***

Panel C: Returns Before Sarbanes Oxley - Sales

	Market Adjusted Returns						Fama French/Momentum Adj Returns					
	AIM=0			AIM=1			AIM=0			AIM=1		
Days	Mean Cumulative Abnormal Return	Portfolio Time-Series (CDA) t	Generalized Sign Z	Mean Cumulative Abnormal Return	Portfolio Time-Series (CDA) t	Generalized Sign Z	Mean Cumulative Abnormal Return	Portfolio Time-Series (CDA) t	Generalized Sign Z	Mean Cumulative Abnormal Return	Portfolio Time-Series (CDA) t	Generalized Sign Z
(-32,-2)	6.40%	19.597***	68.140***	-2.85%	-2.062*	1.15	0.41%	1.557$	13.755***	-8.84%	-8.087***	-11.523***
(-1,3)	0.28%	2.140*	15.051***	-2.52%	-4.543***	-7.027***	-0.46%	-4.324***	-1.421$	-2.56%	-5.828***	-9.322***
(-1)	0.39%	6.575***	17.499***	-0.17%	-0.693	3.141***	0.19%	3.908***	9.417***	-0.33%	-1.702*	-0.539
(0)	0.38%	6.552***	18.327***	-0.15%	-0.612	3.098***	0.18%	3.861***	12.969***	-0.31%	-1.576$	1.192
(1)	-0.14%	-2.390**	-14.248***	-0.81%	-3.277***	-10.944***	-0.25%	-5.205***	-14.739***	-0.77%	-3.913***	-10.668***
(2)	-0.20%	-3.398***	-16.256***	-0.74%	-2.965**	-8.075***	-0.31%	-6.599***	-17.370***	-0.60%	-3.047**	-7.292***
(3)	-0.15%	-2.560**	-13.933***	-0.65%	-2.611**	-6.139***	-0.27%	-5.648***	-13.181***	-0.55%	-2.794**	-6.128***
(4,15)	-2.04%	-10.050***	-22.579***	-6.98%	-8.123***	-19.112***	-3.45%	-21.017***	-49.884***	-6.79%	-9.989***	-22.625***
(16,32)	-3.28%	-13.534***	-27.342***	-7.59%	-7.423***	-13.531***	-5.46%	-27.957***	-57.180***	-8.40%	-10.380***	-21.885***

Panel D: Returns After Sarbanes Oxley - Sales

	Market Adjusted Returns						Fama French/Momentum Adj Returns					
	AIM=0			AIM=1			AIM=0			AIM=1		
Days	Mean Cumulative Abnormal Return	Portfolio Time-Series (CDA) t	Generalized Sign Z	Mean Cumulative Abnormal Return	Portfolio Time-Series (CDA) t	Generalized Sign Z	Mean Cumulative Abnormal Return	Portfolio Time-Series (CDA) t	Generalized Sign Z	Mean Cumulative Abnormal Return	Portfolio Time-Series (CDA) t	Generalized Sign Z
(-32,-2)	4.11%	13.420***	49.834***	-3.51%	-5.969***	-26.572***	1.60%	5.261***	30.705***	-1.98%	-3.350***	-7.685***
(-1,3)	-0.02%	-0.125	-24.174***	-1.11%	-4.700***	-30.966***	-0.51%	-4.134***	-36.331***	-0.89%	-3.737***	-21.527***
(-1)	0.24%	4.435***	-2.612**	-0.10%	-0.97	-5.116***	0.11%	1.956*	-9.959***	-0.10%	-0.918	-7.227***
(0)	0.21%	3.851***	-13.597***	-0.17%	-1.597$	-12.650***	0.09%	1.558$	-18.192***	-0.13%	-1.245	-12.510***
(1)	-0.14%	-2.535**	-35.023***	-0.26%	-2.464**	-14.732***	-0.21%	-3.830***	-41.427***	-0.21%	-1.983*	-17.230***
(2)	-0.18%	-3.279***	-38.769***	-0.30%	-2.791**	-15.703***	-0.24%	-4.443***	-38.798***	-0.20%	-1.872*	-12.528***
(3)	-0.15%	-2.752**	-33.490***	-0.28%	-2.687**	-16.638***	-0.25%	-4.485***	-35.407***	-0.25%	-2.338**	-16.508***
(4,15)	-1.16%	-6.087***	-64.089***	-2.43%	-6.638***	-38.782***	-2.04%	-10.757***	-60.666***	-1.82%	-4.937***	-23.340***
(16,32)	-0.47%	-2.065*	-21.673***	-1.35%	-3.086**	-14.576***	-1.80%	-7.997***	-25.978***	-0.33%	-0.761	-0.113

Table 2.3
Event Study Bid-Ask Spread Before and After Sarbanes Oxley

This table shows the average bid ask spread and the average Chung Charoenwong (1998) abnormal spread for the period January 1 - March 31 of 2002 and 2005. All common stocks on the NYSE, Nasdaq, and AMEX are included which have insider trades during this range. The analysis is divided into 3 periods around the event date: Period 1) -10 to -2 days before the event, Period 2) -1 days before to 3 days after the event, and Period 3) 4 to 15 days after the event. The average bid ask spread represents the average spread for the period of days indicated in relation to the event date. The average Chung Charoenwong (1998) abnormal spread (defined as SAS, the standardized abnormal spread) represents the following equation:

$$SAS_{i,t} = \frac{Spread_{i,t} - \mu_i}{\sigma_i}$$

where μ_i and σ_i represent the sample mean and standard deviation, respectively, of the spread of stock i during the entire estimation period (-10 to +15 days around the event date). AIM represents a measure of the accuracy of asymmetric information, with AIM=0 representing all insider trades, and AIM=1 filtering insider trades for 1) officers and directors only, 2) no conflicting trades in prior 3 months, 3) opportunistic trades only, and 4) active trades only.

Panel A: Bid ask spread for three event periods: Pre-Event, Event, Post-Event

Purchases

	Pre-SOX: 2002				Post-SOX: 2005			
	Aim=0		Aim=1		Aim=0		Aim=1	
Days	Average Bid Ask Spread	Average CC (1998) Abnormal Spread	Average Bid Ask Spread	Average CC (1998) Abnormal Spread	Average Bid Ask Spread	Average CC (1998) Abnormal Spread	Average Bid Ask Spread	Average CC (1998) Abnormal Spread
(-10,-2)	0.2084	0.0043	0.1204	0.0000	0.3091	-0.0042	0.1590	0.0085
Patell Z		*0.54*		*-0.03*		*-0.01*		*0.19*
Sign Z		*-8.05*		*-2.46*		*-20.43*		*-4.48*
N. obs		*5624*		*292*		*8984*		*460*
(-1,3)	0.1976	-0.0033	0.1195	0.0040	0.2813	-0.0075	0.1215	-0.0285
Patell Z		*-0.10*		*0.29*		*-0.04*		*-0.42*
Sign Z		*-6.98*		*-0.79*		*-15.27*		*-7.39*
N. obs		*3188*		*162*		*5022*		*259*
(4,15)	0.1905	-0.0018	0.1170	0.0004	0.3064	0.0052	0.1481	0.0033
Patell Z		*-0.44*		*-0.12*		*0.04*		*0.15*
Sign Z		*-12.67*		*-2.89*		*-21.86*		*-4.31*
N. obs		*7609*		*389*		*11999*		*604*

Sales

	Pre-SOX: 2002				Post-SOX: 2005			
	Aim=0		Aim=1		Aim=0		Aim=1	
Days	Average Bid Ask Spread	Average CC (1998) Abnormal Spread	Average Bid Ask Spread	Average CC (1998) Abnormal Spread	Average Bid Ask Spread	Average CC (1998) Abnormal Spread	Average Bid Ask Spread	Average CC (1998) Abnormal Spread
(-10,-2)	0.1838	-0.0012	0.1648	0.0022	0.1751	-0.0010	0.0789	0.0016
Patell Z		*-0.03*		*-0.16*		*0.04*		*0.19*
Sign Z		*-14.90*		*-5.31*		*-59.13*		*-18.12*
N. obs		*16160*		*2150*		*40646*		*3839*
(-1,3)	0.1781	-0.0037	0.1533	-0.0019	0.1681	-0.0019	0.0715	-0.0017
Patell Z		*-0.58*		*0.05*		*-0.54*		*0.09*
Sign Z		*-14.38*		*-4.36*		*-47.35*		*-11.74*
N. obs		*9141*		*1229*		*22847*		*2164*
(4,15)	0.1793	0.0021	0.1470	-0.0008	0.1795	0.0016	0.0715	-0.0010
Patell Z		*0.35*		*0.07*		*0.26*		*-0.34*
Sign Z		*-16.47*		*-6.82*		*-66.98*		*-20.74*
N. obs		*21796*		*2912*		*54160*		*5090*

Panel B: Bid ask spread for individual days around event

Purchases

	Pre-SOX: 2002				Post-SOX: 2005			
	Aim=0		Aim=1		Aim=0		Aim=1	
Days	Average Bid Ask Spread	Average CC (1998) Abnormal Spread	Average Bid Ask Spread	Average CC (1998) Abnormal Spread	Average Bid Ask Spread	Average CC (1998) Abnormal Spread	Average Bid Ask Spread	Average CC (1998) Abnormal Spread
(-1)	0.1947	-0.0049	0.1206	0.0006	0.2242	-0.0134	0.1224	-0.0284
Patell Z		*-0.12*		*0.01*		*0.00*		*-0.41*
Sign Z		*-3.00*		*-1.26*		*-6.31*		*-4.34*
N. obs		*627*		*31*		*995*		*51*
(0)	0.2047	0.0010	0.1185	-0.0015	0.3212	0.0030	0.1317	-0.0183
Patell Z		*0.05*		*0.04*		*-0.28*		*-0.10*
Sign Z		*-3.19*		*-0.69*		*-9.50*		*-2.34*
N. obs		*662*		*34*		*1045*		*53*
(1)	0.1996	-0.0025	0.1341	0.0244	0.3214	0.0044	0.1026	-0.0502
Patell Z		*-0.01*		*0.42*		*0.17*		*-0.04*
Sign Z		*-2.16*		*0.73*		*-5.88*		*-3.33*
N. obs		*626*		*30*		*1002*		*52*
(2)	0.1952	-0.0021	0.1259	0.0016	0.3184	0.0041	0.1255	-0.0207
Patell Z		*0.17*		*0.02*		*0.04*		*-0.05*
Sign Z		*-2.50*		*-0.87*		*-6.23*		*-1.94*
N. obs		*635*		*33*		*990*		*52*
(3)	0.1933	-0.0082	0.1006	-0.0031	0.2188	-0.0363	0.1253	-0.0250
Patell Z		*-0.31*		*0.17*		*-0.01*		*-0.35*
Sign Z		*-4.75*		*0.34*		*-6.17*		*-4.62*
N. obs		*638*		*34*		*990*		*51*

Sales

	Pre-SOX: 2002				Post-SOX: 2005			
	Aim=0		Aim=1		Aim=0		Aim=1	
Days	Average Bid Ask Spread	Average CC (1998) Abnormal Spread	Average Bid Ask Spread	Average CC (1998) Abnormal Spread	Average Bid Ask Spread	Average CC (1998) Abnormal Spread	Average Bid Ask Spread	Average CC (1998) Abnormal Spread
(-1)	0.1711	-0.0092	0.1579	0.0054	0.1713	-0.0056	0.0737	-0.0005
Patell Z		*-0.33*		*0.19*		*-0.49*		*0.03*
Sign Z		*-7.33*		*-1.94*		*-21.50*		*-6.70*
N. obs		*1812*		*240*		*4505*		*424*
(0)	0.1792	-0.0042	0.1581	0.0013	0.1555	-0.0069	0.0704	-0.0029
Patell Z		*-0.29*		*0.09*		*-0.06*		*0.12*
Sign Z		*-7.22*		*-1.57*		*-21.66*		*-5.02*
N. obs		*1901*		*255*		*4730*		*446*
(1)	0.1827	0.0019	0.1538	-0.0036	0.1385	-0.0073	0.0729	-0.0002
Patell Z		*-0.45*		*-0.10*		*-0.38*		*-0.01*
Sign Z		*-6.77*		*-2.31*		*-22.31*		*-6.02*
N. obs		*1812*		*242*		*4539*		*431*
(2)	0.1775	-0.0035	0.1451	-0.0079	0.1978	0.0047	0.0741	0.0007
Patell Z		*-0.12*		*-0.08*		*-0.06*		*0.19*
Sign Z		*-5.91*		*-1.85*		*-19.64*		*-3.95*
N. obs		*1805*		*247*		*4553*		*432*
(3)	0.1796	-0.0035	0.1516	-0.0047	0.1780	0.0059	0.0665	-0.0056
Patell Z		*-0.10*		*0.00*		*-0.22*		*-0.12*
Sign Z		*-4.91*		*-2.11*		*-20.76*		*-4.58*
N. obs		*1811*		*245*		*4520*		*431*

Table 2.4
PIN Measure

This table provides the parameters of the PIN measure for 10 trading days before and after the event for a small subset of stocks from January 1 - March 31 of 2002 and 2005. The subset contains all insider trading events of firms with a market cap between $100m and $200m in the NYSE, Nasdaq, and AMEX in 2002, and that are still >$100m in 2005. AIM=0 represents all insider trades, while AIM=0,1 represents a mixed dataset of all insider trades and those filtered by the four AIM filters. The following are variable descriptions: α is the probability of an information event, δ if the probability of a bad (low) signal, μ is the rate of informed trade arrival, ε is the arrival rate of buy or sell orders. PIN is the probability of informed trading.

Panel A: PIN measure parameters: Trading Day (-10) to (10)

		Purchases		Sales		Purchases Average	Sales Average	
Estimated	Trading	AIM=0		AIM=0		AIM=0	AIM=0,1	
Parameter	Range	2002	2005	2002	2005	(2002,2005)	2002	2005
α	(-10,-2)	0.22	0.23	0.18	0.26	0.22	0.27	0.23
	(-1,3)	0.21	0.20	0.21	0.23	0.21	0.28	0.22
	(4,10)	0.22	0.27	0.20	0.21	0.24	0.28	0.24
δ	(-10,-2)	0.55	0.31	0.52	0.40	0.43	0.46	0.45
	(-1,3)	0.36	0.41	0.51	0.48	0.39	0.43	0.44
	(4,10)	0.35	0.38	0.59	0.42	0.35	0.48	0.53
μ	(-10,-2)	157.62	270.25	181.72	309.45	213.94	192.18	232.88
	(-1,3)	197.75	251.27	160.03	278.20	224.51	180.58	241.03
	(4,10)	163.31	266.35	169.03	281.05	207.13	181.44	209.32
ε	(-10,-2)	31.91	91.56	29.76	128.89	61.73	46.01	89.77
	(-1,3)	32.93	97.74	30.81	136.54	65.34	44.01	93.42
	(4,10)	32.45	95.82	30.98	128.76	59.65	43.65	85.24
PIN	(-10,-2)	0.34	0.24	0.35	0.23	0.29	0.36	0.23
	(-1,3)	0.39	0.19	0.35	0.19	0.29	0.36	0.22
	(4,10)	0.34	0.26	0.35	0.18	0.31	0.36	0.21

Panel B: PIN measure by trading day around event

	Purchases		Sales		Purchases Average	Sales Average	
Trading	AIM=0		AIM=0		AIM=0	AIM=0,1	
Day	2002	2005	2002	2005	(2002,2005)	2002	2005
(-1)	0.36	0.05	0.35	0.26	0.20	0.38	0.24
(0)	0.47	0.28	0.34	0.16	0.37	0.37	0.22
(1)	0.37	0.26	0.36	0.14	0.31	0.35	0.18
(2)	0.39	0.08	0.35	0.15	0.23	0.36	0.21
(3)	0.34	0.30	0.35	0.23	0.32	0.35	0.24

Table 2.5

Bid Ask Spread Regression

This table presents estimates from an FE regression of bid-ask spreads on two variables of interest: 1) a SOX dummy variable (Post-SOX = 1), and 2) an AIM dummy variable (All 4 AIM filters applied = 1). Regressions are pooled for 4 trading periods around the event: 1) -32 to -2 days before the event, 2) -1 days before to 3 days after the event, 3) 4 to 15 days after the event, and 4) 16 to 32 days after the event. Control variables include (SOX x AIM), an interaction term between the two primary variables, and LTSIZE - log of the dollar amount of the insider trade on the event date (t=0). The other control variables, as follows, use the value for the immediate trading date, in the range (-32,32) trading days. MKTSPREAD is the average market spread on that date. LVOL is the log dollar volume on that date. PRICE is the stock price on that date. NYSE is a dummy variable equal to 1 if the stock is traded on the NYSE. LMKTCAP is the log of market capitalization representing the market dollar value of the firm on that date. LAGSPREAD represents the lagged spread on the previous trading day. Number of observations for each period and adjusted overall r-squared are also included.

Panel A: FE Regression of Purchases in 2002,2005

	Model 1				Model 2				Model 3			
Variable	(-32,-2)	(-1,3)	(4,15)	(16,32)	(-32,-2)	(-1,3)	(4,15)	(16,32)	(-32,-2)	(-1,3)	(4,15)	(16,32)
Intercept	-0.4861 **	0.1304	-0.6659	-0.6280	-0.6445 *	0.2096	-0.7892	-0.7939	-0.0180	0.0719	0.0324	-0.0653
	(-2.04)	(0.24)	(-1.59)	(-1.58)	(-1.88)	(0.31)	(-1.56)	(-1.41)	(-0.49)	(0.90)	(0.58)	(-1.13)
MKTSPREAD	0.8689 ***	0.5954	0.8264 ***	0.9047 ***	1.1129 ***	0.7255	0.9031 ***	1.1465 ***	0.8299 ***	0.5008	0.7239 ***	1.0258 ***
	(5.94)	(1.60)	(3.29)	(3.71)	(5.90)	(1.58)	(3.17)	(3.72)	(5.52)	(1.51)	(3.08)	(3.90)
SOX	-0.0831 ***	-0.0718 *	-0.1100 ***	-0.0545 **	-0.1204 ***	-0.0949 **	-0.1379 ***	-0.0819 **	-0.0559 **	-0.0518 *	-0.0708 **	-0.0300
	(-3.56)	(-1.89)	(-2.87)	(-2.10)	(-3.71)	(-2.13)	(-3.00)	(-2.23)	(-2.03)	(-1.73)	(-2.28)	(-1.07)
AIM	0.0062	-0.0067	0.0003	0.0167	0.0097	-0.0044	0.0003	0.0217	-0.0020	0.0117	0.0086	0.0109
	(0.47)	(-0.46)	(0.02)	(1.41)	(0.53)	(-0.24)	(0.02)	(1.39)	(-0.15)	(0.55)	(0.30)	(0.78)
(SOX x AIM)									0.0169	-0.0450	0.0011	0.0275
									(0.54)	(-1.60)	(0.03)	(0.87)
LTSIZE	0.0003	-0.0008	0.0030	0.0014	0.0001	0.0003	0.0034	0.0024				
	(0.16)	(-0.28)	(1.38)	(0.91)	(0.05)	(0.09)	(1.32)	(1.16)				
LVOL	-0.0039 **	-0.0022	-0.0021	-0.0045 **	-0.0070 ***	-0.0033	-0.0031	-0.0072 ***				
	(-2.17)	(-0.64)	(-0.94)	(-2.22)	(-3.74)	(-0.95)	(-1.35)	(-3.31)				
PRICE	0.0020	0.0042	0.0021	-0.0002	0.0029	0.0052	0.0023	-0.0002				
	(1.29)	(1.36)	(1.17)	(-0.10)	(1.32)	(1.38)	(1.07)	(-0.05)				
NYSE	-0.0201	-0.0010	0.0275	0.0290	-0.0272	-0.0010	0.0306	0.0441				
	(-0.42)	(-0.02)	(0.52)	(1.29)	(-0.40)	(-0.01)	(0.48)	(1.36)				
LMKTCAP	0.0267 **	-0.0056	0.0356	0.0343	0.0376 *	-0.0093	0.0443	0.0449				
	(1.98)	(-0.18)	(1.49)	(1.54)	(1.94)	(-0.24)	(1.54)	(1.41)				
LAGSPREAD	0.2841 ***	0.2274 ***	0.1951 ***	0.2963 ***					0.4293 ***	0.2571 ***	0.3053 ***	0.4073 ***
	(11.53)	(3.79)	(5.32)	(6.53)					(11.09)	(4.74)	(6.06)	(6.40)
No. Obs	26586	4492	10495	15076	26586	4492	10495	15076	28975	4766	11341	16301
Overall R^2	0.3995	0.4712	0.2026	0.2987	0.0801	0.2132	0.0357	0.0050	0.5585	0.4298	0.4108	0.5493

*,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

Panel B: FE Regression of Sales in 2002,2005

	Model 1				Model 2				Model 3			
Variable	(-32,-2)	(-1,3)	(4,15)	(16,32)	(-32,-2)	(-1,3)	(4,15)	(16,32)	(-32,-2)	(-1,3)	(4,15)	(16,32)
Intercept	-1.1558 ***	-3.8911 ***	-1.2628 ***	-3.5504 ***	-1.4393 ***	-4.0400 ***	-1.7129 ***	-5.5574 ***	0.0372	0.0341	0.0311	-0.0593
	(-2.62)	(-3.47)	(-3.33)	(-4.32)	(-2.89)	(-4.34)	(-3.23)	(-4.14)	(1.26)	(0.82)	(0.99)	(-1.12)
MKTSPREAD	0.6536 ***	0.9884 ***	0.7715 ***	0.5269 ***	0.7230 ***	1.0147 ***	0.8762 ***	0.6903 ***	0.7732 ***	0.8640 ***	0.6918 ***	0.7750 ***
	(5.09)	(3.11)	(4.83)	(3.19)	(5.44)	(3.58)	(4.99)	(2.84)	(6.30)	(4.60)	(4.82)	(3.67)
SOX	-0.1447 ***	-0.1649 ***	-0.1048 ***	-0.0685 ***	-0.1811 ***	-0.1740 ***	-0.1602 ***	-0.1245 ***	-0.1044 ***	-0.1224 ***	-0.0823 ***	-0.0321 ***
	(-5.66)	(-4.72)	(-4.89)	(-3.40)	(-6.28)	(-4.71)	(-5.59)	(-3.83)	(-3.91)	(-3.94)	(-5.16)	(-3.51)
AIM	0.0061	-0.0150	-0.0234 ***	-0.0290 **	0.0075	-0.0153	-0.0315 **	-0.0482 **	0.0071	-0.0055	-0.0235 **	-0.0171 **
	(0.64)	(-1.08)	(-2.60)	(-2.27)	(0.63)	(-1.06)	(-2.56)	(-2.27)	(0.44)	(-0.33)	(-2.06)	(-2.39)
(SOX x AIM)									0.0031	0.0034	0.0100	0.0152
									(0.14)	(0.13)	(0.58)	(1.09)
LTSIZE	0.0017	0.0021	0.0002	-0.0024	0.0021	0.0023	0.0001	-0.0038				
	(1.33)	(0.95)	(0.13)	(-1.24)	(1.30)	(1.08)	(0.04)	(-1.26)				
LVOL	-0.0127 ***	-0.0087 ***	-0.0091 ***	-0.0105 ***	-0.0150 ***	-0.0091 ***	-0.0115 ***	-0.0154 ***				
	(-5.49)	(-3.55)	(-4.37)	(-5.04)	(-6.12)	(-3.33)	(-5.08)	(-5.64)				
PRICE	-0.0037 ***	-0.0117 ***	-0.0029 ***	-0.0121 ***	-0.0048 ***	-0.0122 ***	-0.0040 ***	-0.0191 ***				
	(-3.79)	(-3.92)	(-5.39)	(-4.89)	(-6.05)	(-5.77)	(-4.88)	(-4.74)				
NYSE	0.1152 ***	0.1644 ***	0.1156 ***	0.0500	0.1402 ***	0.1724 ***	0.1614 ***	0.0885				
	(4.57)	(3.10)	(5.40)	(1.45)	(4.62)	(3.21)	(5.60)	(1.60)				
LMKTCAP	0.0727 ***	0.2183 ***	0.0730 ***	0.2053 ***	0.0914 ***	0.2269 ***	0.1012 ***	0.3231 ***				
	(3.05)	(3.71)	(3.66)	(4.61)	(3.51)	(4.76)	(3.58)	(4.41)				
LAGSPREAD	0.1894 ***	0.0465	0.2931 ***	0.4032 ***					0.2544 ***	0.2022 ***	0.3270 ***	0.6008 ***
	(2.86)	(0.46)	(14.07)	(20.72)					(3.87)	(8.11)	(20.86)	(8.09)
No. Obs	80177	13303	31367	45074	80177	13303	31367	45074	82630	13562	32239	46449
Overall R^2	0.0002	0.1417	0.0598	0.0168	0.0954	0.1570	0.0651	0.2333	0.4196	0.3176	0.5305	0.7226

*,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

Table 2.6
Bid Ask Spread: Value versus Growth

This table presents estimates from an FE regression of bid-ask spreads for firms separated into high/low groups based on P/E ratio, with the high group designated Growth and the low group designated Value. Two variables of interest are considered: 1) a SOX dummy variable (Post-SOX = 1), and 2) an AIM dummy variable (All 4 AIM filters applied = 1). Regressions are pooled for 4 trading periods around the event: 1) -32 to -2 days before the event, 2) -1 days before to 3 days after the event, 3) 4 to 15 days after the event, and 4) 16 to 32 days after the event. Control variables include (SOX x AIM), an interaction term between the two primary variables, and LTSIZE - log of the dollar amount of the insider trade on the event date (t=0). The other control variables, as follows, use the value for the immediate trading date, in the range (-32,32) trading days. MKTSPREAD is the average market spread on that date. LVOL is the log dollar volume on that date. PRICE is the stock price on that date. NYSE is a dummy variable equal to 1 if the stock is traded on the NYSE. LMKTCAP is the log of market capitalization representing the market dollar value of the firm on that date. LAGSPREAD represents the lagged spread on the previous trading day. Observations for each period and adjusted overall r-squared are also included.

Panel A: FE Regression of Purchases in 2002,2005

	Growth				Value			
Variable	(-32,-2)	(-1,3)	(4,15)	(16,32)	(-32,-2)	(-1,3)	(4,15)	(16,32)
Intercept	-0.4746	-2.4141 *	-1.7220 *	-1.5013	0.0241	-0.3388	0.1020	-0.6548
	(-0.65)	(-1.84)	(-1.92)	(-1.10)	(0.09)	(-0.44)	(0.19)	(-1.48)
MKTSPREAD	0.5122 ***	0.7564 *	0.9939 **	0.4397	1.2049 ***	0.3206	0.9449 ***	1.1892 ***
	(4.14)	(1.71)	(2.00)	(1.25)	(4.98)	(0.56)	(2.66)	(3.18)
SOX	-0.2273 ***	-0.2960 ***	-0.1995 ***	-0.1769 ***	-0.0230	-0.0558	-0.0415	-0.0109
	(-5.83)	(-5.42)	(-4.95)	(-4.91)	(-1.14)	(-1.32)	(-1.05)	(-0.38)
AIM	-0.0019	-0.0178	-0.0206 ***	0.0076	-0.0059	0.0293	0.0213	0.0248
	(-0.65)	(-1.60)	(-2.70)	(1.04)	(-0.36)	(0.89)	(0.66)	(1.14)
(SOX x AIM)	0.0056	0.0107	0.0211 **	0.0002	0.0605 ***	-0.1505 ***	-0.0055	0.0492
	(0.68)	(0.79)	(2.20)	(0.02)	(3.63)	(-4.61)	(-0.16)	(0.82)
LTSIZE	-0.0003	0.0027	0.0024	0.0001	0.0001	-0.0022	0.0014	0.0021
	(-0.16)	(0.48)	(0.69)	(0.05)	(0.06)	(-0.42)	(0.50)	(0.94)
LVOL	-0.0030	0.0014	-0.0002	-0.0028	-0.0041 **	-0.0031	-0.0026	-0.0044
	(-0.77)	(0.28)	(-0.05)	(-0.79)	(-2.18)	(-0.71)	(-0.89)	(-1.54)
PRICE	-0.0002	-0.0027	-0.0021	-0.0046	0.0111 ***	-0.0021	0.0135 **	0.0027
	(-0.05)	(-0.57)	(-0.86)	(-0.96)	(3.05)	(-0.15)	(2.38)	(0.41)
NYSE	0.1260 ***	0.1326 ***	0.1042 ***	0.1116 ***				
	(2.79)	(2.66)	(2.70)	(5.41)				
LMKTCAP	0.0322	0.1312 *	0.0903 *	0.0874	-0.0126	0.0296	-0.0155	0.0308
	(0.78)	(1.85)	(1.91)	(1.18)	(-0.73)	(0.54)	(-0.48)	(1.09)
LAGSPREAD	0.2442 ***	0.0764	0.1516 *	0.3140 ***	0.3027 ***	0.2403 ***	0.1979 ***	0.2673 ***
	(5.52)	(1.08)	(1.91)	(4.84)	(9.32)	(4.56)	(5.08)	(4.31)
No. Obs	8826	1437	3267	4582	14158	2481	5894	8613
Overall R^2	0.2970	0.0517	0.0621	0.0825	0.4685	0.2339	0.4851	0.4803

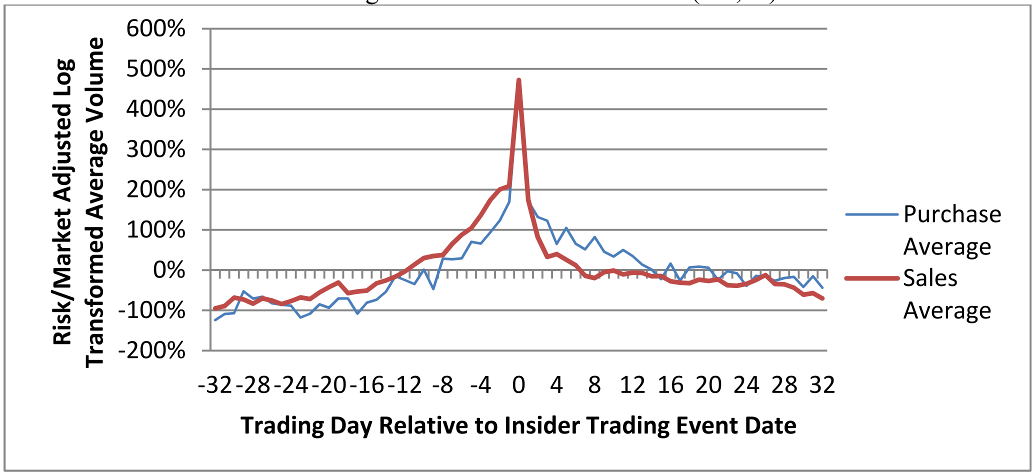
*,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

Panel B: FE Regression of Sales in 2002,2005

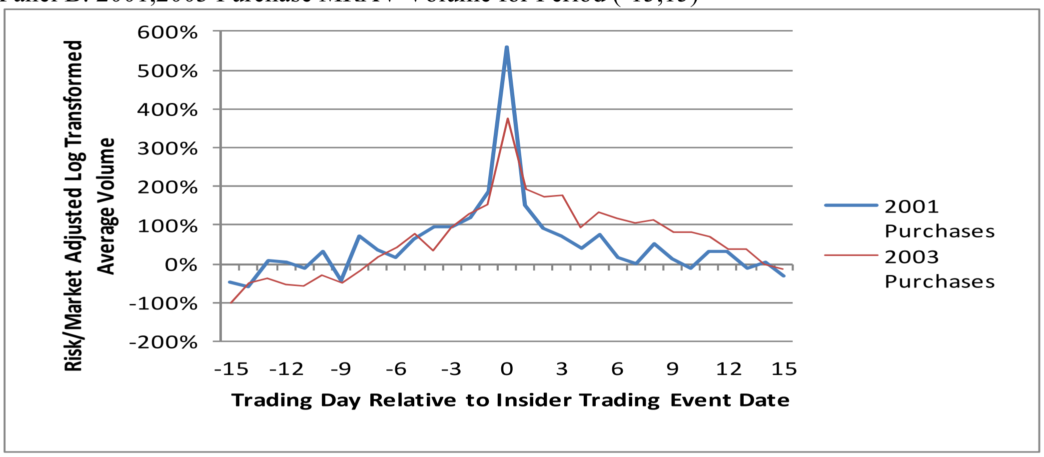
	Growth				Value			
Variable	(-32,-2)	(-1,3)	(4,15)	(16,32)	(-32,-2)	(-1,3)	(4,15)	(16,32)
Intercept	1.1030	-0.2031	0.0559	-2.2828	0.6388	0.7456	0.5073	-2.5225 ***
	(1.18)	(-0.18)	(0.09)	(-1.05)	(1.35)	(1.06)	(0.60)	(-4.25)
MKTSPREAD	0.5011 ***	1.0030 **	0.4053 ***	0.4794 **	0.9344 ***	1.2909 ***	1.5403 ***	0.6290 **
	(2.71)	(2.19)	(3.53)	(2.37)	(6.23)	(4.30)	(3.96)	(2.28)
SOX	-0.2716 ***	-0.2646 ***	-0.0908 ***	-0.1053 ***	-0.0338	0.0330	-0.0065	0.0177
	(-9.53)	(-6.54)	(-2.59)	(-5.23)	(-0.93)	(0.86)	(-0.14)	(0.39)
AIM	0.0258	0.0246	-0.0156 *	-0.0235	-0.0096	-0.0103	-0.0173	0.0016
	(1.49)	(0.92)	(-1.93)	(-1.49)	(-0.48)	(-0.72)	(-0.81)	(0.11)
(SOX x AIM)	-0.0153	-0.0066	0.0126	0.0205	0.0272	0.0094	-0.0048	-0.0147
	(-0.74)	(-0.21)	(1.24)	(0.87)	(1.16)	(0.51)	(-0.16)	(-0.61)
LTSIZE	0.0004	0.0015	-0.0007	-0.0027 *	0.0017	0.0050 *	0.0052 *	0.0010
	(0.29)	(0.56)	(-0.69)	(-1.87)	(1.17)	(1.79)	(1.87)	(0.58)
LVOL	-0.0106 ***	0.0011	-0.0040 *	-0.0021	-0.0095 ***	-0.0070 **	-0.0127 ***	-0.0117 ***
	(-4.26)	(0.21)	(-1.82)	(-0.77)	(-3.47)	(-2.19)	(-3.26)	(-3.93)
PRICE	0.0017	0.0014	0.0008	-0.0046	0.0057 *	0.0000	0.0004	-0.0206 ***
	(0.80)	(0.78)	(0.68)	(-0.93)	(1.95)	(0.00)	(0.10)	(-23.25)
NYSE	0.2611 ***	0.2902 ***	0.1020 ***	0.0788 **				
	(6.97)	(6.64)	(3.87)	(2.04)				
LMKTCAP	-0.0474	0.0047	-0.0017	0.1223	-0.0375	-0.0466	-0.0291	0.1603 ***
	(-0.95)	(0.08)	(-0.05)	(1.08)	(-1.38)	(-1.11)	(-0.60)	(4.96)
LAGSPREAD	0.0650	-0.0675	0.5584 ***	0.3803 ***	0.2615 ***	0.1444 ***	-0.1111	0.3922 ***
	(1.25)	(-1.32)	(4.68)	(11.05)	(9.32)	(3.05)	(-0.74)	(4.97)
No. Obs	41465	6993	16598	23675	32949	5479	12884	18755
Overall R^2	0.2815	0.0286	0.7276	0.1791	0.5491	0.1813	0.0234	0.2123

*,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A: Purchase and Sale Average MRAV Volume for Period (-32,32)



Panel B: 2001,2003 Purchase MRAV Volume for Period (-15,15)



Panel C: 2001,2003 Sale MRAV Volume for Period (-15,15)

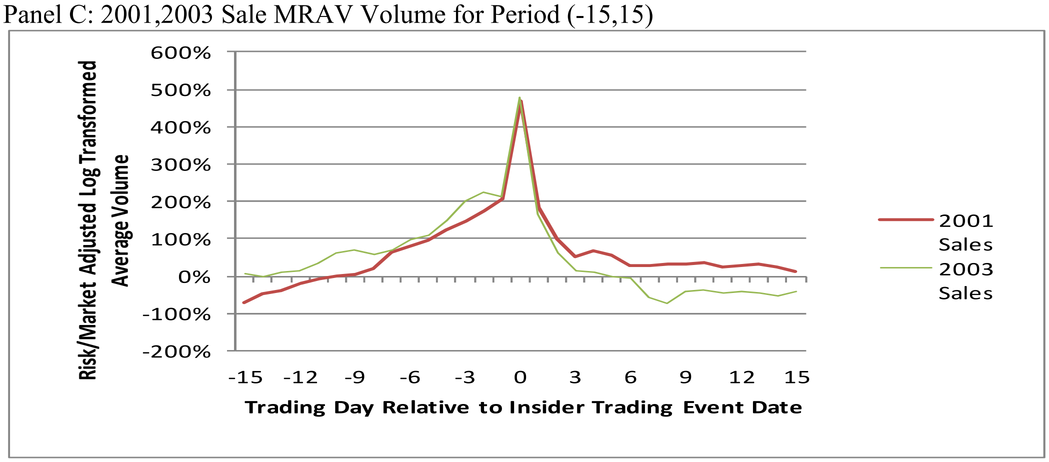


Figure 2.3. Volume

This figure shows the market/risk adjusted log transformed average (MRAV) volume for 2001 and 2003 purchases and sales. Panel A compares average purchases for 2001,2003 combined versus average sales for (2001, 2003) combined. Panels B and C compare 2001 and 2003 purchases and sales, respectively. Panel A covers an event window of (-32,32) trading days, while Panels B and C cover an event window of (-15,15) trading days.

2.8. Appendix B

Panel A: Average Spread Change Over the Event Window (-10,15) for 2002

Panel B: Average Spread Change Over the Event Window (-10,15) for 2005

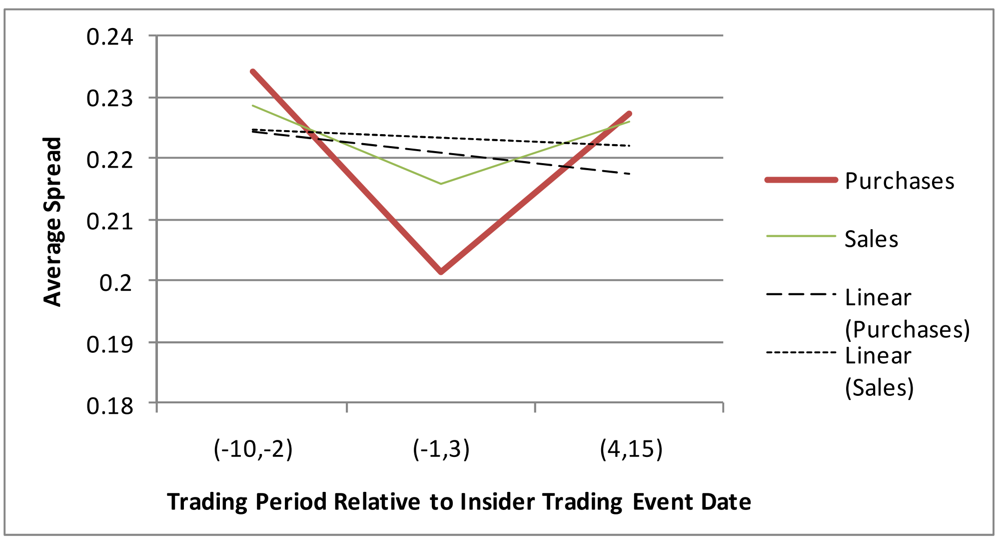


Figure 2.4. Bid-Ask Spread Trend
This figure shows the trend in the average bid-ask spread level over the course of the event window (-10,15). Panel A compares spread levels for purchases and sales for January 1 – March 31, 2002. Panel B compares spread levels for purchases and sales for January 1 – March 31, 2005. Trend lines are drawn for both purchases and sales to allow an easier comparison of how the change in spread proceeds over the event window.

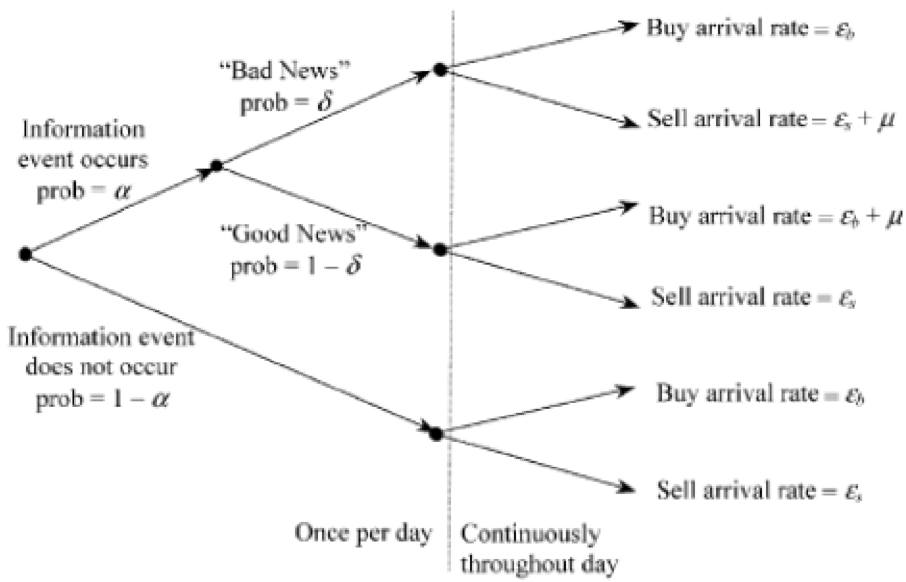
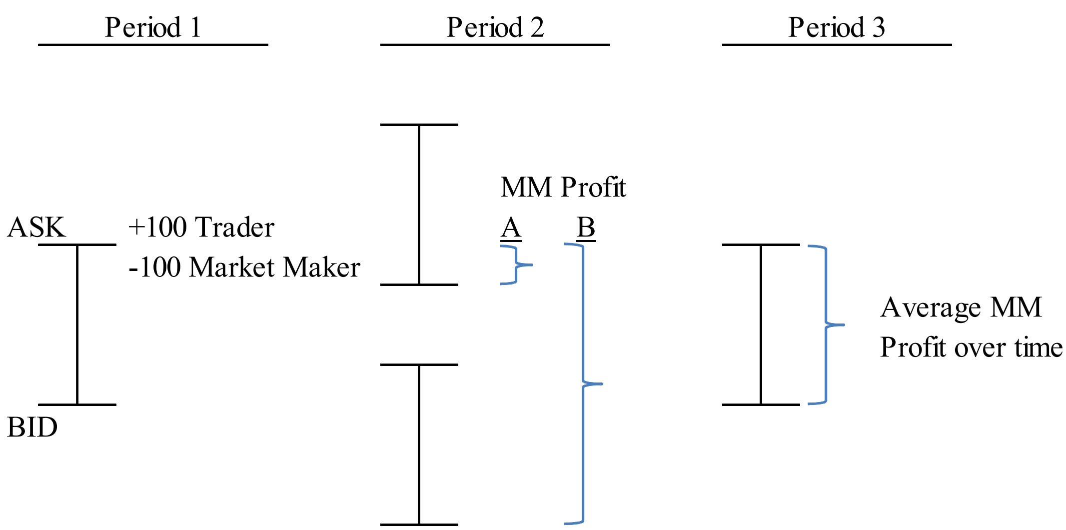


Figure 2.5. EKO Game Tree
This figure represents the game tree of Easley, Kiefer and O'Hara (1997), as shown in Brown, Hillegeist, and Lo (2004).

Figure 2.6. S&P 500 Small Cap Index
Provided by Stockcharts.com - performance of small cap index. TAQ data in this study is from the small cap index for January 1 – March 31 of 2002 and 2005.



Summary

- While random movements will affect MM profits on any given round-trip trade, over time the MM earns the bid-ask spread.
- This only holds for trading with uninformed traders

Figure 2.7. Standard Market Maker Profits Given No Price Trends
This figure presents the standard assumption of market maker profits given random movements in the stock price, and no trends in stock price movement.

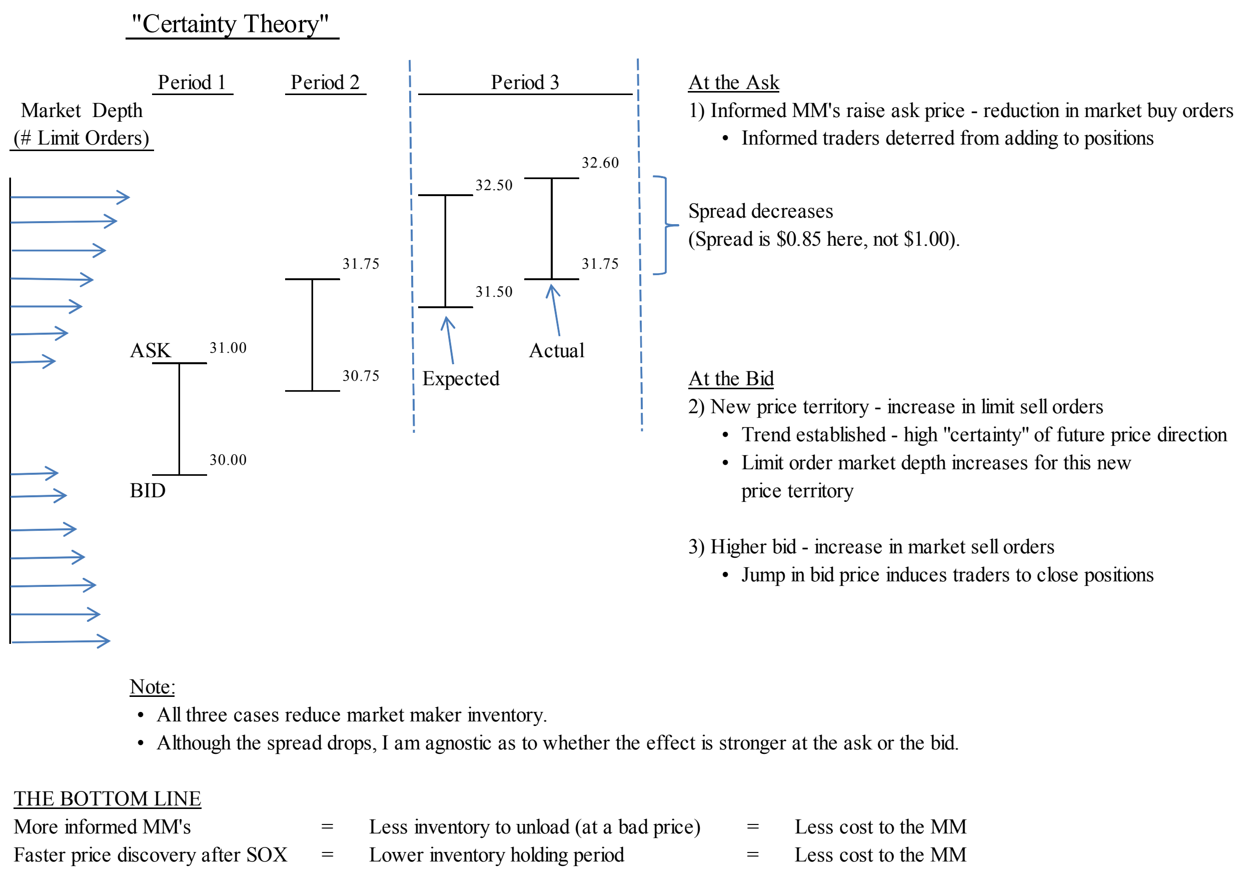


Figure 2.8. Market Maker Bid/Ask Pricing and Inventory Behavior in Price Trends
This figure presents the standard assumption of market maker profits given random movements in the stock price, and no trends in stock price movement.

CHAPTER 3

EXECUTIVE INCENTIVES TO INNOVATE AND GOVERNANCE POLICY

3.1 Introduction

"Stone discussed how visionary founder Jeff Bezos transformed Amazon from an online bookseller into one of the most successful companies in the world through its corporate culture, emphasis on the customer, focus on long-term success over short-term profits, and relentless pursuit of new markets…There were a few stumbles; the board almost asked him to step aside during the dot.com bust but Bezos appears to be on firm ground with the board for many years."

James McRitchie, CorpGov.net[29]
January 22, 2014

Manso (2011) theorizes that the standard pay-for-performance compensation schemes for executive management are not the best suited to promote innovation. While they do promote effort by rewarding success with substantial payoffs, they also punish short-term failure with lower compensation or possibly termination. As Manso notes, the innovative process involves substantial uncertainty with a high potential for short-term failure. Thus, he theorizes that a compensation scheme with high tolerance (or even reward) for short term failure is best suited to promote innovation.

However, while Manso makes a strong theoretical argument supporting this assertion, it is a difficult question to test empirically. Manso develops an individual choice model based on a

[29] "The Everything Store: Jeff Bezos and the Age of Amazon" James McRitchie, CorpGov.net, January 22, 2014.

multi-armed bandit model, but in reality it is challenging to empirically test the true innovative commitment of firm managers as individuals. This comes about for a wide variety of reasons. First, some studies have focused on the level of R&D spending by management to proxy for the innovative efforts of management, but the inherent long time frame that is necessary to produce fruitful innovative results (Hirshleifer, Hsu, and Li 2013; Cohen, Diether, and Malloy 2013) means that the R&D spending used to produce current innovations was likely made years ago by a very different management team. Second, while the measuring of innovation as proxied by current R&D spending or patent filings has been a common method in the literature (Becker-Blease 2011), even measuring patent output per R&D dollar has its flaws, as management could simply require the R&D departments to file more patents, regardless of whether they are lower quality and with less claims. Third, external factors such as the level of competition or financing options (Brown, Fazzari, and Petersen 2009) could also determine how much innovation a company develops, thus creating noise for studies focusing on R&D spending and patenting. Fourth, prior literature has shown that some industries patent at a much higher level than other industries (primarily due to property rights issues), which shows that producing a higher rate of patents should not be difficult for any firm if management simply wants to promote themselves as an innovative firm. Fifth, some boards can pressure management to maintain a certain level of R&D to spend (especially if the board is strong in its advisory role, or if certain long-term institutional investors can strongly influence the board). Finally, and perhaps most importantly, these prior studies tend to look at innovation on a firm level, and cannot discern the innovative motivations of various individual members of the management team. For all these reasons, it is hard to disentangle and evaluate how innovative the members of the management team actually are, and hence how to promote more individual innovation among executives of the firm.

So to answer the question of how to measure the individual innovative efforts of management, I develop a unique proxy for individual manager innovation by measuring the patent filings of managers themselves. I study 1,355 firm-year patent filings by top members of the executive management team between January 1996 and December 2006. Executive management certainly does not need to take such a hands-on role in the innovative process, but some managers seek to do so anyway. I evaluate this proxy in relation to a variety of governance policies introduced by Gompers, Ishii, and Metrick (2003), and by various forms of compensation. I find that there are indeed specific governance policies and compensation measures that a firm can take to help motivate this type of innovativeness.

I contribute to the literature in two important ways. First, this proxy provides a great empirical test of the predictions of the individual choice model of Manso (2011). Second, I find another potential lever the principal (shareholders) can use to either encourage or discourage exploration by the agent (management) by use of various forms of officer liability protection. I build an addendum to the theoretical model of Manso based on these results.

In general I find support for the predictions of Manso (2011) in this paper. However, there are mixed results when considering the various provisions in the governance index of Gompers, Ishii, and Metrick (2003). In contrast to Manso, I find modest evidence that stronger shareholder rights (less entrenchment of management) contribute to higher innovativeness by individuals on the management team. Specifically, I find that stronger shareholder rights relating to the sub-indexes of Delay and Voting (Gompers, Ishii, and Metrick 2003) seem to have the strongest positive effect on management innovation. However, in support of Manso, I find that the Protection sub-index is negative and significant for top executives, indicating that stronger protections for management compensation and wealth (weaker shareholder rights) are important for the production of innovation by management. I further evaluate this Protection sub-index by its six components, and find that in contrast to the predictions of Manso (2011), golden parachutes (and severance agreements) are not a significant motivator for inventor executives. Instead, I find that the corporate governance policies relating to director and officer indemnification from lawsuits and the exclusion of personal liability from lawsuits are much stronger motivators of innovative activity among top executives. This risk protection for personal wealth is apparently a strong requirement for managers wishing to personally pursue innovation in my sample, and thus by its presence or absence can potentially be a tool by shareholders to adjust the exploration vs. exploitation pursuits of managers. This is something that has not been considered in any models of the pursuit of innovation by management to my knowledge, so I contribute to the literature by adding this addition to the Manso model based on this result.

I also find support for the conjecture in Manso (2011) suggesting that option repricing can be a motivator for innovation by allowing a "tolerance for early failure". In addition, I find that a higher ratio of option compensation promoting long term tenure in a firm positively and significantly affects executive patenting. I also evaluate the pay performance sensitivity of the stock and option holdings of top management, and find further support for Manso (2011). Specifically, I find that option holdings sensitive to movement in the stock price (both in terms of absolute movement, and volatility in the movement) are strong positive motivators of innovation for top executives.

Finally, I find that innovations by top executives are a strong driver of firm risk in the year after the patent filing year, thus supporting the idea that the management team is motivated to take risks and face potential early failures in their pursuit of innovation, providing additional support for Manso (2011).

A. Why would managers file their own patents?

Patent filing is an inherently highly risky endeavor for a manager, as it directly places the success or failure of the innovation squarely on the manager (as they cannot blame lower level employees, or prior management for the wrong long-term innovative focus). In addition, patent filing is done under great legal scrutiny, and has specific legal requirements that any inventor listed on the patent must have had a substantial role in the development of the innovation. So it is unlikely for a manager to simply request that their name be added to a patent, or for a lower level employee to seek to ingratiate themselves with management by adding their bosses name to the patent, as doing so could ultimately invalidate the patent itself. While it is likely that the manager coauthored with other inventors on most of their patent filings, they ultimately had to play a substantial role in the product development.

But in addition to the high risks already associated with innovation, there are also intense reputational pressures associated with a manager placing their own name on a patent application. In their seminal paper on investment and herding, Scharfstein and Stein (1990) echo the risks to the long-term investor mentioned by Keynes (1936) "it is better to fail conventionally than to succeed unconventionally"[30]. These statements mirror the effect on a manager pursuing long-term innovations as theorized by Manso (2011), who notes that innovation is also long-term and that early failures are likely. Similar research has found this effect applies to general theories of conformity (Bernheim 1994), and to the herding effect among mutual fund manager and institutional investors (Wermers 1999, Nofsinger and Sias 1999). So it is reasonable to expect

[30] Scharfstein and Stein (1990), in quoting from Keynes (1936) *The General Theory*, "... it is the long-term investor, he who most promotes the public interest, who will in practice come in for most criticism, wherever investment funds are managed by committees or boards or banks. For it is in the essence of his behavior that he should be eccentric, unconventional, and rash in the eyes of average opinion. If he is successful, that will only confirm the general belief in his rashness; and if in the short-run he is unsuccessful, which is very likely, he will not receive much mercy. Worldly wisdom teaches that it is better for reputation to fail conventionally than to succeed unconventionally."

management not to pursue an idiosyncratic management style (including personal patent filings that could fail) unless incentivized properly to compensate for this increased reputational risk. Thus, I would expect a particularly strong incentive package is necessary to encourage a manager to assume the high risk of pursuing innovation, along with the additional high reputational risk of filing patents in their own name.

With that said, many of the managers seem to have qualities of overconfidence that could lead them to weigh the benefits of success much greater than the disadvantages of patent failure. Indeed, some of the most prolific inventor-managers in my sample are also the most successful (and most overconfident) tech managers in history – Steve Jobs of Apple, Jeff Bezos of Amazon, etc. However, even when excluding CEOS from my sample, the results still hold for the other less high profile members of the management team[31]. In fact, in some cases the results are even stronger for the non-CEO members of the management team. It is possible they are more motivated to make a significant impact on the firm, by innovating and filing a patent in their own name, to provide them opportunities for advancement in the future. If this is the case, then understanding how governance affects their innovative behavior could be a helpful way to understand how to increase manager productivity overall.

B. Motivation from Manso (2011) – Innovation, Long-term Commitment, and a "Tolerance for Failure"

As Manso (2011) theorizes, the foundation for this study lies in the central problem defined in the classic principal-agent conflict, in which the principal (shareholders) entrust the agent (management) with financial capital to invest in a manner optimal to the principal.

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[31] The results of this robustness test were reported in earlier versions of this paper, and can be provided upon request.

However, the agent has the ability to invest as they personally desire, and may seek to maximize their own advantage with the funds in contrast to the desires of the principal. So to align interests between management and shareholders, incentive plans need to be devised to encourage management to act in a manner favorable to investors.

However, this incentive plan may not be the same for all organizations. This poses a challenge when desiring to motivate management to focus on innovation. Holmstrom (1989) discusses this problem, and theorizes that a substantial tolerance for failure must be allowed for management that is being encouraged to innovate. A bureaucratic, centralized control structure may be optimal for the completion of routine tasks in an efficient manner, but creates a hostile environment for innovation.

Manso (2011) extends this debate, and argues that the proper compensation plan for innovation should be structured differently from the standard pay-for-performance incentive schemes. He contrasts exploration versus exploitation as introduced in March (1991) as two goals of the firm with opposing incentive requirements. Exploration (innovation) involves experimentation with new ideas that have a high likelihood of failure (at least initially), whereas exploitation is the process of managing a firm to produce higher returns in the short-term. Pay-for-performance, which rewards failure with low compensation or even termination, would not be appropriate if a firm desires to promote innovation. The proper compensation package to promote innovation would allow substantial tolerance (or even reward) for early failure, to allow time for the payoff from a long-term project to emerge. Manso states that the ideal compensation package for innovation would include a combination of option contracts with long vesting periods, the allowance of option repricing, golden parachutes, and managerial entrenchment.

To model this, Manso embeds a bandit problem (normally designed for individual decision making) within a principal agent framework to examine the theoretical implications of management contributions to innovation. He finds that the optimal compensation package to promote innovation is a two-period process. The first period would actually promote some degree of failure, while the second period promotes success. That is, the compensation package would be maximized not from success in both periods, but only by success in the second period. If the compensation scheme rewarded success in the first period, the manager could be tempted to focus on short-term performance goals. Only by maximizing total compensation with second period success exclusively is the manager motivated to focus on long-term performance.

In addition, Holmstrom (1982) argues that when groups of individuals are incentivized, there is a problem of free-riding. That is where my proxy for innovation has an advantage, as it represents individual manager effort, instead of simply the innovative efforts of an entire firm. Even though there may be multiple coauthors on a patent, by law each inventor listed on a patent application must have made a significant contribution, or the patent can be invalidated, so it is less likely the executive was a free-rider on the invention, using their influence within the company to pressure the other co-inventors to add his/her name to the patent. In addition, being the most high profile endorser of the patent within the company, the executive would face enormous risk in the success or failure of the filing, so there are huge potential individual risks involved with filing a patent.

C. Background on Officer and Director Liability

In this paper I also show that three governance provisions from the protection sub-index of Gompers, Ishii, and Metrick (2003) are positive and highly significant contributors to manager innovation. The three are 1) director indemnification, 2) director indemnification contracts, and

3) director liability. All of these apply to both officers and directors as fiduciaries of the firm. While officers are obviously fiduciaries as agents of the firm, directors also act on behalf of shareholders, thus qualifying them as fiduciaries as well (Bishop 2005)[32]. This fiduciary responsibility can place significant liability on these individuals, especially if risky activities related to innovation are pursued by these individuals.

The adoption by many states of the Model Business Corporation Act of 1950[33] has led to a standardization of most state incorporation laws. More importantly, Delaware incorporates over 50% of publicly traded firms, which has come about as a result of its business-friendly Delaware General Corporation Law of 1899. Because of the many firms incorporated in Delaware, it has the most extensive case law on corporations in the U.S., and sets a precedent for other state corporation laws. For this reason, I focus primarily on Delaware law in understanding the legal responsibilities of executive managers. Delaware uses common law, not statutes, to guide fiduciary responsibility, thus the stream of legal proceedings in Delaware in recent years provides a good basis for the necessity of director and officer protection in corporations. In general, officer and director liability in Delaware Law comes under the commonly referred to fiduciary "triad" of 1) Duties of Care, 2) Duties of Loyalty, and 3) Good Faith.

Perhaps the most damaging case in recent years asserting the liability of officers and directories in their fiduciary duties came under the Duty of Care provision in 1985. The case of *Smith vs. Van Gorkom*, in which directors were found liable for not properly valuing their firm

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[32] Bishop (2005) pp. 478-479.

[33] This act, introduced in 1950, provides a standard set of guidelines that firms and fiduciaries of the firm must follow. It has been adopted completely or in part by most states, with a map of recent state adoptions here: http://www.professorbainbridge.com/professorbainbridgecom/2013/11/a-map-of-model-business-corporation-act-states.html While Delaware has not adopted this act (and yet has the largest number of incorporated firms), they have followed the spirit of the act in their policy decisions.

before a takeover (even though the takeover premium was 50%), resulted in massive personal financial losses to these directors, and sent fear through the market for directors.

Indeed, the Duty of Care provision has typically caused the greatest concern for officers and directors, as it can hold them liable for making a decision deemed irrational by the courts. In fact, it can extend even further and hold the individual liable for a seemingly good decision, but based on an unreasonable decision-making process[34]. This has introduced pressure from corporate fiduciaries on the state of Delaware to relax such a vague, yet financially threatening provision, which has resulted in some relief. As Bishop (2005) puts it, "Because directors of a public corporation face massive financial liability for violations of the duty of care that can have enormous financial consequences, Delaware first developed a robust business judgment rule to negate liability not involving gross negligence. When that standard proved too onerous, the Delaware legislature adopted a statutory exculpation standard that eliminated director care liability involving even gross negligence. Since that time, cases have been framed to avoid exculpation".

However, although the state of Delaware has come to allow exculpatory monetary liability clauses in the articles of incorporation for a firm (weakening the impact of the Duty of Care provision on firms), shareholders have pushed back against this weakening by framing their case against firm fiduciaries under the Duty of Loyalty provision. So the pendulum of fiduciary liability has, just since 1985, swung toward fiduciaries at the time of Smith vs. Van Gorkom, away as Delaware allowed exculpatory measures by firms, and back toward fiduciaries as shareholders have framed manager malfeasance under the Duty of Loyalty provision. This has likely had a strong impact on firm management tasked to lead their company toward an

[34] Bishop (2005) pp. 485.

innovative strategy already fraught with a high risk of failure, long term payback, and creative tasks which could be deemed irrational by unfriendly courts.

But there are some that argue that directors and officers have little to worry about in terms of personal liability, and that governance measures designed for their protection are irrelevant. Bebchuck, Cohen, and Ferrell (2009) cite the legal paper of Black, Cheffins, and Klausner (2006) as suggesting that officers and directors have a wide variety of protections against personal liability lawsuits brought against them by shareholders. Thus they discount the three liability and indemnity provisions from Gompers, Ishii, and Metrick (2003) as having negligible effects as governance measures. But it is reasonable to expect directors and officers to remain very nervous about their personal liability, especially when tasked with a long-term, risky innovative focus in the midst of a fast-paced, ever-changing legal environment for the liability of their actions. *Smith vs. Van Gorkom* and the recent pushback by shareholders using the Duty of Loyalty provision to implicate management would suggest that the assumption of Bebchuk, Cohen, and Ferrell (2009) may be a bit too preliminary given the pendulum shifts in the past 30 years.

Thus, it is not surprising to find out that my sample of inventor-managers has a statistically significant positive occurrence of firms offering director and officer liability protection for each of three governance measures previously discussed from the protection sub-index of Gompers, Ishii, and Metrick (2003).

The rest of the paper is organized as follows. Section 3.2 presents the hypotheses and methodologies studied to evaluate inventor-manager patents. Section 3.3 describes the data and the measures used in the analysis. Section 3.4 provides the results and robustness checks to test the hypotheses, while section 3.5 concludes. Section 3.6 Appendix A includes relevant tables and figures.

3.2 Methodology and Hypotheses Development

A. Main hypotheses

A higher level of shareholder rights (less managerial control) places a higher risk of reprimand or termination on a manager who commits any action considered worthy of misconduct. In addition, coupled with prior findings that risky investments like innovation could lead to underinvestment (Stein 1988, Smith and Watts 1992, Bebchuk and Stole 1993) resulting in a greater likelihood of a hostile takeover, the resulting lack of governance safeguards against the risk of a hostile takeover would incentivize managers to make safer, less risky investment decisions. Also, allowing higher levels of entrenchment may allow management to focus on longer-term innovative profits, since they could remain more confident that their tenure would continue until the fruits of their innovative investments appeared. This tends to support the “tolerance for early failure” argument of Manso (2011).

On the other hand, a lower level of managerial rights (higher level of shareholder rights) leading to entrenchment could contribute to empire building (Jensen 1986, Stulz 1990), shirking, or perhaps the “quiet life” effect of Bertrand and Mullainathan (2003) among the management team – all qualities that should have a detrimental effect on innovation. Because innovative managers would likely be younger and more overconfident in their abilities, they might not require lower shareholder rights in order for them to take risks. Plus, it is likely they would expect to be rewarded in the case of a takeover, as they would possess significant intellectual and organization capital valuable to the acquiring firm.

However, it seems most likely that innovation would be encouraged by added protection from takeover / termination threats. Thus, I offer a hypothesis supporting Manso (2011) in this case:

H1: Inventions by managers should occur less often in firms exhibiting an overall higher level of shareholder rights.

Even without the entrenchment provisions, managers can be also be motivated to innovate if they are protected from the potential compensation loss associated with 1) the risk of termination or reprimand from the board that could occur from the early failure of a long-term innovative project, and 2) the risk of termination from the threat of a takeover. This has been studied in Francis, Hasan, and Sharma (2009), who find that golden parachutes lead to higher patenting and more patent citations, and in Manso (2011), which theorizes that golden parachutes may induce innovation by providing management with a tolerance for failure. In addition, Almazan and Suarez (2003) find that a contract consisting of bonus and severance pay can motivate management to invest in firm specific human capital, especially if faced with competition from potential replacement managers.

H2: Manager-inventors will be motivated to innovate if protected from the high risk of compensation loss due to potential termination.

The prior hypothesis deals with the potential loss of income resulting from management engaging in innovative activities. However, there is a much greater threat to management from investing in innovation which has typically been overlooked in the literature. That is the severe liability risk to their personal wealth that could occur from a failed innovation which investors see as reckless or unscrupulous behavior on the part of management. So I hypothesize the following:

H3: Managers will be motivated to innovate only if their higher potential personal return from innovation is balanced with a reduction in the personal increase in risk to their own wealth that innovation creates.

Manso (2011) also theorizes that a manager will stay more motivated if their options are allowed to be repriced in the event of a decline in the firm stock. Quite often long-term innovation can result in a short-term severe stock price decline, if early results are not promising or if investors simply lose confidence for a while. This can reduce motivation for managers if their options are so far out of the money that it makes it appear unlikely that they will ever pay off. By allowing these options to be repriced after the decline to be closer to being at the money will give managers a stronger motivation to continue a long-term innovative project. In fact, Manso says that this is an almost necessary requirement to keep management motivated to innovate past short-term failures. So I hypothesize:

H4: Managers will be motivated to innovate if they are allowed to reprice their options.

Next, I evaluate executive compensation structures that are more favorable toward long-term firm tenure. There are three main types of executive compensation that are more favorable toward long-term tenure: 1) option grants (which typically require an extended vesting period), 2) restricted stock (which the executive will forfeit if leaving the firm before it vests), and 3) long-term incentive plan payouts. So I define a long-term compensation structure as follows: [(option grants) + (restricted stock) + (long-term incentive compensation)] / total annual compensation. If an executive is being motivated to remain with the firm longer, it is more likely that they will interpret this compensation policy as a desire by the firm to retain them even if they experience some failures in the short-term. Thus they would be more likely to engage in long-term and inherently risky innovative projects, comfortable with the notion that the firm will have a "tolerance for early failure". Thus I hypothesize the following:

H5: Compensation structures with a higher ratio of compensation favorable toward long-term tenure will be positively related to executive patent filing.

In addition, the convex nature of option payoffs provides a strong incentive to managers to engage in innovative activities. Similar to the repricing argument, a manager will likely be even more strongly motivated to invent if the change in stock price has a stronger effect on their stock and option holdings. To proxy for this, I use several pay performance sensitivity measures as presented in Core and Guay (2002) and Clementi and Cooley (2010). Pay performance sensitivity is the change in value of the executive's personal stock and/or option portfolio based on the change in value of the firm's stock price. First, I use the delta of the option to evaluate the sensitivity of the executive's option only portfolio to stock price movement. It is likely that many of these options have a strike price close to the current stock price, thus giving the executive a strong upside potential for a successful innovation, with no downside risk from a failed innovation (since the option would simply expire worthless). This should be a strong motivator for an executive contemplating an innovation, so I predict this measure will show strong positive significance with an executive patent filing. Second, I use option vega to evaluate the volatility of the executive's option only portfolio. Prior research has shown a positive relationship between the sensitivity of a manager's stock options portfolio to volatility and the level of R&D investment (Nam, Ottoo, and Thornton 2003). The inherent risk of innovation, with a high potential for failure but also having the potential for a strong payoff, would cause an option portfolio sensitive to vega to go up no matter which direction the stock price moves; thus, I would predict that this measure will show strong positive significance with an executive patent filing. Finally, I evaluate overall pay performance sensitivity (PPS) to consider the effects of both the executive's stock and option portfolio combined. The stock holding component of pay performance sensitivity may be weaker, since stock price movement could result in an equally likely chance of a high or low payoff (given strong price trends due to innovation). However, while the stock portfolio may be ambiguous[35], I expect this measure to be positively related to executive patenting because of the option component. Thus I hypothesize the following:

H6A: Delta will be positively related to executive patenting.
H6B: Vega will be positively related to executive patenting.
H6C: PPS will be positively related to executive patenting.

Finally, I would expect inventor-executive firms to earn higher market returns for the following reasons. First, because innovation is the best driver of value creation in the economy, but at the same time has a high failure rate from uncertainty during the exploration process (hence the need for a "tolerance for early failure" as Manso 2011 suggests), on average I would expect firms with higher innovation to have on average higher returns at least in the short term due to the increase in risk that they introduce. Second, since an inventor-manager would reduce the information asymmetry between the research centers of the firm and firm management, I would expect management to understand and fully support the innovations produced, resulting in a higher likelihood that the firm fully backs the innovation. This would lead to a significant effect for the firm, which would likely be a positive return as I suggest in my first point. Third, since a top executive filing a patent could communicate the idea more clearly to the board, there would be a reduction in information asymmetry between top management and the board, leading to a greater chance that the board would be supportive of plans to develop the innovation, again leading to a significant effect on firm performance. All of these factors should combine to increase potential firm returns from a manager patent filing. In addition, it is highly likely that

[35] Similar to an option, a stock portfolio has an unlimited upside and a limited downside (stock price = $0). However, most executives contemplating innovation would probably expect a more limited range of movement from the current stock price, giving a more equally symmetric payoff distribution for a stock portfolio. This is why I consider a stock portfolio to face similar upside and downside risk.

the visibility of a top manager filing a patent would lead to a strong initial market reaction (perhaps the first year or so), with little market reaction after this period.

> H7: Firms with manager inventions will earn higher market returns in the short term (the first year or so) after a patent filing.

3.3 Data and Summary Statistics

The sample period for the primary dataset ranges from 1996 to 2006[36]. The variables constructed are listed in Appendix A.1. Observations are excluded if they are not in the NYSE, AMEX, or Nasdaq, or if the data is not common stock. Daily, monthly, and annual stock data is provided by the Center for Research in Security Prices (CRSP). Financial statement data is provided by Compustat. In addition, institutional holdings data is gathered from Thompson Reuters 13F filings. I obtain governance data from Riskmetrics for S&P 1500 firms.

The patent data is primarily obtained from the National Bureau of Economic Research (NBER) patent database, which consists of over 3 million patents and 23 million citations between 1976 and 2006. This data was obtained from patents submitted to the U.S Patent and Trademark Office (USPTO) as compiled by Hall, Jaffe, and Trajtenberg (2001). I also utilize the NBER bridge file which links over 1 million of these patents directly to COMPUSTAT firms, and obtain permnos from patent dataset of Kogan, Papanikolaou, Seru, and Stoffman (2012). I obtain utility patent inventor names (first, middle initial, and last) and addresses from the Harvard Business School patent dataverse of Lai, D'Amore, and Fleming (2013).

I obtain the names and addresses of the top five executives from the Execucomp database, in addition to stock and option holding data. Execucomp records the top five to nine

[36] This data range extends up to 3 years before and after the primary sample period for some of the control variables and market returns data.

managers per firm by total compensation for S&P 1500 companies. First name, middle initial, and last names are given for each executive.

A. Inventor Manager Proxy

To create a proxy for the level of innovation among firm managers, I first establish a match between inventions as recorded by the U.S. Patent and Trademark Office (USPTO) and management in publicly traded U.S. corporations. I obtain utility patent inventor names and addresses from the Harvard Business School patent dataverse of Lai, D'Amore, and Fleming (2013). I obtain the names and addresses of the top five managers from the Execucomp database.

I match the patent inventor names to the manager names by an exact match of first and last names using a fuzzy matching algorithm. This type of matching is imperfect, as there may be multiple inventors and multiple managers named "Bob Smith". To account for this, I then screen the matches using a four-step process[37]. First, I exclude matches between inventor and manager names that appear in different combined / metropolitan statistical areas (CSA/MSA). That is, if the actual address of the inventor is located in a different MSA/CSA than the firm's headquarters. While this screener may miss some executives who are long distance commuters[38], I would expect commuter executives to be less likely to engage in patent filing, as the research required to produce the patent would require many hours in the lab that a commuter executive would not be able to provide. Second, I exclude matches between inventor and manager names

[37] It is difficult to try to obtain exact matches directly from company press releases and 10-K's. While some of them report patenting by the firm, or even by the member of the management team, it may not report the number of patents filed by this manager, or indicate the patent number (as only the application number is available to the firm at the time of filing). Thus I solely use my matching methodology above, and do not attempt to double check all matches with firm reports.

[38] "The Commuter CEO" Wall Street Journal Online. May 22, 2006. Steven Gray, Joann S. Lublin, and Joseph T. Hallinan. http://online.wsj.com/news/articles/SB114825047381559015

if the middle initial is different. Third, I eliminate matches where last names are listed in the top 20 English surnames in the U.S., or the top 10 surnames in countries contributing more than 1% of the national total of foreign students in the U.S. (as that should represent similar foreign representation among inventors and managers alike in the U.S.). While this technique excludes some accurate inventor-manager matches, it does so in a random way, and thus should not affect the results[39]. In addition, after matching to the patent dataverse of Lai, D'Amore, and Fleming (2013), it is easier to cumulate patent filings by the individual over time, as Lai et al. provide a unique identifier for each inventor in their database. Fourth, I match the firm gvkey identifier of the top five manager to the firm gvkey identifier of either the NBER patent dataset of Hall, Jaffe, and Trajtenberg (2001) or the patent dataset of Kogan, Papanikolaou, Seru, and Stoffman (2012). I exclude observations where a match is not obtained between the Execucomp gvkey number and at least one of the patent datasets.

I then use this match to create an indicator variable indicating whether any one of the top five members of the management team filed a patent application in a given year. Finally, I count the total number of patent filings by the top five management team in a given year. I count the total number of patents filed (as opposed to creating an indicator variable for the incidence of a filing) as this may indicate an even greater commitment by management team members to innovation. This should not simply be an indicator of the size of the firm, as the number of top managers is similar in all publicly traded firms (for example, every firm has only one CEO, one CFO, etc., no matter its size), and the top five managers are always included in Execucomp. In addition, I limit my analysis to firms reporting at least the top five management team members, and exclude any managers reported ranked below the top five (as some firms report on their

[39] While this is somewhat already evaluated in the Lai, D'Amore, and Fleming (2013) inventor matching process, I add this additional step here to obtain higher accuracy. However, this exclusion only eliminates a small fraction of observations, and results are robust to eliminating this exclusion.

proxy statements). Thus, the presence of multiple patent filings should truly indicate extra effort on the part of the management team, and would likely indicate a stronger focus on innovation.

B. Governance Proxies

I create all proxies for governance as per Gompers, Ishii, and Metrick (2003), hereafter GIM, from data provided by Riskmetrics from 1990-2006. GIM creates 24 distinct corporate governance provisions for roughly 1,500 firms per year during this period. Each provision is an indicator variable coded with a value of 1 for the creation of weak shareholder rights, and a value of 0 for the creation of strong shareholder rights. The provisions are roughly summed to create a "G" index, with values ranging from 1 to 24[40]. For the GIM paper, an index of $1 \leq G \leq 5$ is labeled a "democracy" portfolio with strong shareholder rights, while an index of $14 \leq G \leq 24$ is considered a "dictatorship" portfolio with weak shareholder rights (strong managerial power).

From these 24 provisions, Bebchuk, Cohen, and Ferrell (2009) created an "Entrenchment" index of 6 provisions that have a high tendency to help entrench management (protect management from removal or the consequences of removal). They found that these 6 provisions are the key factors driving the performance differential between the "G" index portfolios, and that the other 18 provisions (defined by Bebchuk et al. as the "O" index) don't really matter. Thus I also evaluate the "E" and "O'" indexes. However, I also break down the 24 provisions of the "G" index into five sub-indices as defined by GIM (delay, protection, voting, other, state) to see if there is a significant impact on innovative firms for any of these subindices. See appendix A.1 for a more detailed explanation of these indices. Since the

[40] The index is close to, but not simply a sum of the subcomponents. See Gompers, Ishii, and Metrick (2003) for a further explanation of how the "G" index is constructed.

governance score only periodically changes, I simply use the most recent governance score (for the provisions, sub-indices, and indices) in my evaluations.

C. Breadth of Inventor-Manager Firms

Because only a limited number of firms / industries file patents, there is the possibility that firms with inventor managers do not accurately represent firm innovation across the spectrum of publicly traded firms. To examine this, I examine executive patenting by year and industry in the following table:

(Insert Table 3.1 here)

I first examine the breadth of inventor manager firms across time and industry by examining the rate of inventor manager patenting across the Fama French 17 industry classifications in Panel A. There seems to be skew toward larger firms, but that is simply because the top five manager names are provided by Execucomp, which only covers the top S&P 1500 firms. Slightly more than 50% of firm-year executive patent filings are in the "Machinery and Business Equipment" industry, so there is some concentration of executive patent filings in a few specific industries.

Panel B shows that firm-year observations are fairly evenly spread across the 1996-2006 sample period. The reduction in firm-year observations in 1996 and 2006 is due to limitations in data availability from the Execucomp sample. Market capitalization is much higher for inventor-manager firms because the data is matched to Execucomp, which represents roughly the S&P 1500 firms, which are larger than the entire sample average. In addition, throughout the period inventor manager firms tend to be older firms, with higher valuations (as given by market-to-book ratios) and higher R&D spending to assets.

Finally, Panel C presents an idea of some of the CEOs who also file patents. CEOs like Steve Jobs and Jeff Bezos are well known to be long-term thinkers with a hands-on innovative approach, so are understandable high ranked in my sample. However, it is possible that the high number of patent filings by these individuals could skew the results. So for robustness throughout this paper, I consider both firm-year patent events per executive (a dummy variable indicating at least one patent filing by that executive in the given firm-year, which is biased toward executives filing less patents) and the total count of patent filings per firm-year (biased toward executives filing more patents).

D. Descriptive Statistics

I present descriptive statistics of the primary dependent and independent variables evaluated in this paper, in addition to the controls used. Throughout this paper I use three levels of controls. First, I use a set of primary controls for innovation that have been used in prior papers evaluating the effects of firm characteristics on innovation – R&D/assets, firm patent citation count / R&D stock, firm age, industry adjusted return on assets, fraction of institutional ownership, count of institutional owners, and the text-based network industry classification Herfindahl measure of Hoberg and Phillips (2010). These controls adjust for certain predictors of innovative behavior based on prior related literature (Hall and Ziedonis 2001; Aghion, Van Reenen, and Zingales 2009; Hirshleifer, Low, and Teoh 2012). I include Herfindahl measures to control for the potential effects of competition on innovation, and firm age to control for patenting likelihood (as younger firms tend to file patents more extensively).

The two measures of institutional ownership are closely related, so I do not include both of them in the same regression. For the regressions evaluating governance measures, I use the fraction of institutional ownership, as it more commonly used in prior literature examining governance and innovation. However, in the other compensation based regressions, I use count of institutional owners, as this provides double-duty as both a measure of institutional presence and as a control for firm governance, as the more institutions owning firm stock will lead to a higher number of individuals lending scrutiny to management practices.

Second, I use the standard asset pricing controls of size, market-to-book, and momentum (using the prior 12-month returns) as a control both for regressions using asset prices as a dependent variable, and for the other regressions considering innovation (as innovation could be driven by similar factors driving asset pricing).

Third, I add some alternate additional controls for some regressions – capital intensity, cash (Becker-Blease 2011), and presence within an innovative industry (Hirshleifer, Low, and Teoh (2012) – as added robustness for some of the regressions. While this third set of controls is not as commonly used in prior innovation literature, I feel that they apply in the regressions in this paper as added measures of robustness. I use the capital intensity ratio to control for its effect on long term spending (as it competes for long-term funds which would otherwise be earmarked for innovation).

I also present general statistics on the primary measures of innovative motivation in this paper – gindex, repricing, pay performance sensitivity, and long-term compensation. The following table contains these summary statistics relating to my sample.

(Insert Table 3.2 here)

3.4 Main Results

A. Executive Innovation and Governance

Table 3.3 shows regressions of the score ranking of various components and sub-indexes of the "G" index of Gompers, Ishii, and Metrick (2003) on the incidence of a manager-invention. I include all three main classifications of controls in this table as described in Table 3.2: primary innovation controls, asset pricing controls, and alternate innovation controls. The general model used in this paper is given below:

$$PatX_{i,t} = \propto_0 + \beta D_{i,t} + \Omega W_{i,t} + \Phi Z_{i,t} + \eta_i + \nu_{i,t} + \varepsilon_{i,t} \qquad (1)$$

where $PatX_{i,t}$ represents either a firm-year patent event or a count of firm-year executive patent filings, represents the intersect term, $D_{i,t}$ represents the primary innovation controls, $W_{i,t}$ represents the asset pricing controls, $Z_{i,t}$ represents alternate innovation controls, η_i is a fixed unobservable firm-specific factor, $\nu_{i,t}$ is a time-varying unobserved factor, and $\varepsilon_{i,t}$ represents the error term.

I include the TNIC Herfindahl measure to control for the potential effects of competition on innovation, capital intensity ratio to determine the effect of other long term spending competing for long-term funds otherwise earmarked for innovation, and firm age as younger firms tend to file patents more extensively.

(Insert Table 3.3 here)

In panel A of Table 3.3 I regress an indicator variable of the occurrence of a firm-year executive patent filing on the G index, along with the 5 sub-indices of Gompers, Ishii, and Metrick (2003): 1) delay, 2) protection, 3) voting, 4) other, and 5) state. The Delay sub-index includes tactics used to delay hostile bidders, and is very similar to the alternative takeover protection index (ATI) of Cremers and Nair (2005), which the authors find creates a positive abnormal return as shareholder rights increase (and takeover potential increases). I find that higher values of this index are negatively associated with inventor-manager patenting. The Voting sub-index, which includes provisions expanding shareholder voting rights in elections, is also negatively and significantly related to inventor-manager patenting, indicating higher shareholder voting rights in elections promotes innovations by managers. Both of these findings oppose hypothesis 1, contrasting Manso (2011) but supporting the "quiet life" theory of Bertrand and Mullainathan (2003). Since innovation creates economic growth and value for the firm, it is possible that managers feel that their compensation and tenure with the firm (even in the event of a takeover) is more secure if embarking on intensive innovative endeavors.

However, in support of Manso, the Protection sub-index is positive and highly significant. This suggests support for hypothesis 2, which states that managers will require certain protections such as golden parachutes to protect them from discipline resulting in compensation loss in the event of early innovative failures, as suggested by the "tolerance for early failure" theory of Manso (2011).

Together, the Delay and Voting sub-indexes seem to offset the positive significant relationship in the Protection sub-index to yield an insignificant g index. The Other index and the State index show insignificant relationships with inventor patenting.

Panel B of Table 3.3 reevaluates these results by regressing a count of the total firm-year patent filings by top five executives on g index, its five sub-indices, and all three control sets, using a negative binomial count regression. I run this additional model for three reasons. First, top executives at larger firms may be able to file more patents than their peers at smaller firms due to greater resources. Similarly, CEOs might be able to get involved in more patent research than their lower ranking peers. So considering patent events may favor smaller firms and lower ranking executives, with patent counts favoring the opposite case. Thus comparing both models would adjust for these biases. Second, a simple binary variable measuring the event of an annual patent filing by a manager may not yield as much information as a count of the number of patents filed by the manager. For example, a manager personally filing multiple patents in a year is likely more motivated to innovate than a manager filing a single annual patent. So I consider the effect of the G index, the E index, and the O index on the annual count of patent filings by 1) CEOs only and 2) all top managers in a negative binomial regression model. Third, using a different model also simply adds robustness to the findings in Panel A. Panel B finds results similar to Panel A.

Because of the strong significance of the Protection sub-index in Panels A and B, and the assertion by Manso (2011) that a component of this index (golden parachutes) is likely to be positively related to innovation, I decompose this signal in Panel C into its six components to evaluate the effect of golden parachutes versus the other five factors. The Protection sub-index can be roughly separated into two parts. First, the sub-index contains 3 provisions protecting managers from compensation loss in the event of a termination (as Manso 2011 suggests): Compensation plans, golden parachutes, and severance packages. The sub-index also contains provisions protecting managers from the loss of their own personal wealth in the event of shareholder lawsuits targeting officers and directors for a violation of the Duty of Care or Duty of Loyalty, as previously mentioned. These 3 provisions are as follows: Director indemnification, director indemnification contracts, and director liability.

Using a negative binomial model similar to Panel B, I find that the compensation protection measures in case of termination – golden parachutes and severance – are both insignificant. This is in contrast to hypothesis 2 (and Manso (2011)) and could be in line with the findings for the Delay and Voting subcomponents of the G index, suggesting that innovative managers will have a higher tendency to be rewarded for their innovative attempts and may not need to fear compensation loss from termination. There are several possible reasons for this outcome. First, overconfidence among top executives could lead them to underweight the value of a golden parachute. Second, boards may be strongly opposed to entrenchment in these cases, since just as innovation is risky, an executive committed long-term to the wrong innovation is also highly risky for them. Third, it is possible that the board does not want to provide the manager an easy option to leave in the case of initial failures in the innovation. Perhaps, boards committed to the idea of "Failure is not an option" do not want to consider, and seemingly incentivize, failure as a possible future outcome for their managers. This could still fit in line with Manso (2011), as it would encourage managers to stay and fix the "early failures" in their innovations, rather than abandoning the innovation (and the shareholders) to failure by accepting a generous severance package or golden parachute. Fourth, golden parachutes are somewhat infamous, and may be strongly avoided by boards facing higher shareholder or media scrutiny for their compensation policies. Fifth, temporary failures may be rewarded with option repricing, so the executive would still have compensation recourse for short-term failures.

Compensation Plan is highly significant, but it relates more to a timing issue allowing executives to exercise their options immediately in the event of a change in control, and not to actual compensation. Thus it is unclear how this might affect the motivation to innovate, but it is possible that the significant human capital involved in the innovative process would suggest that a change in control would result in the loss of the executive's own innovative knowledge base, which could drive down the stock price in the short term as the new executive faces a steep learning curve in understanding the innovation. This would encourage any highly innovative executive to insist upon exercising their options immediately upon a change in control.

In contrast to the findings above, I find strong support for hypothesis 3, which states that managers will pursue innovation only if the vast potential increase in risk to their own wealth is reduced, in that the three closely related liability protection measures – director indemnification, director indemnification contracts, and director liability – are all positive and significant in their effect on a count of firm-year executive patent filings. The importance of protection for officer and director liability has likely been high ever since the *Smith vs. Van Gorkom* case in 1985, so it is highly probable that officer/director liability is significant to provide protection for officers engaging in risky innovative projects. It is also likely high for lowering ranking executives not in the CEO position, who potentially do not have high levels of D&O insurance. (In addition, it is possible that this is higher for the firm's outside directors conducting an advisory role with the inventor-manager and other firm managers, although not measured here. Future extensions using Riskmetrics could evaluate this).

B. Robustness Tests for Liability Protection and Entrenchment Measures

Although some of the prior findings on liability protection coincide with the same ideas that Manso (2011) presents on executives requiring protection from early failures in order to innovate, this type of governance protection is not specifically discussed in Manso or in related literature. So to provide confidence that these results are relevant and significant, I evaluate them further for robustness using the following five models. The dependent variable is listed first, followed by the model type:

Static Models:

1) Patent event – Logit model

2) Patent event – Probit model

3) Patent count – Negative binomial model

Dynamic Models:

4) Patent count – Dynamic OLS model

5) Patent count – Arellano Bond (1991) Difference GMM model

Before performing the regression analysis in Table 3.4, I first construct a new index based on the three liability protection measures of the Gompers, Ishii, and Metrick (2003) index for use in Panel A. It ranges from 0 to 3, and contains the G index components of 1) director indemnification, 2) director indemnification contracts, and 3) director liability. In addition, I construct an adjusted G index without these three liability protection measures, ranging from 0 to 21, for use in Panel B. For all of the regressions in Table 3.4, I use my full set of primary innovation control variables.

(Insert Table 3.4 here)

I first consider Panel A of Table 3.4. The first two static models – logit and probit – are very similar, but yield different results close to the probability extremes. So by considering both models I am able to avoid a bias from either type of model. I find that in both cases, although the magnitudes of the coefficients are very different, the effect of the liability index in year t-1 on the occurrence of a patent event in year t is positive and highly significant, so the models do not contradict each other.

However, the first two models provided limited information on how much liability protection affects executive patenting, as they use a dependent dummy variable on patent filing by executives. So in my third static model I use a negative binomial regression with executive patent count as the dependent variable. Although there might be a bias toward CEOs and executives in larger firms, a count of the number of firm-year patent filings by executives will likely provide more information on how committed an executive is to innovation, so can probably provide more confidence in the results. Similar to the first two static models, I find that the effect of the liability index in year t-1 has a strong and highly significant effect on the occurrence of one or several patent filings by members of the top five executive team in year t.

While these static models yield significant results confirming a similar argument to Manso (2011), other recent papers have insisted that dynamic models are necessary to evaluate studies related to governance, as the governance factors are slow to change over time and causality can be difficult to establish (Wintoki, Linck, and Netter (2012), O'Connor and Rafferty (2014)). For this reason, I also evaluate the use of two types of dynamic models similar to methods used in Wintocki et al. to determine the effect of the liability index on a count of the firm-year patent filings of top five executives.

Column 4 of Panel A uses a dynamic OLS (DOLS) model as in Stock and Watson (1993), which is designed to address the problem of simultaneity among regressors and allows for the integration of variables of different orders. I use both heteroskedasticity and autocorrelation consistent (HAC) standard errors and covariance estimation, controlling for autocorrelation in up to 3 lags. Similar to the static models, I find that the effects of the liability index in year t-1 are positive and statistically significant in year t.

Column 5 of Panel A uses the difference GMM methodology of Arellano Bond (1991), which also addresses causality better than static models, and is helpful in the current case of a short time dimension with a larger number of observations. It also allows for autocorrelation in the variables. I use the second and third lags of the following endogenous variables as instruments: patent count, liability protection index, R&D / assets, and firm-year executive patent citations / R&D stock. I also include the lag of the dependent variable patent count in the main equation as is often done. In Arellano Bond, the second lag or greater is required because they would not be correlated with the error term, while the first lag is assumed to be correlated. I use the following variables as strictly exogenous explanatory variables: industry average return on assets, the fraction of institutional ownership, the TNIC industry competition measure of Hoberg and Phillips (2010). I also include firm age as an instrumental variable not included in the main equation[41]. These variables are then used as their own instruments. I use the two-step estimator to ensure the standard covariance matrix is robust to panel-specific autocorrelation an heteroskedasticity. I also implement the finite-sample corrected two-step covariance matrix to avoid a downward bias in the standard errors.

I find that the effect of the lagged liability protection index on firm-year executive patent filing is positive and highly significant in this model, just as in the static models and the dynamic OLS model. In addition, the model is robust to all of the various autocorrelation and instrument tests typically evaluated in Arellano Bond. First, the number of instruments (58) is far less than the number of groups (403), which is a common rule of thumb for a valid test. Second, the model is robust to the AR tests of autocorrelation. A desired result is to reject the null hypothesis of no autocorrelation in the first lag, but fail to reject in the second lag, which is what I obtain. Third, the Hansen test of overidentifying restrictions also fails to reject the null that the instruments are exogenous, again as desired. Fourth, the Difference-in-Hansen test of the

[41] The results are robust to including firm age in the main equation, and produce the same level of significance for the liability protection index.

exogeneity of the instrument subsets also fails to reject the null that the instrument subsets are exogenous, also as desired.

In summary, all of the models in Panel A support hypothesis 3, that managers will seek to obtain liability protection before personally engaging in innovation as proxied by the filing of a patent.

In panel B of Table 3.4 I evaluate the effect of the Gompers, Ishii, and Metrick (2003) index minus the three liability protection measures using the same models. Supporting earlier results in this paper, I find negative and statistically significant results for the three static models and the dynamic OLS model. However, I fail to find results for the Arellano Bond (1991) difference GMM model. This is more significant based on the fact that the difference GMM model passes all four autocorrelation and instrument tests as discussed for panel A, so the results are not insignificant because of a model misspecification. While this may not mean that the results from the first four models are not meaningful, it weakens the argument that hypothesis 1 should be rejected.

C. Option Repricing

Manso (2011) suggests that executives allowed to reprice their options after a large decline in firm stock will be more motivated to continue their innovations. Innovations are uncertain and pose a high risk that the stock price drops from some failures along the path to completion. After a large price decline, the executive's options could potentially be far out-of-the-money with little chance of becoming in-the-money before the innovations succeed and boost the firm's stock price. Thus, these options would no longer provide a motivation to the executive. However, as Manso suggests, boards that are willing to show a "tolerance for early failure" will allow their executives to reprice their options closer to the current stock price, thus allowing them to once again be motivated by these stock options to complete their innovative activities.

(Insert Table 3.5 here)

Columns 1 and 2 of Panel A of Table 3.5 examine the relationship between repricing firms and executive patenting, while columns 3 through 6 seek to establish which way causality flows in the relationship. In columns 1 and 2, I examine the relationship between a firm-year patent filing by any member of the executive team using a probit model, and firms that repriced at any time between 1992 and 2012. After controlling for all three groups of controls[42], and adding year and industry fixed effects, I still find modest positive significance between executive patenting and repricing, supporting hypothesis 4.

In columns 3 through 6, I further examine causality between executive patent filing and firm repricing in a simple model. Establishing causality between executive patenting and option repricing is important for two reasons. First, option repricings allowed before the inventor-manager filed their patent could have signaled that the firm will allow the repricing of options, thus motivating the inventor-manager to proceed. Second and in contrast, and with causality potentially running the other way, the option repricing may have occurred after the inventor-manager patent was filed, thus showing a responsiveness by the board to be accommodating to the executive after a possible early failure in the innovation. Thus, it is hard to say if the manager was motivated by the potential for repricing, or if the repricing was allowed after the innovation simply as a courtesy to management. Did the manager know that repricing could occur when they filed the patent? It is difficult to say.

[42] I exclude innovind from the repricing regressions, as repricing occurred almost exclusively within the innovative industries as defined in this paper. However, results are robust to the inclusion of this variable.

To examine this causality, I switch the dependent and key independent variables of firm-year executive patenting and a firm-year repricing event, using as the dependent variable the one-year or two-year forward event for each case. I find that higher executive patenting seems to lead firm repricing in both the 1-year case and the 2-year case. However, there is no effect on executive patenting in the 1 or 2 year periods after a repricing event. In general, this suggests support for the Manso (2011) theory that failures are likely after innovation is undertaken, in that repricing was needed after a significant number of these executives filed patents. However, it is still difficult to determine if repricing motivates managers to innovate, as I am unable to find causality from prior repricing events, and I do not have data on whether a firm had a repricing policy before the innovations were undertaken.

D. Long Term Compensation

Even though it is not possible to establish whether a firm holds a repricing policy before an innovation is undertaken, it is possible to determine whether a firm tends to favor long-term innovative projects by examining whether their compensation policy is supportive of long-term executive tenure with the firm. There are three main types of executive compensation that are more favorable toward long-term tenure: 1) option grants (which typically require an extended vesting period), 2) restricted stock (which the executive will forfeit if leaving the firm before it vests), and 3) long-term incentive plan payouts. I construct a ratio of the compensation from these three measures to the total executive compensation as provided by Execucomp to establish the level of long-term motivation for executives by their compensation structure.

In addition, it is possible that firms in the early years after going public may be thinking less about long-term survival, as firms in this stage of development are going through rapid transitions and often high-growth. In addition, most of the compensation structure for the executives of young firms is already heavily weighted in shares of firm stock (Helwege, Pirinsky, and Stulz (2007)) so they would not likely be additionally motivated by added compensation that favors long-term tenure. So I divide my sample into firms aged greater than 10 years since their initial public offering, and firms aged 10 years or less since their IPO.

(Insert Table 3.6 here)

In columns 1-3 of panel A of Table 3.6, I regress both the total count of firm-year executive patents and the occurrence of a firm-year executive patent filing on the one year lag of LTCOMP for firms aged greater than 10 years since their IPO date. I find positive and statistically significant results in all three models that executives in firms with compensation weighted more toward the long term tend to file patents more frequently. However, in columns 4-6 I do not find this in firms aged less than 10 years[43]. This lends support to hypothesis 5.

E. Pay Performance Sensitivity

Panel A of Table 3.7 evaluates the pay performance sensitivity of the inventor-manager's option portfolio delta, option portfolio vega, and the sensitivity of their combined stock and option portfolio. I compare both logit models of the occurrence of a firm-year executive patent event and negative binomial count models of the total number of executive patents filed in a firm-year to adjust for potential bias in either model (as discussed in section IV.A).

(Insert Table 3.7 here)

First, I find strong support for hypothesis 6A for executives. Option delta is positively and significantly related to inventor-manager patent filings for executives for both models, which

[43] Although the sample size is small for the case of firms aged over 10 years, the coefficients are also much smaller, thus indicating limited economic significance even if statistical significance were present in a larger sample.

confirms the idea that option holdings, by creating a strong upside potential and zero downside risk, would provide a strong motivation for a manager to innovate.

Second, I find strong support for hypothesis 6B for executives. Innovations, being high risk with the potential for a high return, would likely lead to high volatility in stock returns. Thus, an option portfolio which increased in value in a high volatility environment would be a strong motivator for innovation, as I find with my inventor-manager dataset.

Third, I find strong support for hypothesis 6C for executives. It is likely that most of the support for the stock and option based pay performance sensitivity measure comes from the delta of their option holdings, but it is helpful for robustness to also present this more comprehensive measure.

Overall, the option structure and pay performance sensitivity measures show that option holdings do play a strong role in motivating innovation among this sample of inventor-managers.

F. Firm Risk

Patents filed by managers are likely to have stronger support from the firm, as top managers would likely be able to explain and push their innovations more effectively to the board and to fellow members of the top management team. This would increase firm risk, as the support for this innovation would be inherently risky to the company.

(Insert Table 3.8 here)

Panel A columns 1-3 of Table 3.8 show the effect of the occurrence of a patent filing on one-year forward firm stock returns net of value-weighted market returns in a fixed effect regression framework. Overall, the results are highly significant for the full sample, and for firms both greater and less than 10 years in age since their IPO. For robustness, columns 4-6 show results for a difference-in-difference regression using a 3-to-1 matched sample to firms in the nearest quintile of firm size, market-to-book, and 1-year momentum, respectively. I use nearest neighbor matching by firm size for the final match. The results (given by the interaction term) indicate that although the significance is slightly weaker, the results match the findings from columns 1-3 for the full sample. However, the significance of the interaction term for older firms is insignificant. In both cases, the coefficients for the models are larger and more significant in the case of young firms, suggesting that executive inventors in younger firms have a larger impact on firm performance than executive inventors in older firms (that may be less innovative overall).

Panel B of Table 3.8 evaluate the effect of the occurrence of a patent filing on one-year forward firm stock returns net of both equal-weighted and value-weighted market returns in a fixed effect regression framework containing all three sets of control variables. Similar to Panel A, the overall results show strong support that executive inventor patent filings increase firm risk. However, there is no significance in either model for firm aged over 10 years since their IPO date. In summary, these results support hypothesis 7 that patent filings by executives do indeed affect firm risk, at least in the first year after a filing.

3.5 Conclusion

In this paper I investigate the effect of corporate governance and executive compensation policies on firm innovation. Manso (2011) identifies several pathways that could be used by a board/shareholders to motivate the management team to innovate. To capture a better measure of the individual contributions to innovation by the management team, I create a proxy of individual innovative activity by identifying 1,355 firm-year patent filings by members of the top management team for U.S. firms from 1996-2006.

I find some evidence that, in contrast to Manso (2011), stronger shareholder rights (less entrenchment of management) contribute to higher innovativeness by management. Specifically, I find that stronger shareholder rights relating to the sub-indexes of Delay and Voting (Gompers, Ishii, and Metrick 2003) seem to have the strongest positive effect on management innovation. However, these results are weakened somewhat by a failure to confirm the results using a difference GMM model of Arellano Bond (1991).

I also evaluate this Protection sub-index of Gompers, Ishii, and Metrick (2003) by its 6 components, and find that in contrast to the predictions of Manso (2011), golden parachutes are not a significant motivator for inventor managers (lending support to the prior findings that stronger shareholder rights may reduce executive innovation, supporting the "quiet life" and managerial slack hypotheses). Instead, I find that the corporate governance policies relating to director and officer indemnification and the exclusion of personal liability from lawsuits are much stronger motivators of innovative activity by CEOs and executives. Although governance data is known to suffer from many endogeneity biases (Wintoki, Linck, and Netter (2012), O'Connor and Rafferty (2014)), I test the results using five static and dynamic regression models and find similar results.

I then examine the role of repricing in the motivation of executive innovation, addressing the endogeneity of firm repricing policy by specifically looking at causality. I find that executive patenting seems to lead to repricing, but I find no evidence that prior repricing leads to executive patenting. This supports the idea from Manso (2011) that innovation can lead to failures that require repricing, but it does not confirm that repricing policy motivates managers to innovate.

I also examine the ratio of compensation geared toward long-term firm tenure (options requiring vesting, restricted grants of stock forfeited upon leaving a firm, and long term incentive plans) over total compensation, and find that binding compensation does increase executive innovation in firms aged greater than 10 years since their IPO. These results suggest that managers who feel that the firm is supportive of a long tenure, even despite potential failures along the way, will feel more comfortable initiating inherently long term innovations.

I also evaluate the option sensitivity of the top management stock and option holdings, and find support for Manso (2011) that option holdings sensitive to movement in the stock price (both in terms of absolute movement, and volatility in the movement) are strong positive motivators of innovation for top executives. I compare both logit and negative binomials to build confidence in these results.

Finally, I find that innovations by top executives are a strong driver of firm risk in the year after the patent filing year, thus supporting the idea that the management team is motivated to take risks and face potential early failures in their pursuit of innovation. I find evidence for this both in a fixed effects panel regression model using the full sample and in a difference-in-difference regression from a sample matched on the asset pricing factors of size, market-to-book, and one-year momentum. I find that the results are stronger for firms aged 10 years or less since their IPO date, and that the results are robust to evaluating firm returns net of both value-weighted market returns and equal-weighted market returns.

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3.6. Appendix A

Table 3.1
Descriptive Statistics - Executive Patent Filings Dataset

This table presents descriptive statistics for the executive patent filings dataset, which is derived from matching top 5 executives in Execucomp with utility patent filings from the patent dataverse of Lai, D'Amore, and Fleming (2013) and design patent filings from the Harvard Business School patent database. Panel A compares total firm-year patent filing events by Fama French 17 industry and size terciles. These terciles are created annually using the total revenue of all firms listed that year in Execucomp. Fama French 17 Industry Classifications are from Ken French's website. Panel B compares total firm-year patent filing events by year with the main sample by market cap, market-to-book ratio, r&d/assets, and firm age. Panel C lists the top 15 CEOs by total patent filings between 1996 and 2006. (See Appendix A.1 for further variable definitions).

Panel A: Patent Events by firm size tercile and Fama French 17 Industry

Total Patent Filings: 1,723. Total Firm-Year Patent Events: 1,355

	Firm-year patent events			Totals Across Terciles
Fama French 17 Ind Classification	Low Revenue	Mid Revenue	High Revenue	
1) Food	0	1	2	3
2) Mining and Minerals	0	0	0	0
3) Oil and Petroleum Products	0	0	7	7
4) Textiles, Apparel & Footware	0	0	2	2
5) Consumer Durables	0	11	82	93
6) Chemicals	0	1	4	5
7) Drugs, Soap, Perfumes, Tobacco	0	91	41	132
8) Construction / Construction Matls	3	3	0	6
9) Steel Works, etc	0	1	0	1
10) Fabricated Products	0	0	0	0
11) Machinery and Business Equip	0	177	581	758
12) Automobiles	5	7	2	14
13) Transportation	0	0	0	0
14) Utilities	0	1	0	1
15) Retail Stores	0	5	18	23
16) Banks, Ins Cos, other Financials	0	23	4	27
17) Other	23	60	200	283
	31	381	943	1,355

Panel B: Sample Characteristics By Year

Year	Firm-Year Obs	Market Cap		Market-to-Book Ratio		R&D / Assets		Firm Age	
	Execs	Full Execucomp Sample	Execs	Full Execucomp Sample	Execs	Full Execucomp Sample	Execs	Full Execucomp Sample	Execs
1996	84	102.12	1109.52	0.46	0.57	0.026	0.094	5.3	13.7
1997	110	120.43	2369.78	0.53	0.90	0.029	0.078	5.8	14.6
1998	105	108.90	1232.06	0.49	0.67	0.029	0.093	6.3	12.3
1999	138	143.18	1896.01	0.44	1.03	0.031	0.084	6.6	13.2
2000	149	106.74	1627.85	0.40	0.96	0.037	0.066	7.3	13.2
2001	107	146.38	3626.75	0.39	0.89	0.041	0.074	8.5	13.8
2002	188	131.98	1252.63	0.34	0.56	0.038	0.081	9.8	13.5
2003	140	270.17	1803.54	0.45	0.66	0.035	0.068	10.8	14.1
2004	152	326.29	1722.80	0.49	0.61	0.035	0.070	11.4	12.8
2005	104	339.09	1672.42	0.54	0.81	0.034	0.084	12.1	14.7
2006	81	398.62	1900.64	0.52	0.69	0.033	0.080	12.8	15.8

Panel C: Top CEOs by patent filings 1996-2006

CEO Name	Patent Filings 1996 - 2006	State	Company Name
Steven P. Jobs	125	CA	Apple Inc.
Balu Balakrishnan	63	CA	Power Integrations Inc.
Patrizio Vinciarelli	54	MA	Vicor Corporation
Samuel H. Maslak	31	CA	Acuson Corporation
Paul E. Jacobs, Ph.D.	18	CA	Qualcomm Inc.
Jeffrey P. Bezos	14	WA	Amazom.com Inc.
Sanjay Mehrotra	13	CA	SanDisk Corporation
James H Roberts	11	CA	Granite Construction Inc.
Richard S. Hill	11	CA	Novellus Systems Inc.
Peter J. Kight	9	GA	CheckFree Corporation
J. Don Brock, Ph.D., P.E.	8	TN	Astec Industries Inc.
Robert Greenberg	7	CA	Skechers U.S.A. Inc.
Lawrence Saper	5	NJ	Datascope Corporation
John C.C. Fan	5	MA	Kopin Corporation
Jonah Shacknai	5	AZ	Medicis Pharmaceutical Corporation

Table 3.2
Descriptive Statistics - Main Dataset

This table presents descriptive statistics for general characteristics of firms with patent filings by the top five highest paid executives and all firms in the full Execucomp sample between January 1996 and December 2006. Panel A lists the number of observations and statistical sample characteristics for 1) a primary set of factors affecting innovation, 2) as set of controls for factors affecting asset pricing, 3) other possible factors affecting innovation, and 4) the primary independent variables of interest in the analysis. Observations are given by firm-year. Market cap is given in $1M (See Appendix A.1 for further variable definitions).

Panel A: Executives filing patents

	Full Sample		Executive patent filing firm years (Execpat=1)			
	Median	N	Median	S.D.	25%	75%
Primary Innovation Controls						
R&D / Assets	0.03	35731	0.08	0.10	0.04	0.12
Firm Patent Citation Cnt / R&D Stock	0.90	9486	0.99	160.55	0.08	4.32
Firm Age	8.75	36621	13.67	13.49	9.50	20.50
IAROA	-0.18	62556	-0.44	5.02	-1.22	-0.18
Fraction of Institutional Ownership	0.38	41350	0.72	0.22	0.54	0.85
Count of Institutional Owners	35.00	61362	174	201.84	102	289
TNIC Herfindahl Index	9.66	59969	10.95	21.52	6.77	21.10
Asset Pricing Controls						
Market Cap	166.67	62738	1665.93	26225.14	543.62	5429.19
Market-To-Book Ratio	0.46	59289	0.71	1.87	0.43	1.23
1 Year Momentum	0.05	56018	0.06	0.86	-0.22	0.37
Alternate Innovation Controls						
Capital Intensity	0.04	56110	0.04	0.05	0.02	0.07
Cash	12.91	61835	93.64	1596.34	27.88	310.73
Innovative Industries	1.00	59313	1	0.15	1	1
Motivating Measures						
Gindex	9.00	16610	8	2.44	6	10
Repricing	0.00	16610	0	0.16	0	0
PPS	7.60	12973	9.20	22.65	4.79	16.71
Comp5aa5	0.42	15378	0.53	0.26	0.33	0.71

Table 3.3
Types of Governance and the Effect on Executive Innovation

This table presents regressions of the effect of governance factors on patent filings by executives. Panel A shows logit regressions of the occurrence of at least one calendar-year patent filing by executives (patent event) on the five governance sub-indices of Gompers, Ishii, and Metrick (2003). These five sub-indices are 1) delay, 2) protection, 3) voting, 4) other, and 5) state, and are defined further in Appendix A. Panel B shows negative binomial regressions of the number of patent filings by firm-year (patent count) on the five governance sub-indices. Panel C shows logit regressions of the occurrence of at least one calendar-year patent filing by executives (patent event) on the six components of the "Protection" sub-index of Gompers, Ishii, and Metrick (2003). These six components are 1) compensation plans, 2) director indemnification, 3) director indemnification contracts, 4) director liability, 5) golden parachutes, and 5) severance. Variables are defined in Appendix A.1 (including log adjustments), and are winsorized at the 1% level. "L." indicates one year lagged observations. Year and SIC 2-digit industry fixed effects are included for all regressions, and standard errors are clustered by firm. Number of observations for each period and r-squared are also included.

Panel A: Logit

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
L.GINDEX	-0.0005					
	(-0.01)					
L.DELAY		-0.2424 **				
		(-2.45)				
L.PROTECTION			0.3323 ***			
			(3.12)			
L.VOTING				-0.3944 **		
				(-2.46)		
L.OTHER					0.1036	
					(0.66)	
L.STATE						0.0373
						(0.26)
R&D/ASSETS	1.9974	1.9082	1.5073	1.6754	2.0246	2.0627
	(1.01)	(0.94)	(0.74)	(0.86)	(1.03)	(1.00)
CITES/RDSTK	0.4025 ***	0.3738 ***	0.3756 ***	0.3785 ***	0.4098 ***	0.4036 ***
	(3.51)	(3.27)	(3.20)	(3.27)	(3.57)	(3.49)
FIRM AGE	-0.0527 ***	-0.0529 ***	-0.0679 ***	-0.0532 ***	-0.0546 ***	-0.0533 ***
	(-6.21)	(-6.44)	(-6.87)	(-6.57)	(-6.47)	(-6.16)
IAROA	-0.0153	-0.0159	-0.0220	-0.0154	-0.0164	-0.0151
	(-0.72)	(-0.74)	(-1.07)	(-0.73)	(-0.76)	(-0.71)
INST OWNF	0.1601	0.0546	0.0526	0.1252	0.1314	0.1760
	(0.26)	(0.09)	(0.09)	(0.21)	(0.21)	(0.29)
HERF	0.4017 ***	0.3983 ***	0.4408 ***	0.4253 ***	0.3923 ***	0.3969 ***
	(2.88)	(2.78)	(2.99)	(2.94)	(2.89)	(2.90)
MKTCAP	0.1549	0.1661	0.1258	0.1359	0.1567	0.1566
	(1.24)	(1.33)	(1.01)	(1.13)	(1.25)	(1.25)
MB RATIO	0.1636	0.1799	0.2088	0.1836	0.1621	0.1625
	(0.77)	(0.88)	(1.06)	(0.87)	(0.76)	(0.76)
MOM1YR	-0.0542	-0.0658	-0.0671	-0.0578	-0.0559	-0.0548
	(-0.34)	(-0.42)	(-0.44)	(-0.36)	(-0.35)	(-0.34)
CAPRATIO	0.8652	0.6746	0.9472	0.9403	0.8898	0.7672
	(0.26)	(0.21)	(0.30)	(0.29)	(0.27)	(0.23)
CASH	0.0228	0.0313	0.0190	0.0056	0.0218	0.0255
	(0.25)	(0.34)	(0.21)	(0.06)	(0.24)	(0.27)
INNOVIND	-0.8517	-0.9657	-1.1904	-0.7765	-0.8377	-0.8665
	(-1.05)	(-1.23)	(-1.51)	(-0.91)	(-1.04)	(-1.08)
Year Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1894	1894	1894	1894	1894	1894
Pseudo R^2	0.136	0.146	0.153	0.145	0.137	0.137

*,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

Panel B: Negative Binomial

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 5
L.GINDEX	-0.0049					
	(-0.11)					
L.DELAY		-0.2557 ***				
		(-2.60)				
L.PROTECTION			0.3112 ***			
			(3.46)			
L.VOTING				-0.3644 **		
				(-2.46)		
L.OTHER					0.0789	
					(0.50)	
L.STATE						0.0354
						(0.20)
R&D/ASSETS	1.7489	1.4135	1.3542	1.4204	1.7940	1.8276
	(0.78)	(0.64)	(0.58)	(0.66)	(0.82)	(0.76)
CITES/RDSTK	0.3787 ***	0.3524 ***	0.3435 ***	0.3577 ***	0.3856 ***	0.3823 ***
	(3.80)	(3.96)	(3.82)	(3.81)	(3.96)	(3.68)
FIRM AGE	-0.0527 ***	-0.0531 ***	-0.0672 ***	-0.0530 ***	-0.0544 ***	-0.0537 ***
	(-6.80)	(-7.43)	(-9.09)	(-7.72)	(-7.20)	(-6.54)
IAROA	0.0013	-0.0006	-0.0066	0.0017	0.0004	0.0012
	(0.07)	(-0.03)	(-0.37)	(0.09)	(0.02)	(0.06)
INST OWNF	0.4386	0.3108	0.3759	0.3985	0.4262	0.4547
	(0.81)	(0.57)	(0.70)	(0.74)	(0.78)	(0.85)
HERF	0.3447 ***	0.3495 ***	0.4049 ***	0.3652 ***	0.3370 ***	0.3399 ***
	(2.67)	(2.64)	(2.89)	(2.72)	(2.70)	(2.76)
MKTCAP	0.2377 *	0.2369 *	0.1898	0.2076 *	0.2388 *	0.2398 *
	(1.68)	(1.85)	(1.47)	(1.68)	(1.68)	(1.70)
MB RATIO	-0.0152	0.0294	0.0708	0.0254	-0.0189	-0.0184
	(-0.06)	(0.15)	(0.39)	(0.12)	(-0.08)	(-0.08)
MOM1YR	0.0250	0.0145	-0.0005	0.0112	0.0230	0.0260
	(0.17)	(0.11)	(0.00)	(0.08)	(0.16)	(0.18)
CAPRATIO	2.3923	1.9507	1.6745	2.3625	2.4193	2.3178
	(0.84)	(0.75)	(0.65)	(0.87)	(0.84)	(0.80)
CASH	0.0193	0.0346	0.0148	0.0062	0.0186	0.0224
	(0.20)	(0.38)	(0.16)	(0.07)	(0.20)	(0.23)
INNOVIND	-0.1108	-0.1167	-0.1369	-0.0546	-0.0951	-0.1246
	(-0.25)	(-0.31)	(-0.37)	(-0.16)	(-0.22)	(-0.28)
Year Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2149	2149	2149	2149	2149	2149
Pseudo R^2	0.113	0.121	0.121	0.120	0.113	0.113

*,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

Panel C: Components of Protection - Negative Binomial

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
L.COMPPLAN	0.7848 ***					
	(3.15)					
L.DIRIND		0.7093 **				
		(2.43)				
L.DIRINDC			0.5541 *			
			(1.78)			
L.DIRLIAB				0.9169 ***		
				(2.63)		
L.GOLDPAR					-0.0625	
					(-0.26)	
L.SEVERANCE						0.1266
						(0.34)
R&D/ASSETS	1.5408	1.8668	1.8073	1.4911	1.7835	1.7333
	(0.68)	(0.86)	(0.82)	(0.65)	(0.82)	(0.78)
CITES/RDSTK	0.3485 ***	0.3700 ***	0.3803 ***	0.3620 ***	0.3796 ***	0.3800 ***
	(3.69)	(4.05)	(4.39)	(4.17)	(3.82)	(3.80)
FIRM AGE	-0.0582 ***	-0.0606 ***	-0.0552 ***	-0.0733 ***	-0.0529 ***	-0.0530 ***
	(-8.13)	(-8.76)	(-7.59)	(-7.81)	(-7.29)	(-7.65)
IAROA	0.0045	-0.0054	-0.0020	-0.0058	0.0014	0.0011
	(0.24)	(-0.28)	(-0.11)	(-0.32)	(0.08)	(0.06)
INST OWNF	0.2367	0.5680	0.4700	0.5236	0.4587	0.4417
	(0.44)	(1.06)	(0.87)	(0.98)	(0.83)	(0.81)
HERF	0.3940 ***	0.3817 ***	0.3887 ***	0.3667 ***	0.3444 ***	0.3403 **
	(2.88)	(2.93)	(2.88)	(2.74)	(2.67)	(2.57)
MKTCAP	0.2298 *	0.2195 *	0.2117 *	0.2054	0.2389 *	0.2391 *
	(1.78)	(1.68)	(1.68)	(1.60)	(1.69)	(1.66)
MB RATIO	-0.0305	0.0098	0.0204	0.0269	-0.0254	-0.0227
	(-0.14)	(0.05)	(0.11)	(0.14)	(-0.11)	(-0.10)
MOM1YR	0.0129	0.0130	0.0100	0.0020	0.0243	0.0271
	(0.10)	(0.09)	(0.08)	(0.02)	(0.17)	(0.19)
CAPRATIO	2.3831	1.9398	1.7999	2.2797	2.3855	2.3702
	(0.88)	(0.75)	(0.70)	(0.88)	(0.84)	(0.83)
CASH	0.0157	0.0117	0.0240	0.0054	0.0183	0.0187
	(0.17)	(0.13)	(0.26)	(0.06)	(0.19)	(0.20)
Year Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2152	2152	2152	2152	2152	2152
Pseudo R^2	0.120	0.120	0.115	0.117	0.113	0.113

*,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

Table 3.4
Liability Protection, Entrenchment, and Executive Patenting

This table shows the effect of the liability protection governance factors of Gompers, Ishii, and Metrick (2003) on executive patenting in a variety of static and dynamic models. Panel A regresses executive patenting on an index of liability protection (count of dummy indicators for director indemnification, director indemnification contracts, and director liability), while Panel B regresses executive patenting on the G index (minus these liability protection factors). The dependent variable for the logit and probit models is an indicator variable for the occurrence of a firm-year patent filing by any top five executive, while the dependent variable for the negative binomial, dynamic OLS, and difference GMM models is the total count of firm-year patent filings by top five executives. I use a bandwith of 4 to control for three lags of autocorrelation for the dynamic OLS model, and I control for year fixed effects. For the Arellano Bond (1991) difference GMM model, I use instruments as follows: R&D / assets, total firm-year patent citations / R&D stock, industry average return on assets (IAROA), and the fraction of institutional ownership. Firm age is used as an exclusion instrument. AR(1) and AR(2) are tests for first-order and second-order serial correlation in the first-difference of the residuals (null = no serial correlation). The Hansen test indicates whether the model is over-identified (null = all instruments are valid). The Diff-in-Hansen test is a test of exogeneity (null = instruments used for the equations in levels are exogenous). Variables are defined in Appendix A.1 (including log adjustments), and are winsorized at the 1% level. "L." indicates one year lagged observations. Year and SIC 2-digit industry fixed effects and clustering of standard errors by firm are performed for all of the static models. Number of observations for each period and r-squared are also included. I adjust standard errors to be robust to heteroskedasticity for all models.

Panel A: Liability Protection

	Static Models			Dynamic Models	
Variable	Logit	Probit	Negative Binomial	Dynamic OLS	Difference GMM
L.Liabindex	0.4777 ***	0.2335 ***	0.4669 ***	0.0384 **	0.2618 ***
	(3.17)	(2.84)	(3.60)	(2.28)	(2.71)
L.Execpatct					0.1623 *
					(1.88)
R&D/ASSETS	1.4193	0.9086	0.9695	0.1759	-0.2400
	(0.77)	(0.88)	(0.42)	(0.65)	(-0.53)
CITES/RDSTK	0.4047 ***	0.2130 ***	0.3921 ***	0.0674 ***	0.0032
	(3.47)	(3.14)	(4.21)	(2.64)	(0.34)
FIRM AGE	-0.0637 ***	-0.0324 ***	-0.0644 ***	-0.0063 ***	
	(-6.66)	(-6.55)	(-8.39)	(-6.54)	
IAROA	-0.0266	-0.0150	-0.0149	-0.0025	-0.0023
	(-1.28)	(-1.32)	(-0.80)	(-0.84)	(-1.60)
INST OWNF	0.5120	0.2494	0.7978	0.0356	0.0226
	(0.93)	(0.84)	(1.58)	(0.61)	(0.56)
HERF	0.3696 ***	0.2021 ***	0.3080 ***	0.0323 **	0.0204
	(2.98)	(2.93)	(2.95)	(2.35)	(1.53)
Observations	1959	1959	2219	2219	1631
R^2	0.142	0.139	0.109	0.085	
AR(1) Test					0.000
AR(2) Test					0.212
Hansen Test					0.827
Diff-in-Hansen Test					0.928

*,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

Panel B: Entrenchment

Variable	Static Models: Logit	Static Models: Probit	Static Models: Negative Binomial	Dynamic Models: Dynamic OLS	Dynamic Models: Difference GMM
L.Gindexadj	-0.1027 *	-0.0542 *	-0.1071 *	-0.0187 ***	0.0046
	(-1.71)	(-1.72)	(-1.71)	(-2.86)	(0.33)
L.Execpat					0.1404
					(1.56)
R&D/ASSETS	1.1854	0.7289	0.6636	0.1093	-0.3204
	(0.64)	(0.70)	(0.27)	(0.39)	(-0.76)
CITES/RDSTK	0.3791 ***	0.2016 ***	0.3694 ***	0.0642 ***	0.0077
	(3.16)	(2.91)	(3.29)	(2.62)	(0.78)
FIRM AGE	-0.0431 ***	-0.0230 ***	-0.0432 ***	-0.0047 ***	
	(-6.16)	(-6.21)	(-6.52)	(-6.51)	
IAROA	-0.0161	-0.0108	-0.0019	-0.0021	-0.0012
	(-0.75)	(-0.92)	(-0.10)	(-0.72)	(-0.91)
INST OWNF	0.3472	0.1786	0.5593	0.0422	0.0416
	(0.63)	(0.60)	(1.12)	(0.71)	(1.28)
HERF	0.3278 **	0.1842 ***	0.2601 **	0.0348 **	0.0122
	(2.56)	(2.67)	(2.27)	(2.46)	(1.27)
Observations	1959	1959	2219	2219	1631
R^2	0.129	0.128	0.109	0.088	
AR(1) Test					0.000
AR(2) Test					0.217
Hansen Test					0.735
Diff-in-Hansen Test					0.258

*,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

Table 3.5
Option Repricing and Executive Innovation

This table evaluates causality between executive patenting and firm repricing policy by showing probit regressions of the effect of top five executive patenting on firm repricing and vice versa. The dependent variables / primary independent variables are 1) patent event (dummy variable = 1 for the occurrence of at least one calendar-year patent filing by a top five executive; zero otherwise), repricing firm (dummy variable = 1 for the occurrence of at least one top five executive option repricing between 1996 and 2006; zero otherwise), and repricing event (dummy variable = 1 for the occurrence of at least one option repricing during the year by a top five executive; zero otherwise). Columns 1 and 2 examine the relationship between repricing firms and executive patenting, while columns 3-6 evaluate the lead-lag effects of specific firm-year executive patenting vs. repricing. Variables are defined in Appendix A.1 (including log adjustments), and are winsorized at the 1% level. "F1." indicates one year forward observations, while "F2." indicates two year forward observations. Year and SIC 2-digit industry fixed effects are included for all regressions, and standard errors are clustered by firm. Number of observations for each period and pseudo r-squared are also included.

Panel A: Repricing vs. Innovation

	Repricing Firm vs. Exec Patenting		Repricing Event vs. Exec Patenting			
	Reprice Firm	Execpat	F1.Reprice Event	F1.Execpat	F2.Reprice Event	F2.Execpat
Execpat	0.3529 *		0.6472 ***		0.6847 **	
	(1.77)		(2.86)		(2.50)	
Reprice Firm		0.3532 *				
		(1.83)				
Reprice Event				0.4402		0.3370
				(1.15)		(0.74)
R&D/ASSETS	4.1799 ***	-0.6877	2.0057	0.6509	1.6301	0.4944
	(2.98)	(-0.56)	(1.14)	(0.57)	(0.98)	(0.45)
CITES/RDSTK	0.0184	0.1246 ***	0.0257	0.1004 **	0.0961	0.0896 **
	(0.36)	(2.88)	(0.41)	(2.36)	(1.49)	(2.17)
FIRM AGE	-0.0219 ***	-0.0264 ***	-0.0099	-0.0229 ***	-0.0023	-0.0213 ***
	(-3.77)	(-6.33)	(-0.96)	(-5.56)	(-0.26)	(-4.96)
IAROA	0.0129	-0.0159	0.0136	-0.0034	-0.0476	0.0057
	(0.95)	(-1.34)	(0.47)	(-0.26)	(-1.25)	(0.41)
INST OWNF	1.0060 **	-0.0082	-0.0574	-0.0546	0.6522	-0.3367
	(2.13)	(-0.02)	(-0.09)	(-0.18)	(1.21)	(-1.11)
HERF	-0.2869 ***	0.3056 ***	-0.0259	0.2431 ***	-0.3294	0.2192 ***
	(-2.72)	(3.92)	(-0.15)	(2.96)	(-1.38)	(2.60)
MKTCAP	-0.0536	0.1106	-0.3184 **	0.0864	-0.0843	-0.0394
	(-0.61)	(1.61)	(-2.13)	(1.25)	(-0.54)	(-0.57)
MB RATIO	-0.0384	0.0826	0.3332	0.0895	0.2211	0.1777 *
	(-0.33)	(0.82)	(1.55)	(0.85)	(0.96)	(1.67)
MOM1YR	0.0874	-0.0027	-0.5286 **	0.0707	0.2167	0.0974
	(1.36)	(-0.04)	(-2.40)	(0.94)	(1.24)	(1.24)
CAPRATIO	0.2153	1.2135	3.0283 *	0.4556	2.1964	-0.6747
	(0.11)	(0.75)	(1.69)	(0.27)	(1.14)	(-0.40)
CASH	0.0693	0.0126	0.3380 ***	0.0115	0.0750	0.0692
	(1.03)	(0.25)	(2.65)	(0.23)	(0.76)	(1.35)
Year Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2076	2061	1626	1894	1225	1669
Pseudo R^2	0.249	0.151	0.241	0.120	0.248	0.120

*,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

Table 3.6
Long Term Compensation

This table shows three different regression models of the effect of a high ratio of compensation favorable toward long-term executive tenure on top five executive patent filing. The probit and logit models use the event of a firm-year patent filing as the dependent variable, while the negative binomial model uses the total count of executive firm-year patent filings as the dependent variable. Columns 1-3 show the effect of long term compensation on executive patent filing in firms less than 10 years since going public, while columns 4-6 show the effect of long term compensation on executive patent filing in firms aged over 10 years since going public. Variables are defined in Appendix A.1 (including log adjustments), and are winsorized at the 1% level. "L." indicates one year lagged observations. Year and SIC 2-digit industry fixed effects are included for all regressions, and standard errors are clustered by firm. Number of observations for each period and pseudo r-squared are also included.

Panel A: Three model comparison of long-term compensation on executive patenting

	Age > 10 Years			Age 10 Years or Less		
	(Probit)	(Logit)	(Negative Binomial)	(Probit)	(Logit)	(Negative Binomial)
	Execpat	Execpat	Execpatct	Execpat	Execpat	Execpatct
L.LTCOMP	0.1707 ***	0.3388 ***	0.2942 **	0.0246	0.0319	0.0177
	(2.88)	(2.77)	(2.45)	(0.24)	(0.17)	(0.14)
R&D/ASSETS	3.8224 ***	6.9828 ***	5.6804 ***	1.2605	2.1019	1.7975
	(3.49)	(3.57)	(3.19)	(0.92)	(0.82)	(0.86)
CITES/RDSTK	0.1954 ***	0.3786 ***	0.4017 ***	0.5640 ***	0.9686 ***	0.6363 ***
	(2.98)	(3.11)	(3.47)	(4.43)	(4.24)	(5.15)
IAROA	-0.0157	-0.0262	0.0021	-0.0075	-0.0122	-0.0155
	(-1.23)	(-1.10)	(0.10)	(-0.23)	(-0.21)	(-0.39)
INST OWNC	-0.1989	-0.3763	-0.6235 **	0.2855	0.5414	0.1714
	(-1.06)	(-1.12)	(-2.00)	(0.60)	(0.62)	(0.25)
HERF	0.1083	0.2258 *	0.1082	0.2994 **	0.5061 *	0.3165
	(1.55)	(1.69)	(0.90)	(2.13)	(1.90)	(1.37)
MKTCAP	-0.0248	-0.0514	0.0878	-0.2542	-0.4391	-0.3736
	(-0.22)	(-0.24)	(0.44)	(-1.02)	(-0.98)	(-0.96)
MB RATIO	0.1212	0.2296	0.2813	0.3431 *	0.5595 *	0.5307
	(1.19)	(1.18)	(1.47)	(1.89)	(1.71)	(1.48)
MOM1YR	0.0448	0.0719	0.0068	-0.1021	-0.1752	-0.0191
	(0.50)	(0.43)	(0.04)	(-0.72)	(-0.66)	(-0.10)
CAPRATIO	1.4966	3.0447	3.9829	-2.3074	-3.6250	-2.2584
	(0.87)	(0.90)	(1.37)	(-1.07)	(-0.93)	(-0.62)
CASH	0.0286	0.0582	0.0627	0.1147	0.1941	0.2448 **
	(0.60)	(0.60)	(0.67)	(1.43)	(1.40)	(1.97)
Year Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2503	2503	2869	337	337	381
Pseudo R^2	0.103	0.103	0.060	0.108	0.105	0.185

*,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

Table 3.7
Option Structure, Pay Performance Sensitity, and Executive Innovation

This table shows logit and negative binomial regressions of the effect of the delta, vega, and pay performance sensitivity measures of Core and Guay (2002) on patent filing by executives. The logit model uses the event of a firm-year patent filing as the dependent variable, while the negative binomial model uses the total count of executive firm-year patent filings as the dependent variable. Variables are defined in Appendix A.1 (including log adjustments), and are winsorized at the 1% level. "L." indicates one year lagged observations. Year and SIC 2-digit industry fixed effects are included for all regressions, and standard errors are clustered by firm. Number of observations for each period and pseudo r-squared are also included.

Panel A: Comparison of Delta, Vega, Pay Performance Sensitivity

	Delta		Vega		PPS	
	Logit	Negative Binomial	Logit	Negative Binomial	Logit	Negative Binomial
	Execpat	Execpatct	Execpat`	Execpatct	Execpat	Execpatct
L.Delta	0.3691 ***	0.6614 ***				
	(2.81)	(4.14)				
L.Vega			0.1306 *	0.3806 ***		
			(1.71)	(4.04)		
L.PPS					0.1995 **	0.4031 ***
					(2.10)	(3.44)
R&D/ASSETS	0.4195	1.8373	0.7181	1.4400	0.5892	2.0820
	(0.36)	(1.24)	(0.61)	(0.76)	(0.51)	(1.32)
CITES/RDSTK[a]	0.2380 ***	0.4558 ***	0.2368 ***	0.2431 ***	0.2746 ***	0.5412 ***
	(2.62)	(4.61)	(2.61)	(4.18)	(2.88)	(5.88)
FIRM AGE	-0.0475 ***	-0.0468 ***	-0.0523 ***	-0.0510 ***	-0.0512 ***	-0.0476 ***
	(-5.63)	(-6.39)	(-6.11)	(-8.01)	(-6.13)	(-6.57)
IAROA	-0.0467 **	-0.0238	-0.0450 **	-0.0323 **	-0.0477 **	-0.0205
	(-2.35)	(-1.37)	(-2.25)	(-1.96)	(-2.46)	(-1.28)
INST OWNC	-1.1064 ***	-0.6043	-1.1002 ***	-0.6955 *	-0.8773 ***	-0.4433
	(-3.93)	(-1.47)	(-3.84)	(-1.85)	(-3.15)	(-1.24)
HERF	0.1186	0.3218 ***	0.0944	0.3468 ***	0.1249	0.2533 **
	(1.01)	(2.87)	(0.82)	(3.14)	(1.11)	(2.34)
MKTCAP	0.3742 **	0.5526 **	0.2425	0.2367	0.2384	0.3414
	(2.23)	(2.42)	(1.48)	(1.06)	(1.51)	(1.50)
MB RATIO	0.2920 **	-0.1355	0.3509 **	-0.0625	0.3391 **	-0.0388
	(2.02)	(-0.66)	(2.46)	(-0.31)	(2.41)	(-0.19)
MOM1YR	0.0553	-0.1188	0.1205	0.0271	0.0886	-0.0743
	(0.67)	(-0.97)	(1.42)	(0.23)	(1.10)	(-0.67)
CAPRATIO	0.5678	1.1420	0.3529	2.1564	0.7506	2.3029
	(0.32)	(0.53)	(0.20)	(0.96)	(0.45)	(1.04)
CASH	-0.0348	0.0540	-0.0230	0.0265	-0.0348	0.0876
	(-0.55)	(0.75)	(-0.37)	(0.37)	(-0.55)	(1.23)
INNOVIND	-1.3676 ***	0.3908	-1.3961 ***	-0.2160	-1.5345 ***	-0.1153
	(-2.58)	(0.75)	(-2.70)	(-0.50)	(-3.20)	(-0.32)
Year Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2840	2495	2840	2567	3149	2738
Pseudo R^2	0.229	0.140	0.223	0.126	0.228	0.136

*,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

[a] - Cites/R&D stock except for column 4, which uses cites alone to allow convergence.

Table 3.8
Executive Innovation and Firm Risk

This table shows regressions of the effect of the occurrence of at least one calendar-year patent filing by executives on one-year forward firm returns. Each panel shows effects for all firm ages, firms aged ten or less years since going public, and firms over ten years since going public. Panel A columns 1-3 show fixed effect panel regressions of firm returns net of value weighted market returns on firm-year executive patent events . Panel A columns 4-6 show difference-in-difference regressions of returns net of value weighted market returns on firm-year executive patent events, in a 3-to-1 matched sample of firms located in the nearest quintile of size, market-to-book, and one-year momentum, respectively. Panel B adds additional controls and shows fixed effect panel regressions of firm returns net of value weighted market returns (columns 1-3) or equal weighted market returns (columns 4-6) on firm-year executive patent events. Variables are defined in Appendix A.1 (including log adjustments), and are winsorized at the 1% level. "F." indicates one year forward observations. Year and SIC 2-digit industry fixed effects are included for all regressions, while standard errors are clustered by firm. Number of observations for each period and r-squared are also included.

Panel A: Model Comparisons - Full Sample Vs. Matched Sample

	Full Sample			Matched Sample		
		Firm Age <= 10	Firm Age > 10		Firm Age <= 10	Firm Age > 10
	F.Ret1yrV	F.Ret1yrV	F.Ret1yrV	F.Ret1yrV	F.Ret1yrV	F.Ret1yrV
R&D/ASSETS	0.4193 ***	0.4990 ***	0.3572 ***	0.5310 ***	0.6276 *	0.4018 *
	(4.23)	(3.54)	(2.78)	(2.81)	(1.82)	(1.80)
IAROA	0.0019	0.0007	0.0027	0.0000	0.0041	-0.0013
	(1.24)	(0.21)	(1.61)	(0.03)	(0.68)	(-0.50)
INST OWNC	-0.0642 ***	-0.0969 ***	-0.0588 ***	-0.0600 ***	-0.0924 ***	-0.0454 ***
	(-5.01)	(-3.79)	(-3.81)	(-4.58)	(-2.59)	(-3.23)
INNOVIND	-0.0280	-0.0626	-0.0313	0.0271	0.0925	0.0251
	(-1.35)	(-1.47)	(-1.30)	(0.62)	(1.14)	(0.46)
MKTCAP	-0.3384 ***	-0.4664 ***	-0.3175 ***			
	(-30.75)	(-21.78)	(-23.72)			
MB RATIO	-0.0115	0.0039	-0.0179			
	(-1.26)	(0.23)	(-1.59)			
MOM1YR	0.0150 **	0.0531 ***	-0.0042			
	(2.36)	(4.74)	(-0.53)			
POSTEVENT				-0.0845 ***	-0.0859	-0.0840 ***
				(-3.95)	(-1.63)	(-3.81)
TREATMENT				-0.0346	-0.0777	-0.0085
				(-1.05)	(-1.07)	(-0.23)
INTERACTION				0.0765 **	0.1266 *	0.0587
				(2.18)	(1.69)	(1.51)
EXECPAT	0.0369 **	0.0978 ***	0.0381 *			
	(2.31)	(3.19)	(1.86)			
Year Fixed	Yes	Yes	Yes	N/A	N/A	N/A
Industry Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Observations	35289	11071	24218	3609	1015	2594
Pseudo R^2	0.016	0.025	0.013	0.034	0.046	0.036

*,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

Panel B: Model Comparisons - Value Weighted Returns Vs. Equal Weighted Returns

	Returns - Net of Value Weighted Market Returns			Returns - Net of Equal Weighted Market Returns		
		Firm Age <= 10	Firm Age > 10		Firm Age <= 10	Firm Age > 10
	F.Ret1yrV	F.Ret1yrV	F.Ret1yrV	F.Ret1yrE	F.Ret1yrE	F.Ret1yrE
EXECPAT	0.1072 ***	0.2912 ***	0.0573	0.1044 ***	0.2812 ***	0.0532
	(3.61)	(5.15)	(1.61)	(3.71)	(5.18)	(1.61)
R&D/ASSETS	0.5165 **	0.5760 **	0.5442 *	0.4783 **	0.5164 **	0.5282 *
	(2.56)	(2.23)	(1.90)	(2.50)	(2.13)	(1.95)
CITES/RDSTK	0.0326 **	-0.0167	0.0427 ***	0.0303 **	-0.0201	0.0416 ***
	(2.56)	(-0.53)	(3.22)	(2.53)	(-0.68)	(3.34)
IAROA	-0.0001	-0.0062	0.0028	-0.0002	-0.0046	0.0017
	(-0.02)	(-0.97)	(1.01)	(-0.09)	(-0.78)	(0.66)
INST OWNC	-0.1096 ***	-0.2230 ***	-0.0375	-0.1214 ***	-0.2266 ***	-0.0516
	(-2.83)	(-3.35)	(-0.80)	(-3.26)	(-3.54)	(-1.14)
HERF	-0.0002	0.0226	-0.0033	-0.0031	0.0185	-0.0054
	(-0.01)	(0.46)	(-0.16)	(-0.16)	(0.39)	(-0.28)
MKTCAP	-0.4830 ***	-0.5812 ***	-0.4598 ***	-0.4544 ***	-0.5501 ***	-0.4329 ***
	(-16.68)	(-10.96)	(-13.09)	(-16.55)	(-10.89)	(-12.96)
MB RATIO	0.0009	0.0559	-0.0290	0.0112	0.0606	-0.0168
	(0.04)	(1.31)	(-1.23)	(0.55)	(1.50)	(-0.74)
MOM1YR	0.0450 ***	0.0863 ***	0.0092	0.0500 ***	0.0828 ***	0.0191
	(2.78)	(3.34)	(0.43)	(3.22)	(3.35)	(0.94)
CAPRATIO	0.1584	0.2438	-0.1099	0.1356	0.2113	-0.1565
	(0.55)	(0.51)	(-0.31)	(0.49)	(0.45)	(-0.47)
CASH	0.0078	0.0371 *	0.0035	0.0072	0.0320	0.0047
	(0.82)	(1.74)	(0.33)	(0.80)	(1.56)	(0.48)
INNOVIND	0.0588	0.1523	-0.0732	0.0528	0.1276	-0.0708
	(0.62)	(1.03)	(-0.55)	(0.59)	(0.90)	(-0.57)
Year Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7981	2623	5358	7981	2623	5358
Pseudo R^2	0.024	0.042	0.019	0.018	0.035	0.012

*,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

Appendix Table 3.A.1: Variable definitions

Variables	Definition (*Data sources*)
Innovation Classifications	
Exec Pat (1/0)	Binary variable equal to 1 for firms recording at least one patent filed by a top executive (as indicated by Execucomp) during the year, zero otherwise. *(Source: Execucomp; NBER Patent Data file of Hall, Jaffe, and Trajtenberg (2001); Sampat (2011) Harvard patent file; Lai, D'Amore, and Fleming (2013) patent dataverse; Kogan, Papanikolaou, Seru, and Stoffman (2012) patent data).*
Exec Pat Ct	Count variable of the number of patents filed by the all top executives (as recorded by Execucomp) for a firm during the year, zero otherwise. *(Source: Execucomp; NBER Patent Data file of Hall, Jaffe, and Trajtenberg (2001); Sampat (2011) Harvard patent file; Lai, D'Amore, and Fleming (2013) patent dataverse; Kogan, Papanikolaou, Seru, and Stoffman (2012) patent data).*
Governance Classifications	
G Index (0-24)	"Governance" index of Gompers, Ishii, and Metrick (2003) composed of the incidences of 24 governance rules. A higher score indicates a reduction in shareholder strength.
G Index Adj (0-21)	"Governance" index of Gompers, Ishii, and Metrick (2003) composed of the incidences of 24 governance rules, minus the three protection subindex provisions of Dirind, Dirindc, and Dirliab.
Liab Index (0-3)	Index of the three Gompers, Ishii, and Metrick (2003) governance protection subindex provisions of Dirind, Dirindc, and Dirliab.
E Index (0-6)	"Entrenchment" index of Bebchuk, Cohen, and Ferrell (2009) composed of 6 provisions of the G index that the authors find can lead to entrechment of management and a reduction in firm value.
O Index (0-18)	"Other" index of Bebchuk, Cohen, and Ferrell (2009) composed of the remaining 18 provisions of the G index that the authors find do not have a significant impact on firm value.
Delay (0-4)	Subindex constructed by Gompers, Ishii, and Metrick (2003) of 4 provisions of the G Index used as tactics for delaying hostile bidders.
Protection (0-6)	Subindex constructed by Gompers, Ishii, and Metrick (2003) of 6 provisions of the G Index used to provide officers and directors compensation after a termination, or to protect them against job related liability.
Voting (-2-4)	Subindex constructed by Gompers, Ishii, and Metrick (2003) of 6 provisions of the G Index used to establish shareholder voting rights in elections or charter/bylaw amendments. Two provisions (secret ballot and cumulative vote) are negative if they occur.
Other (0-6)	Subindex constructed by Gompers, Ishii, and Metrick (2003) of 6 provisions of the G Index composed of other miscellaneous takeover defenses.
State (0-6)	Subindex constructed by Gompers, Ishii, and Metrick (2003) of 6 provisions of the G Index regarding state laws.
Compplan (1/0)	Provision of the Protection subindex of the G index that provides a compensation plan to participants to accelerate bonus payments or cash out options in the event of a change in control.
Dirind (1/0)	Provision of the Protection subindex of the G index that indicates whether a firm has a clause in their bylaws, charter, or both that indemnifies officers and directors from certain legal expenses/judgments incurred from lawsuits pertaining to their conduct.
Dirindc (1/0)	Provision of the Protection subindex of the G index that indicates whether a firm has specific contracts indemnifying individual officers and directors from certain legal expenses/judgments incurred from lawsuits pertaining to their conduct.
Dirliab (1/0)	Provision of the Protection subindex of the G index that indicates whether a firm has charter amendments to limit officer and director personal liability (to the extent provided by state incorporation laws) for breaches of the duty of care.
Goldpar (1/0)	Provision of the Protection subindex of the G index that provides compensation to top executives when a termination occurs not due to a change in control following a takeover.
Severance (1/0)	Provision of the Protection subindex of the G index that provides cash and non-cash compensation to top executives when a termination occurs due to the event of a change in control following a takeover.

Long Term Compensation and Pay Performance Sensitivity Measures

LT Comp	Long Term Compensation Ratio. [(Black-Scholes value of option awards) + (Restricted stock) + (Long term incentive compensation)] / (salary + bonus + other annual + restricted stock grants + LTIP payouts + all other + value of option grants). I take the log transformation (log(x/1-x)) for the regressions. *(Source: Execucomp).*
PPS	Pay performance sensitivity. Sensitivity of an individual's firm stock and option portfolio to a change in the price of the firm stock. I take log(1+x) for the regressions. *(Source: Core and Guay (2002), Clementi and Cooley (2010)).*
Delta	Sensitivity of an individual's firm option portfolio only to a change in the price of the firm stock. I take log(1+x) for the regressions. *(Source: Core and Guay (2002), Clementi and Cooley (2010))*
Vega	Sensitivity of an individual's firm option portfolio only to a change in the volatility of the firm stock. I take log(1+x) for the regressions. *(Source: Core and Guay (2002), Clementi and Cooley (2010))*

Firm Characteristics

Mktcap	Market capitalization of the firm. I take log(x) for the regressions. *(Source: CRSP)*
M/B Ratio	Market value / Book value of a firm. I take log(x) for the regressions. *(Source : Compustat)*
Mom1yr	Rank of the prior 12-month return of a firm against the prior 12-month return of NYSE, Nasdaq, and AMEX firms. *(Source: Jegadeesh and Titman (1993), CRSP)*
Capratio	Capital Expenditure Ratio, which equals (capital expenditure / total assets). I take log(1+x) for the regressions. *(Source: Compustat)*
Cites / R&D Stock	Total executive patent citations / R&D stock. The ratio of all adjusted future patent citations by top five executive firm-year patent filings divided by the stock of R&D for the current and prior 4 years (R&D stock straight line depreciated at 15% per year by the perpetual inventory method). Patent citations are adjusted using the adjustment factor of Hall, Jaffe, and Trajtenberg (2001)). I take log(1+x) for the regressions. *(Source: Compustat, Hall, Jaffe, and Trajtenberg (2001), Lai, D'Amore, and Fleming (2013) patent dataverse, Sampat (2011) Harvard patent file).*
IAROA	Industry Adjusted Return on Assets=annual firm market return / total assets. *(Source: Wintocki, Linck, and Netter (2012), CRSP, Compustat)*
Revenue	Sales revenue of the firm (in $M). I take log(x) for the regressions. *(Source: Compustat)*
Cash	Total cash of the firm (in $M). I take log(x) for the regressions. *(Source: Compustat)*
R&D / Assets	R&D / Assets. The ratio of annual research and development expenses to assets. Similar to Hirshleifer, Low, and Teoh (2012), if R&D is missing for a year, I record the value of R&D spending as zero. However, I add the additional filter that a firm must have recorded at least one R&D expense between 1996-2006, or R&D is left as missing. I take log(1+x) for the regressions. *(Source: Compustat)*
Ret1yrE	One-year firm returns net of equal-weighted market returns. *(Source: CRSP)*
Ret1yrV	One-year firm returns net of value-weighted market returns. *(Source: CRSP)*
Firm Age	Number of years since the IPO date of the firm. *(Source: SDC Platinum)*
Inst Own C	Total number of institutional owners of a stock. I take log(x) for the regressions. *(Source: Thomson Reuters)*
Inst Own F	Fraction of institutional owners / total owners of a firm's stock, as per Aghion, Van Reenen, and Zingales (2009), Becker-Blease (2011), and Hirshleifer, Low, and Teoh (2012). *(Source: Thomson Reuters)*
Herf	Herfindahl index measure of the size of the firm in relation to its industry using the Hoberg and Phillips (2010) fixed industry Herfindahl index measure, calculated from 1996-2008 data. I use the 400 industry series. I take log(x) for the regressions. *(Source: Hoberg and Phillips Data Library)*.

Difference-in-Difference - Executive Patent Filing Events and Firm Returns

Postevent (1/0)	Indicator variable equal to 1 in the year after an executive files a patent, 0 in the year before an executive files a patent (Note: This excludes the patent filing event year).
Treatment (1/0)	Indicator variable equal to 1 for firms experiencing an executive patent filing event, 0 for firms not experiencing an executive patent filing event (Source: Execucomp and Lai,D'Amore, and Fleming (2013) patent dataverse).

Miscellaneous

Reprice Firm (1/0)	Binary variable equal to 1 for firms recording at least one option repricing event anytime between 1992 and 2012, zero otherwise. *(Source: Execucomp)*
Reprice Event (1/0)	Annual binary variable equal to 1 for each year a firm records at least one option repricing event between 1992 and 2012, zero otherwise. *(Source: Execucomp)*

CHAPTER 4

ORGANIZATION CAPITAL AND FIRM RISK – TESTING THE OUTSIDE OPTION

4.1 Introduction

"The rate of return on education, training, migration, health, and other human capital is supposed to be higher than on nonhuman capital, however, because of financing difficulties and inadequate knowledge of opportunities…Economists have long emphasized that it is difficult to borrow funds to invest in human capital because such capital cannot be offered as collateral, and courts have frowned on contracts that even indirectly suggest involuntary servitude."

Gary S. Becker
"Human Capital". Second Edition 1975.

Intangible capital is a valuable asset to firms, but is also often considered one of the most risky for shareholders, especially when held by the firm's employees. Employee costs and training are significant expenses for a firm, as SG&A costs alone represent over ¼ of firm sales[44]. While some intangible assets (such as brand names, etc.) can be safely held by the firm, much of it is possessed by the employees themselves, who can simply leave the firm at any time and go to another firm, taking valuable intellectual property and training with them, and potentially even damaging the firm with it if they go to a competitor. In fact, Becker (1964) summarizes a belief among economists for a strong tendency for skilled individuals possessing significant firm training to leave and go to a competitor. Indeed, in his model, the training firm can never win in a bidding war with a competitor, since the competitor can easily outbid the

[44] 26.4% of sales for a sample of 7,629 firms over a 20-year period in Anderson, Banker, and Janakiraman (2003).

training firm for the skilled employee, since the competitor will not have to outlay any funds to train the already well-trained individual.

It is within this context that Eisfeldt and Papanikolaou (2013) develop a proxy for organization capital (based on selling, general, and administrative stock over total assets) which they describe as intangible capital embodied in the firm's key employees. Organization capital, as introduced by Prescott Vischer (1980), is defined as the accumulation of information as an asset of the firm, and is produced simultaneously with the primary outputs of the firm. Eisfeldt et al. find that firms with higher organization capital earn 4.6% higher returns than firms with lower levels, and attribute this higher return to shareholders as compensation for the increase in the risk of organization capital loss – specifically, that key firm talent might exercise their "outside option" to exit the firm and take significant organization capital with them. They develop a theoretical model in which firm risk should increase with this increased risk of organization capital loss, and provide indirect support for the effect of labor flows on firm risk via suggestions in 10-K filings and managerial surveys that the loss of key employees is a significant risk factor to the firm.

However, they do not provide a direct connection between organization capital and its effect on the actual labor flows of key firm employees in two important ways. First, they do not provide any specific evidence that key talent actually exercises this outside option and leaves the firm under certain conditions. Second, they do not provide a direct link to factors (legal or compensatory) that might actually affect the probability that key talent will exercise this outside option.

This is important, because other research suggests their proxy for firm risk may represent other risk factors for the firm. First, Lev and Thiagarajan (1993) find support for the traditional fundamental analysis assertion that an increase in the ratio of SG&A costs to sales is interpreted as a negative signal about future firm profitability due to management issues, not the threat of employee loss. An increase in SG&A represents the inability or unwillingness of management to control costs. Although this could be caused by a wide range of factors, they suggest that this could represent an agency cost, due to the fact that most efforts to reduce SG&A would require wage reductions or employee terminations, which is a difficult decision for a manager to make. Avoiding such activity might maximize the manager's efforts to maintain personal relationships and status within the firm, but would act against the shareholders' best interests (Jensen and Meckling 1976). Second, and supporting this agency cost hypothesis (as opposed to the outside option threat of Eisfeldt Papanikolaou (2013)), a seminal paper by Anderson, Banker, and Janakiraman (2003) find that selling, general, and administrative costs are "sticky" – in other words, they find that SG&A costs rise .55% per $1 increase in sales, but only decrease 0.35% per $1 decrease in sales. Thus, in the event of a downturn in performance for the firm, the industry, or the overall market, a firm with a high proportion of SG&A expenses may have less management willingness or ability to reduce costs and avoid bankruptcy in extreme conditions. However, Anderson et. al (2003) also suggest that management may simply want to hold on to committed firm resources until it is better established that the decline in demand is more permanent. Anderson, Banker, Huang, and Janakiraman (2007) build on this third idea, suggesting that managers utilize their specific knowledge of the organization capital in a firm during market downturns to rationally determine whether or not to retain key employees. Management may maintain high levels of SG&A in the expectation that earnings will increase in the future, and that the SG&A resources retained will assist the firm in maximizing those future earnings. Indeed, Anderson et al (2007) find that portfolios long on firms with high SG&A

ratios (and short on low SG&A ratio firms) earn higher returns, if formed during a period of revenue decline. Instead of being a risk factor, they attribute these higher returns to management savvy and foresight. Fourth, recent research by Novy-Marx (2013) suggests that the level of SG&A costs may not pose a risk factor at all, and it may simply mask as a risk factor by correlating closely with overall gross firm profitability, which is the real source of the return premium normally associated with SG&A. Indeed, it is even possible that firms with high organization capital may be better equipped to retain key employees, which would suggest that the threat of loss of key talent is lower in these firms and should reduce their firm risk. Thus, any risk increase created by high SG&A should be coming from a source other than the outside option threat.

However, none of these alternate models consider the choices surrounding the key talented individuals employed at the firm, and their individual motivations to either stay with the firm or take their valuable organization capital and leave. These alternate models generally consider the risks from SG&A as stemming from management decisions, either to cut wages or reduce employment. In contrast, Eisfeldt and Papanikolaou (2013) support the idea of SG&A as an individual choice risk factor, and develop a theoretical model in which firm risk should increase with this increased risk of organization capital loss due to the choice of key individuals to exercise their outside option and leave, but they only provide indirect empirical evidence to support this theory.

In general, the plan for this paper can be summarized as follows. I seek to show evidence that the outside option increases firm risk by evaluating four key areas:

1) I first look at actual labor movements in a raw sample of inventor switches. Eisfeldt and Papanikolaou (2013) only provided indirect evidence that the outside option

affected labor movement and firm risk. By following the movements of over 22,000 inventors, I am able to provide direct evidence supporting their claim.

2) I next consider the interaction of these labor movements with organization capital. If higher levels of organization capital create higher firm risk due to a greater risk from the outside option, then one would expect higher flows of inventors out of the firm when organization capital was higher. In addition, one would expect higher overall turnover for inventors in firms with higher organization capital, as the cost of retraining job-hopping workers is also an outside option risk factor. I find evidence supporting both of these cases.

3) I then ensure that the results are not being driven simply by executive compensation levels or the legal pressures on labor movement, but that they are actually robust to these effects. I find that after controlling for these factors, organization capital remains a risk factor, indicating that organization capital is a risk factor due to voluntary labor moves, wage pressures at the non-executive level, or other factors.

4) I finally perform a series of robustness tests using instrumental variables, headquarter moves, and an exogenous switch in non-compete laws to confirm the preceding results.

Specifically, I make several contributions in this paper. Overall I contribute to the debate over the risk contribution of SG&A by actually measuring the flow of key talent between firms using one of the primary databases used for measuring skilled employee movement between firms – inventor firm switches based on changes in publicly traded patenting firm from patent filings between 1976-2006 as in Lai, D'Amore, and Fleming (2011). For the inventor patent filings, I apply additional filters and ultimately evaluate the movement of 22,021 inventors between publicly traded firms spanning from 1976-2006, from a total of 1.41M publicly traded firm utility patent filings by roughly 432,088 inventors. The contributions I make are as follows.

First, I determine whether organization capital has an impact on whether inventors choose to switch in or out of a firm by examining individual firm switches. I find that as organization capital increases, there is an increase in the likelihood that key talent will move away from a firm. This supports the idea that high organization capital can increase firm risk not only by the fact that there is more intangible value at stake for that firm, but also because key talent is more likely to leave a high organization capital company.

Second, I examine cumulative firm inventor switches, by studying the net flow of inventors in and out of a firm, and the overall turnover rate of firm inventors. I use the patent filings database to develop these two proxies for labor movement between firms as follows: 1) I measure the direct labor flow of key talent between firms by calculating the net inflow/outflow of inventors who have patented in a firm, and 2) I use a proxy for inventor velocity (turnover) similar to Marx, Strumsky, and Fleming (2009) which looks at the total number of inventors who have either joined or left a firm. As in the case of individual firm switches, I find that high organization capital firms experience a net outflow of firm inventors, supporting the idea that high organization capital increases firm risk as a result of the outside option. In addition, I find that high organization capital increases firm velocity, which supports the idea that high organization capital increases firm risk by placing these firms in a class of companies that experience high skilled labor turnover.

Third, I verify the findings of Eisfeldt Papanikolaou (2013) and find that firms with higher organization capital face increased risk as proxied by 1-year firm returns. I find that labor velocity (which previously was shown to have a positive relationship with organization capital) has a strong positive impact on future 1-year abnormal returns.

Fourth, I investigate the outside factors (compensatory and legal) affecting the strength of the outside option for skilled employees. Compensation is considered the strongest voluntary motivation tying an employee to a firm, and I specifically evaluate the ratio of total compensation to binding forms of compensation designed to retain key employees by "binding" them to a firm. While these long-term binding compensation measures reduce firm risk, they also appear to increase velocity when interacted with organization capital. I also look at the legal environment affecting skilled labor mobility by examining the effect of state non-compete laws on inventor flow and velocity using an index of non-compete law strength from Garmaise (2011). I find modest support that both of these measures increase firm risk, but neither of them has as strong an effect as organization capital.

Fifth, I further test the effect of the legal environment on organization capital using an exogenous change in non-compete laws in Michigan. In 1985, Michigan effectively repealed an unenforced non-compete law statute, creating ambiguity in the use of non-compete agreements, which had been effectively banned "as a matter of public policy" since 1905. In 1987 the MARA amendment to the 1985 repeal cleared the confusion by confirming that non-compete agreements could be used. Marx, Strumsky, and Fleming (2009) find that overall labor velocity of inventors was reduced after this change due to the added friction on labor movement from the law change. I find that this exogenous shock reduced firm risk for companies with high organization capital as well.

Sixth, I use 1) changes in selling, general, and administrative expenses, 2) changes in staff expenses, and 3) changes in total employment between 1994 and 2012 to determine the effect of wage and hiring pressure coming from the industry immediately outside of the firm as an exogenous test to determine the impact of the outside option for key firm talent on firm risk. I develop three instrumental variables to proxy for the level of current pressure from the outside by 1) dividing the ratio of the firm's SG&A/total assets by the average SGA/total assets of the SIC 2-digit industry of the firm, 2) dividing the ratio of the firm's staff expenses/total assets by the average staff expenses/total assets of the SIC 2-digit industry of the firm, and 3) dividing the ratio of the firm's employees/total assets by the average employees/total assets of the SIC 2-digit industry of the firm,. It is important to note that executive compensation data is more plentiful and varied than this dataset; however, the limited sample of key talent as represented by the top five executives may not accurately represent the effect of the entire population of key talent within a firm. So these broad measures of firm wages and employment likely capture the true level of the outside option for a company. I find that these proxies for the outside option significantly increase firm returns.

Seventh, I test the effect of firm headquarter moves between states with different levels of non-compete laws based on the Garmaise (2011) index. I find support for the hypothesis that high organization capital firms can reduce firm risk when moving to states with stronger non-compete laws.

The rest of the paper is organized as follows. Section 4.2 presents the hypotheses and their development. Section 4.3 describes the data and the measures used in the analysis. Section 4.4 provides the results and robustness checks to test the hypotheses, while section 4.5 concludes. Section 4.6 Appendix A includes relevant tables and figures.

4.2 Hypotheses Development

B. Main hypotheses

Eisfeldt Papanikolaou (2013) introduce the theory that firms with high levels of organizational capital (as proxied by selling, general, and administrative stock / total assets) should earn higher returns as compensation for the loss of skilled employees. However, alternate theories suggest that returns in higher SG&A firms is due to management inability or unwillingness to reduce wage costs or terminate employees in the event of a firm, industry, or market downturn. So to back up their theory, Eisfeldt et al show indirect empirical support for the idea that organization capital increases firm risk, but do not show any direct support. I directly test the effect of organization capital on the movement of skilled labor into and out of firms using the inventor database of Hall, Jaffe, Trajtenberg (2001).

While it seems obvious that firms with high organization capital would face higher firm risk due to the sheer level of their organization capital, it is also possible that these firms are better able to counter the threat of skilled employee loss, which would indicate that higher organization capital actually reduces firm risk (and that the risk increase noticed by Eisfeldt Papanikolaou (2013) is arising from another factor affecting SG&A). However, I hypothesize that these high organization capital firms are not able to retain these key employees due to the higher level of training that is taking place (as suggested by Eisfeldt et al). This supports the idea in Becker (1964) that firms which train employees face a higher risk that these employees will leave. Thus, my first hypothesis is as follows:

H1: Firms with high levels of organization capital should experience a net outflow of skilled employees.

Although there might be a higher net outflow of skilled labor from high organization capital firms, it is also likely that the fact that the firm spends a copious amount on SG&A should allow the firm to also heavily recruit key talent from other firms. So in some cases where there is no net outflow of key talent, there still may be heavy turnover (called "velocity" in much of the labor economics literature) in key skilled employees of the firm. So I hypothesize the following:

> H2: Firms with high levels of organization capital should experience a higher velocity of skilled employee movement in and out of the firm.

If firms with high organization capital truly cannot retain their key employees, then high organization capital firms should face higher firm risk via higher cumulative abnormal firm returns. While Eisfeldt Papanikolaou (2013) find this result for high and low portfolios of firms formed by their level of organization capital, I seek to verify this for my sample using the entire range of organization capital. Thus I hypothesize:

> H3A: Firms with high levels of organization capital should earn a higher return as compensation for the risk of the loss of skilled employees.

However, while the prior hypothesis seeks to verify the results of Eisfeldt et al, it still does not prove that this risk increase is coming from the outside option threat. So next I test this versus actual inventor labor moves. If firms experience a net outflow of inventors, then it seems likely that the outside option is strong for that particular firm, and that the continued outflow of key talent, along with the valuable organization capital they possess, should continue to flow out of the firm. Thus it is likely that investors will see organization capital loss as a higher risk for this particular firm, especially if this firm is a high organization capital firm to begin with. So I hypothesize the following:

H3B: High organization capital firms with net outward skilled labor flow should earn higher returns as compensation for the increased outside option risk.

It is also likely that, while high organization capital firms face the higher risk of skilled employee loss, this outflow may be masked by the fact that these firms also hire a large amount of skilled labor. While this may seem to cancel the risk, prior research suggests that the hiring firm will still have to spend a moderate amount to retrain the employee on the firm's specific processes (Becker 1964).

A recent court case hints at this problem, as a class action lawsuit has been filed against anti-poaching agreements in California between 2005 and 2009. The court documents allege that Steve Jobs masterminded a scheme to limit labor movement between technology giants such as Apple and Google. Prior research has indicated that California is a unique labor environment, partly owing to its complete ban on non-compete agreements. The environment pertaining to Silicon Valley has been referred to as a "high-velocity" labor market, due to the tendency of key talent to switch from firm-to-firm in order to advance their careers.

With this said, it is important to note that some attribute this movement to the success of Silicon Valley, as new ideas are introduced to a firm, leading to beneficial advances in firm knowledge and potential. It also seems reasonable that if a firm loses five skilled employees, but gains five skilled employees, that the firm is no better or worse off. However, the wide scope of these anti-poaching allegations, along with prior research suggesting the need to at least partially retrain skilled workers coming from other firms, suggests that labor velocity is a firm risk. Thus I hypothesize:

H3C: High organization capital firms with higher overall skilled labor velocity should earn higher returns as compensation for the increased outside option risk.

It is possible that other factors endogenous to firms with high organization capital may be driving the increase in firm risk, or may interact with organization capital to affect the risk profile of firms. In particular, certain types of compensation structures or legal policies may tend to "bind" skilled labor to their firm and reduce the risk produced by the "outside option"[45].

For example, non-compete laws have been shown to affect skilled labor mobility and compensation. Marx, Strumsky, and Fleming (2009) find that firms facing an exogenous increase in non-compete law strength in Michigan in the 1980s experienced lower labor mobility after the increase. Garmaise (2011) finds that increased non-compete law enforcement reduces total compensation, and shifts its form more toward salary (which would suggest a shift away from other "binding" forms of compensation, as they would be less necessary).

Additionally, compensation should provide a strong effect on whether or not key talent remains with the firm or exercises their outside option to go to another firm. While a firm could reduce an employee's outside option by simply increasing their total compensation, this would of course come at the expense of firm profits, and funds that could be used elsewhere in the firm. Thus it is more likely that the firm would attempt to adjust the employee's compensation structure to "bind" the employee more closely to the firm, by reducing the proportion of compensation based on salary and increasing stock options requiring vesting, offering more restricted grants, and increasing long-term incentive compensation. This also would be similar to the finding of Garmaise (2011), that firms with high non-compete law protection pay a higher proportion of their compensation with salary (as opposed to these "binding" forms of compensation).

[45] This is suggested in the opening quote by Becker (1975) in his second edition of "Human Capital".

Also, interactions between a high ratio of total compensation to binding compensation and weak non-compete laws and high organization capital should also increase overall firm risk jointly. Thus I hypothesize the following:

H4A: High organization capital firms in a weaker non-compete law environment (Garm) should earn higher returns as compensation for the increased outside option risk.

H4B: High organization capital firms with lower binding compensation (NoBind) should earn higher returns as compensation for the increased outside option risk.

In addition, this same effect could occur for the exogenous increase in sector skilled labor employment relative to the employees within a firm. Marx, Strumsky, and Fleming (2009) show that employee skills are most transferable to closely related firms in the same industry or sector. This means that a significant proportion of the outside option threat will come from changes taking place within the firm's industry or sector. Most likely this would come from outside wage pressure. However, even if wages are similar between the firm and its industry/sector, the "key talent" for a firm will likely be offered significantly higher wages from recruiting firms within the sector, if they are seeking to expand their employment base. Thus I develop three instrumental variables representing the outside wage pressure and the outside employment pressure. All three of these instruments should serve to proxy for an increase in the outside option. So I hypothesize the following:

H5A: An exogenous increase in industry wages over the firm's wages should increase organization capital, thus increasing firm risk.

H5B: An exogenous increase in industry employment over the firm's employment should increase organization capital, thus increasing firm risk.

It is also possible that non-compete law strength is endogenous with high organization capital levels in firms. In other words, founders of firms with high organization capital risk may tend to locate in environments more protective of their organization capital, thus skewing any connection drawn between organization capital and firm risk. In addition, it is possible that over time a concentration of firms with high or low organization capital in a certain region have lobbied state legislatures to establish laws more favorable towards their organization capital risk level.

To avoid this endogeneity, I use the Michigan exogenous change in non-compete laws in 1985 to test the effect of organization capital on firm risk. In 1985[46], the Michigan legislature passed the Michigan Antitrust Reform Act (MARA) which, among a wide range of provisions on the bill, repealed a 1905 statute prohibiting non-compete agreements. Pynonnen (1994) notes in the Ohio State Law Journal that from 1905 to 1985, Michigan state law declared all non-compete agreements within the state to be null and void, and as against public policy[47]. Marx, Strumsky, and Fleming (2009) provide an extensive literature review of this incident, and verify its exogenous nature. Thus, the 1985 law change provides a natural experiment to test if the initiation of enforcement of non-compete laws leads to a decrease in firm risk for high organization capital firms. So I hypothesize:

H6: The exogenous increase in non-compete law strength by the passing of MARA in Michigan in 1985 should have decreased firm risk for high organization capital firms.

[46] Due to the inadvertent nature of this repeal of the 1905 statute, some confusion remained over this policy until a 1987 amendment to MARA further clarified this non-compete ban repeal.

[47] Pynonnen (1994) states "Prior to 1985, it was easy for Michigan attorneys to deal with covenants not to compete: all such covenants were illegal and void". Pynonnen also quotes Michigan Supreme Court Chief Justice Williams in the 1976 case *Woodward v. Cadillac Overall Supply Co.* "There is no authority in Michigan as to the treatment of overbroad covenants not to compete ancillary to an employment contract partially for the simple reason that any such covenant, no matter how limited, has been illegal. . since 1905." With the Michigan legal community seemingly fully aware of the illegality of non-compete agreements in Michigan, and with the lengthy time period that this statute had been in place, it seems implausible that firms would have believed non-compete agreements to apply before the 1987 amendment.

Although the direct measure of actual skilled labor flows between firms is an obvious representation of the strength of the outside option, there still may be endogenous reasons for skilled talent outflows or velocity to occur, even after controlling for the prior measures in this paper. Non-pecuniary benefits, or issues of employee treatment or status may also affect the flow of key talent in and out of a firm. As seen by the anti-poaching allegations in California, there may also be other hidden influences within the firm that affect the ability of skilled employees to move in and out of the firm. In addition, it is possible that skilled talent outflows do not increase because the firm simply increases their level of wages. So in this case, outflows of key talent would not be seen, but firm risk should still increase because now a larger portion of their earnings would go to compensation payments instead of training or other factors that could improve firm growth and performance.

Thus, an exogenous change in forces exterior to the firm that affect the outside option could provide a helpful robustness test to the idea that high organization capital affects firm risk via the outside option. While the previous instrumental variable test addressed endogeneity in compensation related influences on the outside option, and the 1985 Michigan exogenous shock addressed endogeneity in legal influences on the outside option, a change in firm location may address many factors at once. Since non-compete laws are established at the state level, the movement of a firm's headquarters from one state to another state with differing non-compete law strength should produce a change in the outside option strength for key firm employees, and thus a change in the risk caused by organization capital. So I hypothesize the following:

H7: An exogenous increase in non-compete law strength via a move in firm headquarters should reduce firm risk for high organization capital firms.

4.3 Data and summary statistics

The sample period for the primary data sample ranges from 1984 to 2012[48]. I combine data from several sources as described below. The patent data is primarily obtained from the National Bureau of Economic Research (NBER) patent database, which consists of over 3 million patents and 23 million citations between 1976 and 2006. This data was obtained from patents submitted to the U.S Patent and Trademark Office (USPTO) as compiled by Hall, Jaffe, and Trajtenberg (2001). I then utilize the NBER bridge file which links over 1 million of these patents directly to COMPUSTAT firms. In addition to this bridge file, I also match patents to firms using the Kogan, Papanikolaou, Seru, and Stoffman (2012) patent database. Afterwards, I merge this patent data with inventor names and addresses from the Harvard Business School (HBS) patent dataverse of Lai, D'Amore, and Fleming (2011), which extends from 1975-2008. Lai et al. develop an algorithm to create a unique inventor identifier to track inventor patenting and firm moves over time.

Daily, monthly, and annual stock data is provided by the Center for Research in Security Prices (CRSP) for the period 1980 – 2012. Observations are excluded if they are not in the NYSE, AMEX, and Nasdaq, or if the data is not common stock. Financial statement data is provided by Compustat for the period 1980 – 2012. I obtain executive compensation data from Execucomp for the period 1994 – 2012.

I also gather wage and employment data from Compustat for the period 1980-2012. The variables constructed from these datasets are described in the following sections, and in Appendix A.1.

[48] For some tables, this data range does not start until 1993 due to lack of data availability. In addition, some analyses stop in 2006 primarily because of the patent data derived from Hall, Jaffe, and Trajtenberg (2001), who match patents with Compustat firms until 2006 only. However, in some cases where data is available, I extend the range from 1980 to 2010 to improve the robustness of the results.

C. Organization Capital Measurement

The measure for organization capital is constructed from the Compustat database as per Eisfeldt Papanikolaou (2013). Specifically, it is calculated as the ratio of the stock of selling, general, and administrative (SG&A) expenses in years t-4 through t, divided by total assets in year t. I depreciate SG&A stock by 15% each prior year using the perpetual inventory method. To account for potential inflationary bias lowering the impact of the lagged SG&A stock, especially in the early years of the sample, I additionally scale both SG&A stock and total assets to the consumer price index in 2012 dollars[49].

Because of potential differences in levels of organization capital per industry, I also set up a rank variable for organization capital per year and Fama French 17 industry classification[50]. I then rank each firm into quintiles per year and industry. Although data on SG&A becomes common by 1980 in the Compustat database, the sample of organization capital only extends from 1984-2012 because of the five-year formation period for SG&A stock.

D. Inventor Mobility

a. Inventor Mobility Dataset

I construct the dataset on inventor mobility by merging three inventor datasets with publicly traded firm identifiers and inventor names. First, I obtain U.S. utility patent data identifying the publicly traded firm issuing the patent from the NBER patent data project of Hall, Jaffe, and Trajtenberg (2001), which extends from 1976-2006. I combine their dataset on patent assignee names with their dataset identifying the parent company (gvkey) of those assignees

[49] This is done similarly to CPI scaling for variables in Hirshleifer, Low, Teoh (2012).
[50] I use Fama French 17 industries as per Eisfeldt Papanikolaou (2013).

each year. I then match this dataset with a third NBER dataset they provide which gives more details of each utility patent (this data is used to construct the control variables used to measure individual inventor moves). Second, I match patents to firms using the Kogan, Papanikolaou, Seru, and Stoffman (2012) patent database, which provides a unique permno for each firm[51]. Third, I merge these two datasets with another patent dataset containing inventor names from the Harvard patent network dataverse of Lai, D'Amour, and Fleming (2011), which extends from 1975-2008. All of these datasets are merged by patent number.

b. Inventor Firm Switchers

I construct the dataset on inventor firm switchers by identifying inventor switches from firm to firm. I start with the Lai, D'Amore, and Fleming (2011) inventor database, which creates a unique identifier of inventors filing multiple patents over time. This builds upon prior matching algorithms introduced by Marx, Strumsky, and Fleming (2009), Singh (2008), Fleming, King, and Juda (2007), and Trajtenberg, Shiff, and Melamed (2006). I further screen the data in two stages, to identify a patent history for each inventor, and to identify inventors who are likely to have voluntarily switched firms. I perform the first stage of screening on the data in the following order:

1. I require all inventors to belong to publicly traded firms matched by the NBER patent dataset of Hall, Jaffe, Trajtenberg (2001) or the Kogan, Papanikolaou, Seru, and Stoffman (2012) patent database. These datasets have already gone through extensive cleaning and screening to match the individual patents to their parent companies.

[51] I match these permnos to gvkeys using the Crsp-Compustat merged database link provided by Wharton Research Data Services.

2. For last names I expect that there will be many false matches for common surnames. Although the Lai, D'Amore, and Fleming (2011) database makes adjustments for this, I perform a second screening here to ensure a better identification of inventor pairs. Although most inventors in the U.S. would likely have English surnames, many inventors originated from outside the U.S. To better identify the source of these inventors, I identify all countries that are the source of greater than 2% of our country's international students[52], as this would be a likely proxy for the proportion of inventors originating from outside of the country. These countries include (from the largest to smallest proportion respectively) China, India, South Korea, Saudi Arabia, Canada, Taiwan, Vietnam, Japan, and Mexico[53]. I exclude the top 20 most common English surnames, and the top 10 most common international surnames from the countries with a high likelihood of inventor presence in the U.S.

I then perform the second stage of screening as follows. To identify inventors who likely switched firms, I first record patent filing pairs between the same inventor who filed under one firm name initially (the source firm) and under a new firm name in the second filing (the destination firm), and I then perform a more extensive second-stage screening process to try to accurately record the firm switchers. Throughout this screening process, I seek to identify only voluntary firm switchers, as that would yield the most accurate information on the strength of the outside option. The screening process is thus extended as follows:

1) I first sort by inventor and patent filing date, and identify inventors who are matched to a different publicly traded firm in the most recent patent filing date. These are my initial group of firm switchers.

52 Http://www.iie.org/Research-and-Publications/Open-Doors/Data/International-Students

53 I exclude filtering for Canadian surnames, as they would likely be similar to U.S. surnames. In addition, I consider Taiwanese surnames to be similar to Chinese surnames.

2) I exclude inventors that appear to switch back to the source firm eventually, as it may signify a problem with the name matching. In other words, it is possible that two inventors with the same name are simultaneously filing patents for different firms over the course of several years, and it could appear that the same person is job-hopping back and forth between two firms, which is highly unlikely. Thus I eliminate all inventors that appear to return to their prior firm after one year. I allow for overlap within a one year period, as it is possible an inventor worked on a patent for one firm early in the year (which didn't get filed until after the inventor left the company), switched to another firm, and filed a patent for the new firm later in the year.
3) I exclude all inventor moves due to merger activity. First, I bring in merger data from SDC Platinum between 1979 and 2008, and identify all cases where the inventor source firm and destination firm experienced a direct merger within the period between patent filings for that inventor (which would identify an involuntary firm switch). I also identify all prior mergers for each firm listed to see if the source firm had merged with a third firm between patent filings, which then later merged with the destination firm. In this way, I can screen for intermediate mergers too, not just direct mergers.
4) I exclude all switches "out" of a firm in the case that the source firm is not in existence at the time of the patent filing at the destination firm. This helps to record a legitimate switch "out" of the firm, and avoid cases in which the inventor was forced to switch firms because of a bankruptcy or delisting from the NYSE, Nasdaq, and AMEX.
5) I also exclude all switches "in" to a firm in the case that the source firm is not in existence at the time of the patent filing at the destination firm. While there may be less biases for these types of switches (as switchers from a bankrupt firm likely have a myriad

of choices of firms to relocate to), there still may be bias if the inventors have more industry-specific skills, and tend to relocate only to firms within a certain industry, etc.

Following is a table describing inventor-level descriptive statistics resulting from this screening process:

(Insert Table 4.1 here)

For Table 4.1, overall I record 22,021 inventors voluntarily switching firms, out of roughly 432,088 inventors filing 1.41 million patents for publicly traded firms. Given the extensive filtering in identifying voluntary firm switchers, this number of firm switchers likely far underestimates the number of actual inventors switching firms[54]. However, the sample is still fairly large, and provides a more accurate analysis in this paper. Following Eisfeldt Papanikolaou (2013), I divide the patent switchers into the Fama French 17 industry classification. While there is a wide distribution in the switching of inventors by industry (with all industries represented), the most switching takes place in the following Fama-French 17 industries: Machinery and Business Equipment, the catch-all Other industry, and Drugs, Soap, Perfumes, and Tobacco. In addition, firm switching appears to increase each decade, but there are two potential biases for this in this sample. First, in order to determine a switch, I need several years of prior patenting to establish a "first" location for an inventor, so determining a switch in the early sample years is more difficult. Second, patenting has tended to increase in general over the years of the sample, so more switches can be picked up toward the end of the sample period. However, I am not concerned that this would affect any results in this paper, as I control for year fixed effects throughout.

[54] I thus select a smaller but more accurate sample by favoring type 1 errors (eliminating some voluntary firm switchers from my sample) to avoid the noise created by type II errors (allowing non firm switchers or involuntary firm switchers from appearing in the sample).

c. *Inventor Labor Flow and Labor Velocity*

After identifying firm switchers, I first sum up the total number of inventors joining a firm in the prior five years, and then sum up the total number of inventors leaving a firm in the prior five years, and subtract the total inventors joining from the total inventors leaving to establish the net number of inventors flowing in or out of a firm in the prior five years. I call this variable "labor outflow".

However, this variable may not capture the true impact of the cost of key employee talent switching in and out of the firm, as heavy turnover of talented employees is also likely disruptive to the firm. As mentioned in the hypothesis section, a recent massive class-action lawsuit alleging employee anti-poaching schemes, which involves over 64,000 programmers seeking billions of dollars in damages, provides strong anecdotal evidence as to the extent managers will go to reduce the loss of key talent from their firm[55]. So I also construct a variable representing this turnover, called "labor velocity", which adds the total number of inventors joining a firm in the past five years to the total number of inventors leaving a firm in the past five years.

E. *Background of Legal Restriction on Labor Mobility*

Legal restrictions on labor mobility primarily arise as a result of agency costs stemming from the transfer of skilled labor between firms[56]. Agency costs arise when the interests of the principal and agent diverge (Jensen and Meckling (1976)). In the case of labor mobility, the principal would be the employer who is entrusting costly training to be placed in the hands of the

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[55] http://www.nytimes.com/2014/03/01/technology/engineers-allege-hiring-collusion-in-silicon-valley.html. http://dealbook.nytimes.com/2014/04/07/tech-firms-may-find-no-poaching-pacts-costly/?_php=true&_type=blogs&_r=0.

[56] Ch.5 of "The basics of finance: An introduction to financial markets, business finance, and portfolio management" Drake and Fabozzi, 2010, which states "Principals can reduce agency costs by "bonding"; that is, making commitments that would be costly if interests diverge (e.g., a non-compete clause if the manager leaves the employment of the company)").

agent, who is the employee. While the principal (employer) wants to see this training investment earn a return by producing valuable outcomes for the firm, the agent (employee) may take the investment in training and go to a higher paid job at a competitor. In fact, in his seminal work on human capital and labor mobility, Becker (1964) notes the potentially negative consequences of labor mobility, stating that a firm that trains workers in skills useful to other firms, may ultimately lose that employee because other firms can outbid the training firm since they incurred no expenses in the training of the individual. In the absence of property rights over an investment in employee training, firms will not provide it. Thus, if the employee cannot fund their own training (through educational institutions, etc.), then training will not take place. Ultimately, this situation could lead to a shortage of skilled labor. However, others argue that the recruiting firm cannot assess the potential benefit that the trained employee can provide due to information asymmetries between the training and recruiting firm (Katz Ziderman 1990). This would make training of employees a viable investment, and thus negate the need for instituting labor mobility frictions between firms. Wu (2004) relates this idea to non-compete agreements, stating "Non-compete agreements also protect employer investment in employees. Employers put significant resources into employee training, and they do not want to spend time and money on training only to quickly lose their employees to a competitor."[57][58]

Most economists find that empirical evidence points to both cases, and that firms will still train, even though the training is considered higher risk as their valuable employees could still leave. As an example, Graves and Diboise (2006) state that since the 1960s, Silicon Valley had

[57] Derived from footnote 97. Christine M. O'Malley, Note, Covenants Not to Compete in the Massachusetts Hi-Tech Industry: Assessing the Need for a Legislative Solution, 79 B.U. L. REV. 1215, 1217 (1999).

[58] This represents an old concept. Rassas (2008) U. Penn Journal of Business Law mentions "Non-compete agreements can be traced back to British courts of equity that sought to balance an employer's interest in protecting his investment in an employee against an employee's interest in career mobility." (Cited in Rassas as from Packer and Cleary 2007).

become an incubator to a growing number of start-up firms. Its primary competitor, Route 128 in Boston, had similar success but focused more strongly on the big company model. By the mid-1990s, Silicon Valley had emerged as the stronger of the two high-tech regions. Graves and Diboise further go on to mention, “This led two prominent scholars, Professors Ronald Gilson of Stanford and Annalee Saxenian of Berkeley, to publish separate analyses of possible reasons for the disparity. Both theorized that Silicon Valley’s success was related to the tendency of skilled employees to move from company to company, and to more easily apply the knowledge they developed along the way.”[59] In addition, Graves and Diboise (2006) go on to say “Employee mobility – or the ease by which a skilled employee can leave one job, join another company, and immediately apply his or her skills – is a necessary ingredient of a successful venture-backed business region. Almost by definition, small and creative start-up companies funded by venture capital are short-lived and require the ready availability of skilled founders and employees.” While weak non-compete environment firms may gain success, I find support that they do so at the price of higher risk.

Non-compete agreements are established by employment law, not corporate law, and are typically defined at the state level. I test the effect of non-compete agreements using two measures. First, I use the Non-compete Enforcement Index built by Garmaise (2011) to initially measure the strength of non-compete laws in a state. This index is built from 12 questions asked by Malsberger (2008) for each region, and scored 1 if non-compete rules exceed a certain threshold for that question, and zero otherwise. Garmaise totals the results of the 12 questions for the 50 states, and computes an index ranging from 0 to 12, with higher scores indicating

[59] Silicon Valley is located in California, a state banning non-compete agreements, while Route 128 is in Massachusetts, a state allowing non-compete agreements and ranking high on the Garmaise (2011) index.

tougher non-compete laws. Effectively, the 50 states and the District of Columbia produce an index ranging from 0 to 9[60].

This index has been used in a wide variety of studies, and in a broad range of disciplines. In the field of finance, Dahiya and Yermack (2008) find that states with low Garmaise scores tend to show support for tighter "sunset rules"[61] when managers are more likely to leave the firm. Kumar, Page, and Spalt (2011) also find a relationship between the Garmaise index and employee stock option grants. Kedia and Rajgopal (2009) look more closely at the Garmaise index, and find that states that are less likely to enforce non-compete agreements experience higher broad based option grants. However, they find that this effect is primarily driven by the low Garmaise score in California.

Second, I use the Michigan exogenous repeal of their non-compete ban in 1985, as introduced in Marx, Strumsky, and Fleming (2009), as explained in prior sections. Together, these two measures of non-compete laws should provide a good test of their effect on the outside option, and the risk the outside option imposes on organization capital.

F. Background of Compensation Effects on Labor Mobility

Compensation amount and structure likely plays a major role in the employee turnover of skilled labor. While it seems obvious that higher firm compensation can serve as an important factor in the retention of key employees, it would come at the cost of funds that could be used elsewhere by the firm. Thus, compensation structure has recently been seen as playing a more

[60] For this paper, I subtract 9 from this index to create a "modified" Garmaise index. This allows coefficients in the tables to be interpreted more easily as a higher coefficient indicates more firm risk, because a higher score will indicate weaker non-compete laws, and potentially more risk by increasing the outside option.

[61] Dahiya Yermack (2008) define "Sunset rules" as policies focused on the modification of option contracts when managers leave the firm.

important role in employee retention and firm risk than differences in total compensation, as there are types of compensation that are better able to "bind" employees to the firm.

I construct a measure of the proportion of executive compensation that helps to bind employees called NoBind, which is constructed by dividing total compensation by binding forms of compensation[62]. The denominator includes the following compensation: 1) option awards, 2) restricted grants, and 3) long-term incentive plan (LTIP) payouts. Option awards may either require a vesting period to be exercised by the employee to obtain their full value, or they may be out-of-the-money and currently worthless. This is significant, because a voluntary departure often requires employees to exercise their stock grants within 30 to 90 days after exiting the firm, so an employee expecting future upside in firm returns may want to remain with the firm a little longer. Restricted grants typically offer more value at vesting, but are usually forfeited immediately upon departure from a firm, and have been called a "golden handcuff"[63] for that reason. LTIPs are typically awards of shares given for meeting certain performance goals, with half awarded in the present, and the other half typically awarded after a predefined number of years has passed, thus also serving to bind employees to a firm.

I use as the numerator total compensation, similar to two measures of total compensation as listed by Execucomp, and constructed from the following variables: Salary, bonus, other annual compensation, restricted grants, LTIP payouts, all other compensation, value of options exercised, and the Black-Scholes value of option grants. None of these additional forms of

[62] See appendix A for more details on variable construction. I build the variable in this manner so that an increase in the coefficient increases firm risk, so it is easily comparable to the other key variables in this paper.
[63] https://www.mystockoptions.com/articles/index.cfm/ObjectID/B1750B46-204C-477F-A2F82EE536C70D9A

compensation serve as significant binding agents, and thus can be mostly considered current compensation with no employment restrictions[64].

While this ratio of compensation likely gives an viable estimation of the effect of binding compensation on labor mobility, it only applies to the top five firm executives. To provide for a better estimate of the strength of the outside option on all skilled firm employees, I construct three instrumental variables to measure outside wage and recruitment pressure on firm employees. The first instrumental variable is inspired by the instrumental variable in Bae, Kang, and Wang (2011) used to predict employee treatment by considering industry-level wage rates. Part of their justification for using industry-level comparisons is that certain firm structure measurements (like capital structure) should not affect industry level wages, but high firm wages relative to the industry should serve as a good proxy for productivity, which is likely to be rewarded by better employee treatment. Using industry comparisons as motivation, I construct my first instrumental variable as follows. First, I obtain selling, general, and administrative data (SG&A) and total firm asset data (TA) from Compustat for the period 1980-2012. Second, I average this SG&A data for the 2-digit SIC industry of the firm, subtracting the SG&A of the firm itself from this calculation. Third, I average the total asset data similarly to the SG&A data. Fourth, I divide the industry SG&A data by the average industry TA data to obtain an industry average SG&A/TA. Fifth, I divide the firm's SG&A data by the firm's TA data. Finally, I divide the firm's SG&A/TA ratio by the industry's SG&A/TA ratio, which I simply call the "SG&A ratio". For the second and third instrumental variables, I perform similar calculations,

[64] What Execucomp lists as "other annual compensation" or "all other compensation" is a catch-all term for many other types of compensation, which could include binding employment restrictions. However, since these represent only a small part of total compensation, any effects of binding restrictions from these variables is not likely to affect the results.

substituting staff expenses and total employees for SG&A. I call these two instrumental variables the "staff expenses ratio" and the "employment ratio" respectively.

It is important to note that executive compensation data is more plentiful and varied than this dataset; however, the limited sample of key talent as represented by the top five executives may not accurately represent the effect of the entire population of key talent within a firm. So these broad measures of firm wages and employment likely capture the true level of the outside option for a company.

In addition, based on unreported tests on my inventor dataset and results from Marx, Strumsky, and Fleming (2009), immediate industry skills are considered perhaps the most transferable; thus, a higher level of this ratio should indicate more wage pressure from immediately outside the firm, and hence higher firm risk from the increased outside option pressure on employees.

G. Background on Firm Headquarter Moves

Pirinsky and Wang (2006) study the stock returns of firms based on their headquarter location, and find that firms moving their headquarters experience greater return comovement with geographically close stocks in that new area. Since the Compustat database only records the current firm headquarters location, I use a software program to analyze 10-K cover pages and record state-level firm headquarter moves. To filter out spurious matches from a data entry mistake, I require at least 2 years at the previous headquarter location, and 2 years at the current headquarter location, to identify a good match.

H. Miscellaneous Control Variables

I also construct the other control variables as per appendix A.1. The following control variables are from Marx, Strumsky, and Fleming (2009), and control for individual factors affecting inventor switching: Firm specificity, patents per firm, technical specialization, patents per inventor, and time since last patent. I also control for firm switching with factors that affect compensation (and thus potential outside option forces affecting firm switching) with firm size, book-to-market, and return on assets. In addition, the level of inventor switching or velocity would be highly correlated with the total number of employees at the firm (even more than firm size, most likely), so I include the number of employees in all regressions considering inventor moves. I also include an indicator variable for innovative industries as per Hirshleifer, Low, and Teoh (2012)[65]. This is done to determine if any of the results are being driven by more high-tech firms.

I. Firm-Level Data and Descriptive Statistics

(Insert Table 4.2 here)

Table 4.2 presents descriptive statistics on the firm-level dataset for the years 1984-2012. The dataset contains 100,020 firm-year observations. Inventor velocity and inventor outflow only extend from 1984-2006 due to limitations on the data availability from the NBER patent dataset of Hall, Jaffe, and Trajtenberg (2001). I divide the sample into two groups – high organization capital, and low organization capital – to show how different levels of O/K relate to other firm characteristics.

[65] P. 1476 of Hirshleifer, Low, Teoh (2012) defines their measure for industry innovativeness.

In general, high organization capital firms earn higher returns, are smaller in market capitalization, have higher market-book ratios, and are more innovative. The fact that the high O/K firms have smaller market caps, but have similar numbers of employees, is in part indicative of why they are more overweight in selling, general, and administrative expenses to total assets. Total executive compensation is lower in high O/K firms, but this could be partly due to their lower market cap (also, this data is limited in the sample, so other biases could cause this). I include observations for inventor velocity and inventor flow if a firm has ever patenting during the time is has traded publicly. Most entries for the variables are zero, since even for a firm with many inventors, most years will not reveal an inventor switching in or out of a firm, due to the strict screening process for inventor moves that I employ.

4.4 Main Results

A. Organization Capital as a Risk Factor

Organization Capital (SG&A stock / total assets) is an important consideration for a firm, as SG&A costs represent a large proportion of firm spending. Anderson, Banker, and Janakiraman (2003) find that 26.4% of sales are dedicated to SG&A[66], thus representing a significant potential risk consideration for firms. For this reason, some have suggested that high levels of SG&A increase risk substantially for firms, especially because SG&A tends to be "sticky" and not fall as easily in a market downturn (Anderson et al 2003), or because they can indicate a decline in firm profitability (Lev and Thiagarajan 1993). So I first evaluate the impact of organization capital risk versus the three Fama French (1993) risk factors to provide an idea of why this is an important research topic.

[66] For a sample of 7,629 firms over a 20-year period.

(Insert Table 4.3 here)

Panel A shows that organization capital risk increases steadily for each quintile increase, with very large risk for the highest quintile. In fact, this risk compares similarly to the premium for small versus large firms or for high book/market versus low book/market firms for the period 1990-2010[67]. While the goal of this paper is not to qualify organization capital as another general risk factor to use in evaluating firms, this still provides a strong motivation for determining how much organization capital risk is due to the outside option value for employees who are considering whether or not they should leave the firm.

B. *Inventor Firm Switches and Organization Capital*

Before evaluating cumulative switchers by firm, I consider the impact of individual firm switches on organization capital, so I can control for individual inventor characteristics. I use the inventor characteristic controls of Marx, Strumsky, and Fleming (2009), which include five control variables that predict patenting behavior – firm specificity, patents per firm, tech specialization, patents per inventor, time since last patent. I also add in controls for firm performance characteristics (size, market/book, ROA) which affect compensation (Agarwal (1981); Core, Guay, and Larcker (2003)), as that could also impact the propensity of an inventor to switch firms. Finally, I use the number of employees as a control, as the number of employees is likely highly correlated with the number of inventors filing patents.

The general regression model is specified as follows:

$$Switch_{i,t} = \propto_0 + \theta M_{i,t} + \Omega A_{i,t} + \Phi E_{i,t} + \eta_i + \nu_{i,t} + \varepsilon_{i,t} \quad (1)$$

[67] Momentum is a little more difficult to compare as a risk factor, as it has actually reversed its impact since the 1990s in terms of quintiles.

where $Switch_{i,t}$ represents a firm switch in or out of the firm (-1 = out,0 = no move since the last patent filing, 1 = in for the ordered logit; 0 = out, 1 = in for the standard logit), $\propto_0$ represents the intersect term, $\theta M_{i,t}$ represents the inventor characteristic controls, $\Omega A_{i,t}$ represents the firm performance characteristics controls, $\Phi E_{i,t}$ represents firm employment, η_i is a fixed unobservable firm-specific factor, $\nu_{i,t}$ is a time-varying unobserved factor, and $\varepsilon_{i,t}$ represents the error term.

(Insert Table 4.4 here)

Panel A of Table 4.4 column 1 uses an ordered logit model, with -1 for inventors switching out of the firm, 0 for no switching since the last patent filing, and +1 for inventors switching into the firm. For this sample, which includes all patent filings, I find that inventors tend to switch out of firms with higher organization capital. This supports the idea from Eisfeldt Papanikolaou (2013) that the outside option may indeed be a risk factor for high organization capital firms, and it supports the Becker (1964) theory that there will be a high tendency for skilled employees to leave their firm and go to other companies, because the new companies will not have to pay for training and can outbid the training firm.

Since column 1 could introduce significant noise due to a large number of zeroes, I also evaluate the sample in columns 2-6 with firm switchers only, using a logit model with 0 for switches out of firm, and 1 for switches into a firm. I find similar results when considering only firm switchers, for both high and low O/K firms, and for inventor switches identified in less than five years (TSLP < 5) and for inventor switches that were identified in five or more years (TSLP ≥ 5). Overall these results confirm the predictions in hypothesis 1.

It is important to note that separating into high versus low organization capital groups reveals that the results seem to be driven by the low organization capital group. It is possible that it does not take much of an investment in increasing worker skills to encourage the tendency of inventors to switch, and that the added risk factor for high organization capital firms simply comes from the higher total investment in these employees. That is, even if high O/K employees do not show much of an increased tendency to switch out of a firm (versus the upper end of the low O/K group), they would take much more training value with them when they leave the firm.

C. Relationship between Labor Outflow and Organization Capital

It is possible that firms that spend large amounts on organization capital understand that the outside option is a significant risk, and are actually better able to prevent employee movement in and out of their firms, in which case they would face reduced risk (not increased risk) by having higher organization capital, at least in terms of labor movement. So if organization capital is truly a risk factor for a firm because it affects the tendency of skilled employees to exercise their outside option, then organization capital should have a significant impact on the tendency of inventors to join or leave a firm. In fact, to serve as a risk factor, there should be more employees leaving than joining high organization capital firms, to fit the theories of Becker (1964) and indicate higher risk for higher organization capital.

However, there are two other significant factors that could potentially affect whether or not a skilled employee will leave a firm which need to be controlled for. First, the proportion of executive compensation concentrated in measures binding an employee to a firm (option vesting requirements, restricted grants, long term incentive compensation) would reduce the strength of the option for that employee to leave the firm. Executives represent members of the group of skilled workers at a firm, and a compensation structure for these individuals including more "binding" forms of compensation would likely be reflected in other skilled employees, thus serving as a good proxy for an overall potential reduction in the outside option of skilled workers. In addition, the modified Garmaise Index represents the strength of non-compete agreements per state, and would likely affect the outside option if skilled employees could not transfer to certain firms deemed off-limits by the non-compete agreement.

(Insert Table 4.5 here)

Panel A of Table 4.5 model 1 shows that higher organization capital significantly correlates with increased labor outflow from the firm, confirming hypothesis 1 for firms as a whole. This also holds after adding the controls in models 2-4. Models 2 and 4 show that legal restrictions on movement seem to have little impact on labor outflow when controlling for organization capital. Surprisingly, model 3 shows that the interaction between organization capital and the NoBind ratio is negative and significant. However, it is possible that binding compensation policies are added simply to soften a previously high outside option risk. In any case, the coefficient on this factor is much smaller than the coefficient on organization capital. Overall, Table 4.5 supports hypothesis 1.

For this table and the remaining tables evaluating firm level patenting, I use control variables as per Eisfeldt and Papanikolaou (2013) – CAPM, size, momentum, and market / book. I also control for total executive compensation, as wages are likely a proxy for the motivation of employees to exercise their outside option. I control for the number of employees, as the number of employees is likely highly correlated with the number of inventors patenting, and switching in and out of the firm. I also initially control for innovative industries as proxied by Hirshleifer, Low, and Teoh (2012), as is it possible that more innovative firms have natural tendencies to patent more, with a resulting higher incidence of firm switches. However, because most of these patenting firms are considered more innovative, I only use this control in the initial tables.

D. Relationship between Labor Velocity and Organization Capital

Higher organization capital would also likely have an impact on labor velocity for a firm, as it would indicate both a high tendency for skilled employees to leave (Becker 1964), and also a potential for the recruitment of skilled workers, as a high organization capital firm is by default willing to spend large amounts on wages and training for employees. Indeed, a current class action lawsuit against Steve Jobs and other giants of Silicon Valley shows the concern management has for high skilled labor turnover as a risk factor[68], as mentioned previously. This fits the idea that while gaining a skilled employee still provides value to the hiring firm, the value of the training is not 100% transferable, and that high labor velocity could produce a net loss in value for the firms involved.

(Insert Table 4.6 here)

Panel A of Table 4.6 model 1 shows high organization capital does indeed correlate with high labor velocity in a firm, supporting hypothesis 2. Models 2-4 show that organization capital still stays highly significant in its relationship with labor velocity, and shows mixed results for the binding compensation and the modified Garmaise index. A high ratio of non-binding compensation (NoBind) actually correlates negatively with labor velocity, which is somewhat surprising, as it seems it should have had the opposite effect. However, I do not explore causality here, and it could be that firms offer more binding compensation in an effort to deter

[68] New York Times. April 7, 2014 "Tech firms may find no-poaching pacts costly". Andrew Ross Sorkin. http://dealbook.nytimes.com/2014/04/07/tech-firms-may-find-no-poaching-pacts-costly/?_php=true&_type=blogs&_r=0

future losses after experiencing prior high employee velocity. In addition, the effect of controlling for organization capital in the same model may reduce or change the impact of this type of compensation.

The modified Garmaise index appears insignificant overall. While it is difficult to determine exactly why, allegations in the previously described class action lawsuit on employee poaching indicate that the conspiracy could date to the 1980s. Thus, it is possible that this weakened the overall effect of the modified Garmaise index during the sample period.

E. *Effect of O/K, Inventor Flow, and Inventor Velocity on Firm Risk*

Eisfeldt Papanikolaou (2013) showed that organization capital is a significant risk factor for firms by comparing a high-low portfolio. I first confirm their results, and hypothesis 3A, using both a Fama MacBeth (1973) regression model and a fixed effects panel model for the period 1984-2012 in the first two columns of panel A of Table 4.7, finding that organization capital does indeed have a significant positive effect on firm risk for my sample.

However, although this confirms the findings of Eisfeldt et al, it still does not answer the question of whether or not this risk is caused by a higher risk of employees leaving the firm by executing their outside option to leave. There are many other factors that could cause the high SG&A spending in high organization capital to increase risk for the firm. So I interact labor flows and labor velocity with organization capital to see if they have a joint effect in Table 4.7.

(Insert Table 4.7 here)

Models 1 and 2 of Panel A of Table 4.7 regress one-year abnormal firm returns on organization capital and confirm the findings in Eisfeldt Papanikolaou (2013) that high organization capital has a strong positive relationship with firm risk. This confirms hypothesis

H3A. In Models 3-5, I test the interaction of organization capital with labor outflow[69] and labor velocity on three-year abnormal returns. I find that the interaction of O/K with outflow produces a positive and significant result in model 3, supporting hypothesis 3B. In fact, the significance of O/K actually disappears when adding this interaction, indicating a strong effect from labor outflows. However, I cannot confirm that the same effect happens with labor velocity in hypothesis 3C. In addition, I find that the joint interaction of outflow and velocity produces a positive and significant result, although the significance is low. In other words, high labor outflow combined with high labor velocity increases firm risk.

F. O/K and Risk: The Effect of Legal and Compensatory Factors

It is possible that legal or compensatory factors play a larger role in the employment decision than the employee's own personal choice of whether or not to stay at the firm based on their outside options of employment. This is important, because if other means could be used to effectively bind an employee to the firm, it would reduce or eliminate high organization capital as a risk factor for employee movement. I test organization capital against the two potentially most powerful means of binding an employee to a firm – 1) the ratio of nonbinding compensation, and 2) score on the modified Garmaise Index – as discussed earlier. In panel A of Table 4.8 I test the effect of the interaction of these binding agents with organization capital on one-year abnormal returns. Models 2 and 4 show that high nonbinding compensation seems to slightly increase firm risk independently of organization capital; however, when interacted with organization capital in model 2, there is no significance. This weakly supports hypothesis 4B. Models 3 and 4 generally show that a high modified Garmaise Index (a low non-compete,

[69] This is simply the negative of flow, so that an increasing value of outflow increases risk in a parallel manner to an increasing value of labor velocity to allow for the interaction to provide a proper outcome.

potentially high velocity labor market) significantly increases firm risk as an independent factor, supporting hypothesis 4A. However, models 3 and 4 show that the interaction of the modified Garmaise Index and binding compensation (by themselves or interacted with organization capital) actually decrease firm risk. While this is surprising, it is likely that these factors are endogenous with firms that already are located in environments with high outside option risk.

However, the key takeaway throughout this panel is that the effect of organization capital remains highly statistically and economically significant, and that legal and compensatory factors do not subsume the other risk factors affecting organization capital (including the outside option), thus further supporting hypothesis 3A.

(Insert Table 4.8 here)

As an alternative, panel B of Table 4.8 evaluates the effect of these binding agents and their interaction with organization capital on three-year abnormal returns. In this longer term case, the modified Garmaise Index seems to actually reduce firm risk in model 1, but the significance is very low, and no significance arises from the modified Garmaise Index in the other models. Similar to panel A, Model 2 shows that high nonbinding compensation seems to increase firm risk independently of organization capital, further supporting hypothesis 4B; however, when interacted with organization capital in model 2, there is no significance. Organization capital remains statistically and economically significant in all models except for model 2, further supporting hypothesis 3A.

G. Instrumental Variable Regressions of Returns on the Outside Option for O/K

In the prior tests I have been able to establish a connection between organization capital and firm returns as a function of labor flows and labor velocity. This establishes a direct connection between the outside employment option and firm risk. In fact, based on unreported tests on my inventor dataset and results from Marx, Strumsky, and Fleming (2009), immediate industry skills are considered perhaps the most transferable; thus, a higher level of wage or employment growth from firms in the same industry should indicate more wage pressure from immediately outside the firm, and hence higher firm risk from the increased outside option pressure on employees.

However, there could be extensive endogeneity issues when comparing organization capital (proxied by SG&A/assets) and returns, as prior literature shows that many factors in SG&A other than wage growth and training could potentially lead to higher firm risk. So for robustness, it would make sense to evaluate alternate methods of measuring the strength of the outside option on firm risk for companies with high levels of organization capital.

To accomplish this, I test a shift in wage growth in a firm using three instrumental variables: 1) the differential growth of annual wages in a firm versus its industry using a broad measure of firm wages (selling, general, and administrative expenses), 2) the differential growth of annual wages in a firm versus its industry using a more precise measure of firm wages (staff expenses), and 3) the differential growth of annual employment in a firm versus its industry using a simple count of total employment. These are inspired by one of the instrumental variables in Bae, Kang, and Wang (2011), which looks at industry level wage rates as a proxy for employee treatment.

(Insert Table 4.9 here)

Panel A of Table 4.9 shows the results of these three IV's in various combinations for the wage and employment growth of organization capital versus firm abnormal returns. I obtain negative significance in the first stage of all of the IVs in all four models, which is consistent with the idea that an increase in industry wages or employment relative to the firm would cause the firm to increase wages, training, etc., to stay competitive, thus causing O/K for the firm to increase. The second stage confirms that this predicted increase in firm O/K also increases firm risk, as the coefficient on predicted O/K is positive and highly significant in all four models.

I perform three tests to confirm the validity of these IV's. First, I confirm the strength of these IV's using the first-stage F-test of Stock and Yogo (2005), with p-values strongly rejecting the null that the IV's are weak. Second, I use the Hansen's J test of overidentification and confirm that the overidentifying restriction is valid in models 1, 3, and 4. However, model 2 is borderline on this test with a p-value = .0460 (rule of thumb, $\rho > 0.05$). Third, I test the endogeneity of variables using the Durbin-Wu-Hausman test of endogeneity and find confirming results in a variety of model combinations in unreported statistics.

Overall, these results strongly support hypothesis 5A and 5B, and also provide further support for hypothesis 3A.

H. Michigan Experiment

It is possible that firms with high organization capital risk due to the outside option may locate in states with strict non-compete laws to reduce the risk of their key talent leaving the firm. However, in March 1985 the Michigan legislature passed the Michigan Antitrust Reform Act (MARA), which was a large bill that accidentally repealed a 1905 statute prohibiting non-compete agreements. Marx, Strumsky, and Fleming (2009) provide a detailed account of the exogeneity of this event, as described in hypothesis 6. Thus this event provides an exogenous test of the effect of non-compete law strength on the portion of organization capital risk due to the outside option.

To test this, I create a matched sample of firms in Michigan in 1983 to U.S. firms outside of the state. I create a roughly 4-to-1 matched sample of non-Michigan firms to the treatment Michigan firms, matching from the same quintile of momentum, market-to-book, and market capitalization. As a last step, I sort the matched group by market capitalization (as size would likely be the most important factor), and match the two firms before and after the treatment Michigan firm. This final matching step should serve to avoid any bias from drift within the quintiles.

I then run a difference-in-difference-in-difference regression of 1-year returns on organization capital, a Michigan state indicator variable, and a postevent indicator variable by evaluating the identical set of matched firms described previously before and after the event. Although continuous variables such as organization capital are not used as often in DIDID regressions, they still work effectively. I use abnormal returns for the year 1984 to indicate pre-event period returns, and abnormal returns in 1990 to indicate post-event returns. I use this period several years after the event for two reasons: 1) Although the exogenous event took place in 1985, Marx, Strumsky, and Fleming describe a lengthy period of uncertainty after the event on what the actual status of non-compete law was in the state of Michigan (partly because the repeal was an accidental and exogenous change). In fact, it was actually unclear immediately after passage if the non-compete ban was repealed, so in December 1987 an amendment to MARA was passed by the Michigan legislature upholding the repeal of the ban on non-compete agreements. However, it is likely that this shock took some time to be absorbed by the market, and since most short-term risk events (Jegadeesh and Titman (1993), Debondt and Thaler (1985)) lose their significance after three years, I analyze the returns three years after the event window (which is between 1985 and 1987) in the year 1990, to see if there was a longer lasting change in risk among Michigan firms.

(Insert Table 4.10 here)

Panel A of Table 4.10 shows the impact of this event on firm risk. I consider the triple interaction term (post x treatment x O/K) to evaluate the impact of this event on firm risk for high organization capital firms. For the entire sample, I find that high organization capital firms in Michigan saw a significant reduction in firm risk after it was established that non-compete laws were enforceable. To ensure that this was not driven by the auto industry, I exclude the auto industry in column two and find that the results still hold. In columns 3 through 5, I further limit the matched sample to high organization capital firms (the top two quintiles of O/K), and add a filter for firms located within other states enforcing non-compete bans, as per Marx, Strumsky, and Fleming (2009). In all three cases the results still hold. All of these results support hypothesis 6.

I. Headquarter Moves and Non-Compete Laws: The Effect on the Outside Option

As a final robustness test of the legal environment impact on organization capital, I analyze the movement of firms between states with varying levels of non-compete law strength, as measured by the modified Garmaise (2011) index, from the year 1995-2009.

I first create a treatment sample of firms that switch the location of state headquarters between 1995 and 2009 using an analytics software package screening 10-Ks[70]. This is required because Compustat only includes current firm headquarter location, and does not measure headquarter location changes in the past. To avoid data entry mistakes from the SEC documents,

[70] Specifically, I use SEC Analytics Suite to obtain this information.

or temporary headquarter relocations, I require that firms must have been present at the old location for 3 years prior to the switching year, and for three years after the switching year. I then create a matched sample of firms switching headquarter location to firms not switching. I create a roughly 4-to-1 matched sample of non-switching firms to switching firms, matching from the same quintile of momentum, market-to-book, and market capitalization. As a last step, I sort the matched group by market capitalization (as size would likely be the most important factor), and match the two firms before and after the treatment switching firm. This final matching step should serve to avoid any bias from drift within the quintiles.

In addition, because of the unique environment California plays on firm performance (they are considered a unique high-velocity labor market by Saxenian (1996) and Gilson (1999)), I exclude California firms from the sample. Also, since there may be little change in returns between states with almost identical modified Garmaise scores, I further limit the switchers and matches to firms moving 2 or more points on the modified Garmaise index (which varies from 0 to 9).

(Insert Table 4.11 here)

Panel A of Table 4.11 shows that firms moving to a state with non-compete laws that are more strict face lower overall risk, as seen by their 3-year returns. This is shown with weak significance in the triple interaction term of post x treatment x O/K. Overall, this provides modest support for hypothesis 7.

4.5 Conclusion

I contribute to the debate over the effect of the outside option on firm risk by empirically examining the largely theoretical predictions of Eisfeldt Papanickolaou (2013). I measure this by actually measuring the flow of key talent between firms using one of the primary databases used for measuring skilled employee movement between firms – inventor firm switches based on changes in publicly traded patenting firm from patent filings between 1976-2006 as in Lai, D'Amore, and Fleming (2011). For the inventor patent filings, I evaluate the movement of 22,021 inventors between publicly traded firms spanning from 1976-2006, from a total of 1.41M publicly traded firm utility patent filings by 432,088 inventors.

I find that as organization capital increases, there is an increase in the likelihood that key talent will move away from a firm, as proxied by firm inventors. This supports the idea that high organization capital can increase firm risk not only by the fact that there is more intangible value at stake for that firm, but also because key talent is more likely to leave a high organization capital company.

I also find that high organization capital firms experience a net outflow of firm inventors, supporting the idea that high organization capital increases firm risk as a result of the outside option. In addition, I find that high organization capital increases firm velocity, which supports the idea that high organization capital increases firm risk by placing these firms in a class of companies that experience high skilled labor turnover.

I verify the findings of Eisfeldt Papanikolaou (2013) and find that firms with higher organization capital face increased risk as proxied by 1-year firm returns. More importantly, I find that labor flow has a strong positive impact on future 1-year abnormal returns when interacted with organization capital, and that the significance of organization capital disappears when the outside option risk is accounted for.

I also investigate the outside factors (compensatory and legal) affecting the strength of the outside option for skilled employees. Compensation is considered the strongest voluntary motivation tying an employee to a firm, and I specifically evaluate the ratio of total compensation to binding compensation (NoBind) designed to retain key employees by "binding" them to a firm. I also look at the legal environment affecting skilled labor mobility by examining the effect of state non-compete laws on inventor flow and velocity using an index of non-compete law strength from Garmaise (2011). While both factors seem to have a moderate effect on firm risk, organization capital stays significant throughout interactions with these measures, indicating that organization capital cannot be subsumed as a risk factor by risk-reducing legal or compensatory environments.

I further test the effect of the legal environment on organization capital using an exogenous change in non-compete laws in Michigan in 1985. In 1985, Michigan effectively repealed an unenforced non-compete law statute, creating ambiguity in the use of non-compete agreements, which had been effectively banned "as a matter of public policy" since 1905. Marx, Strumsky, and Fleming (2009) find that overall labor velocity of inventors was reduced after this change due to the added friction on labor movement from the law change. I find that this exogenous shock reduced firm risk for companies with high organization capital as well.

I also use instrumental variables proxying for outside hiring pressure from within the same industry a firm belongs in order to determine the effect of wage and hiring pressure on firm risk for high organization capital firms. I find that these proxies for the outside option of organization capital significantly increase firm risk.

Finally, I test the effect of firm headquarter moves between states with different levels of non-compete laws based on the Garmaise (2011) index. I find modest support for the hypothesis that high organization capital firms can reduce firm risk when moving to states with stronger non-compete laws.

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4.6. Appendix A

Table 4.1
Descriptive Statistics - Patent Filings Dataset

This table presents descriptive statistics for general characteristics of the final sample, which is derived from the NBER utility patent filings dataset of Hall, Jaffe, Trajtenberg (2001), the inventor dataset of Lai, D'Amore, and Fleming (2011), and the patent dataset of Kogan, Papanikolaou, Seru, and Stoffman (2012). Variable definitions and scaling are given in Appendix A.1. Size is divided by 1 billion here for comparison purposes. Fama French 17 Industry Classifications are from Ken French's website. Panel A lists the key variables, firm performance control variables, and patent filing control variables from Marx, Strumsky, and Fleming (2009). Panel B compares total patent filings and inventor firm switches (as per the matching algorithm of Lai, D'Amore, and Fleming (2011) and additional screeners for this paper) from 1976-2006. I separate the data by decades, adding 1976 to the first decade to give 11 years of data for that period. "Total Inventors" is based on the sample used in this paper.

Panel A: Utility Patents 1976-2006

Variable	N	Mean	S.D.	Percentile 5%	Percentile 25%	Percentile 75%	Percentile 95%
Organization Capital	1,076,114	0.83	0.47	0.23	0.51	1.04	1.62
Firmspec	1,409,545	0.21	0.34	0.00	0.00	0.33	1.00
Firmpatct	1,409,545	502.82	776.18	6	57	557	2681
Invidindconc	1,219,708	6,385.36	2,770.57	2,397	3,956	10,000	10,000
Ipt	1,409,545	13.38	28.85	1	2	13	49
Tslp	1,021,014	1.95	2.15	1	1	2	6
Size	1,409,445	33.06	58.90	0.16	2.01	34.00	170.15
Market / Book	1,394,606	4.43	39.07	0.74	1.54	4.92	11.38
ROA	1,408,231	0.03	0.18	-0.15	0.02	0.09	0.17
Employees	1,400,968	94.01	135.83	0.58	13.02	109.40	329.37

Panel B: Patent Filings / Inventor Switches Per Industry And Decade

Total Patent Filings: 1,409,545. Total Inventors: 432,088

Fama French 17 Ind Classification	Total Patent Filings 76-86	Total Patent Filings 87-96	Total Patent Filings 97-06	Inventor Firm Switches 76-86	Inventor Firm Switches 87-96	Inventor Firm Switches 97-06	Totals Across Industries
1) Food	4,176	5,002	5,659	38	92	109	239
2) Mining and Minerals	464	224	276	4	7	3	14
3) Oil and Petroleum Products	24,703	18,977	9,137	226	238	224	688
4) Textiles, Apparel & Footware	1,355	1,260	983	11	25	21	57
5) Consumer Durables	11,886	25,684	24,567	106	246	270	622
6) Chemicals	34,878	38,205	23,666	220	465	455	1,140
7) Drugs, Soap, Perfumes, Tobacco	25,166	49,907	58,515	158	850	1,202	2,210
8) Construction / Construction Matls	9,717	6,979	6,143	62	110	110	282
9) Steel Works, etc	4,108	3,790	2,335	58	74	69	201
10) Fabricated Products	1,728	1,491	1,568	24	71	54	149
11) Machinery and Business Equip	57,823	131,099	267,712	565	2,380	5,339	8,284
12) Automobiles	15,270	29,623	30,787	90	317	1,029	1,436
13) Transportation	22,281	28,106	18,988	278	449	380	1,107
14) Utilities	293	234	156	8	5	2	15
15) Retail Stores	262	313	606	0	5	11	16
16) Banks, Ins Cos, other Financials	399	718	1,759	12	17	37	66
17) Other	58,818	137,294	202,495	468	1,768	3,259	5,495
			Totals Across Decades:	2,328	7,119	12,574	22,021

Table 4.2
Descriptive Statistics - Firm Totals Dataset

This table presents descriptive statistics for general characteristics of the final sample of inventor total movements by firm. The sample excludes observations missing a value for organization capital. Variable definitions and scaling are given in Appendix A.1. Size is divided by 1 billion here for comparison purposes. Each panel lists the organization capital proxy, firm performance control variables, and variables affecting the "outside option". I divide the sample into high and low organization capital groups per year, with Panel A providing statistics per low organization capital group, and Panel B providing statistics per high organization capital group for comparison. Because of the formation period of the organization capital proxy, and limited availability of SG&A expense data in Compustat before 1980, the sample starts later than the inventor movement dataset. This sample ranges from 1984-2012.

Panel A: Firm Measures 1984-2012

				Percentile			
Low Organization Capital	N	Mean	S.D.	5%	25%	75%	95%
Organization Capital	50,002	0.34	0.24	0.04	0.09	0.54	0.76
1-Year Returns	46,290	0.09	0.66	-0.65	-0.24	0.29	0.98
Garm	49,006	5	2	2	4	6	9
Inventor Velocity	18,095	3.10	20.63	0	0	0	12
Inventor Outflow	18,095	0.27	11.85	-1	0	0	1
Size	49,954	2.25	12.43	0.01	0.05	0.91	7.79
Momentum	49,106	0.15	0.68	-0.59	-0.18	0.35	1.08
Market / Book	48,831	2.81	37.81	0.41	0.99	2.55	6.04
Total Comp	11,763	2,609.25	4,687.24	314.55	674.31	2,741.40	8,863.64
NoBind Ratio	7,800	-0.34	0.20	-0.68	-0.48	-0.20	0.00
Employees	47,491	7.40	23.95	0.04	0.29	4.91	33.48
Innovative Industry	30,457	0.63	0.48	0	0	1	1
High Organization Capital							
Organization Capital	50,018	1.77	1.60	0.77	1.02	2.02	3.91
1-Year Returns	44,875	0.17	1.13	-0.70	-0.29	0.34	1.47
Garm	49,444	5	2	2	4	6	9
Inventor Velocity	24,663	2.33	20.94	0	0	0	5
Inventor Outflow	24,663	0.49	11.41	0	0	0	0
Size	49,922	1.57	10.12	0.00	0.02	0.41	4.65
Momentum	49,135	0.14	0.96	-0.69	-0.30	0.35	1.33
Market / Book	48,288	4.12	51.63	0.41	1.02	3.37	9.88
Total Comp	10,372	2,128.55	3,096.84	306.70	596.47	2,400.15	7,148.19
NoBind Ratio	6,410	-0.34	0.20	-0.68	-0.48	-0.19	0.00
Employees	48,982	7.39	40.49	0.04	0.18	3.29	28.94
Innovative Industry	31,699	0.76	0.43	0	1	1	1

Table 4.3

O/K Versus Fama French Risk Factors

This table shows equal weight averages of one-year abnormal returns for O/K versus the three Fama French (1993) risk factors for the period 1990-2010. The sample is separated into five quintiles by risk factor, and contains 73,566 firm-year observations. I require the sample to include only nonmissing observations for all four risk factors, and include common stock returns in the Nasdaq, NYSE, and AMEX.

Panel A: Equal-Weight Quintiles of 1-Year Returns by Risk Factor

Variable	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
O/K	0.0825	0.1123	0.1475	0.1722	0.2752
Size Inverse[1]	0.0920	0.0966	0.1232	0.1664	0.3238
Momentum[2]	0.2716	0.1497	0.1309	0.1247	0.1154
Book / Market	0.0858	0.1039	0.1445	0.1703	0.2863

[1]Returns by the inverse of size are listed, to evenly compare factors from low risk to high risk by increasing quintile

[2]Momentum in my sample yields the opposite outcome to that established by Fama French (1993). For robustness, I included missing observations in my sample for O/K, size, book / market, dropped observations post-2000, and compared the high-low decile, which yielded essentially the same results as Jegadeesh and Titman (1993,2001).

Table 4.4
Inventor Firm Switches and Organization Capital

This table presents the relationship between organization capital and individual inventor job switches in and out of a firm. I use an ordered logit model for column 1, with the dependent variable an indicator variable equal to -1 for switches out of a firm, 0 for no firm switching since the last patent filing, and 1 for switches into a firm. Columns 2-6 use a logit model and only consider inventors switching firms, with the dependent variable an indicator variable equal to 0 for switches out of a firm, and 1 for switches into a firm. Variables are defined in Appendix A (with identification of variables logged and log-transformed), and are winsorized at the 1% level. Year and Fama French 17 industry fixed effects are included for all regressions. Standard errors are robust to heteroskedasticity, and are clustered by firm. T-statistics are given in parentheses. Number of firm-year observations and pseudo r-squared are also included.

Panel A: Ordered Logit / Logit Regressions of Inventor Firm Switches on Organization Capital

	Firm Switchers - All Patents	Firm Switchers - Firm Switching Patent Pairs Only				
Variable	All	All	TSLP < 5	TSLP ? 5	O/K Low	O/K High
O/K	-0.1846 *	-0.4014 ***	-0.4101 ***	-0.5113 ***	-0.4598 **	-0.2267
	(-1.87)	(-3.52)	(-2.93)	(-2.74)	(-2.11)	(-1.12)
Firm Specificity	0.0753 ***	0.1758 ***	0.1819 ***	0.2301 ***	0.2096 ***	0.1572 ***
	(3.98)	(6.45)	(6.26)	(3.83)	(4.85)	(4.67)
Patents Per Firm	-0.0945	-0.0207	-0.0400	0.1531	0.0058	-0.0133
	(-1.62)	(-0.33)	(-0.62)	(1.16)	(0.07)	(-0.17)
Tech Specialization[1]	-2.1800 **	-1.3500	0.2510	-9.2800 **	-1.6600	-1.3400
	(-2.48)	(-0.86)	(0.15)	(-2.55)	(-0.73)	(-0.64)
Patents Per Inventor	0.1661 ***	0.6796 ***	0.6698 ***	1.2971 ***	0.5936 ***	0.7629 ***
	(4.38)	(10.74)	(10.47)	(7.40)	(6.54)	(7.77)
TSLP	0.3642 ***	0.2278 ***	0.4564 ***	0.0571 *	0.2283 ***	0.2290 ***
	(10.09)	(13.66)	(11.94)	(1.73)	(10.33)	(9.73)
Size	0.1002 *	0.1363 *	0.1872 **	-0.0971	0.0431	0.3200 ***
	(1.83)	(1.79)	(2.23)	(-0.78)	(0.38)	(3.04)
Market / Book	-0.1115	-0.1513	-0.2421 *	0.2161	-0.0263	-0.3512 *
	(-1.08)	(-1.15)	(-1.69)	(0.97)	(-0.12)	(-1.80)
ROA	0.7828 *	1.2472 ***	1.4746 ***	-0.1381	0.3882	1.4670 ***
	(1.90)	(3.07)	(3.10)	(-0.15)	(0.53)	(2.98)
Employees	-0.1857 **	-0.4251 ***	-0.4604 ***	-0.3189 **	-0.3321 ***	-0.6534 ***
	(-2.47)	(-4.66)	(-4.49)	(-2.15)	(-2.66)	(-4.86)
Intercept[2]		-2.5381 *	-3.8434 ***	1.8467	-1.9191	-5.2865 ***
		(-1.87)	(-2.64)	(0.75)	(-0.80)	(-3.14)
Year Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.0251	0.1774	0.1645	0.1924	0.1692	0.1872
No. Obs	192842	5666	4373	1256	2635	3027

*,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

[1] - Multiplied by 100,000 here so coefficient appears

[2] - I exclude reporting the two cut points for the ordered logit model

Table 4.5
Relationship between Labor Outflow and Organization Capital

This table shows the effect of organization capital on inventor labor flows in and out of the firm, in the presence of varying state non-compete law strength and the ratio of long-term compensation to total compensation. I limit the sample to firms with an absolute value of labor flows > 0 for the past 5 years. The dependent variable is labor outflow. In each panel, Columns 1 and 3 use fixed effects panel models, while columns 2 and 4 use random effects panel models to account for the time-invariance of the Garmaise Index. Variables are defined in Appendix A (with identification of variables logged and log-transformed), and are winsorized at the 1% level. Year and Fama French 17 industry fixed effects are included for all regressions. Standard errors are robust to heteroskedasticity, and are clustered by firm. T-statistics are given in parentheses. Number of firm-year observations and adjusted r-squared are also included.

Panel A: Panel Regressions of Labor Outflow on O/K

		Interactions		
Variables	Model 1	Model 2	Model 3	Model 4
Intercept	-45.8950	-114.8200 **	-106.7280	-95.8165 **
	(-0.91)	(-2.33)	(-1.35)	(-2.07)
O/K	15.4398 ***	16.0494 *	40.2288 ***	11.0282 ***
	(2.79)	(1.89)	(2.73)	(2.97)
Garm		-0.2755		-0.2693
		(-0.46)		(-0.35)
NoBind Ratio			-1.7202	-4.7286
			(-1.25)	(-1.30)
O/K x Garm		-0.9068		
		(-0.74)		
O/K x NoBind Ratio			-6.4880 **	
			(-2.00)	
Garm x NoBind Ratio				0.3144
				(0.68)
1-Year CAPM	-0.0815 **	2.2235 ***	0.4336 ***	-0.5008
	(-2.50)	(3.02)	(3.54)	(-0.58)
Size	2.0868	3.1616	3.6408	2.4367
	(0.77)	(1.32)	(0.95)	(1.06)
Momentum	-0.3814	2.0307	-2.3789	3.0810
	(-0.37)	(1.13)	(-0.73)	(1.58)
Market / Book	-0.3359	-4.6929	9.9312	-3.9930
	(-0.08)	(-0.96)	(0.98)	(-0.80)
Employees	-2.7674	3.3981	11.3553	3.5095
	(-0.57)	(0.90)	(0.97)	(0.94)
Total Comp		1.0406	-0.5021	1.7302
		(0.67)	(-0.23)	(0.97)
Innovative Industries	1.6300			
	(0.54)			
Year Fixed	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes
Observations	3533	1896	1889	1800
Adj R^2	0.026	0.113	0.028	0.120

*,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

Table 4.6
Relationship between Labor Velocity and Organization Capital

This table shows the effect of organization capital on total inventor labor velocity per firm (count of the total flow in and out of the firm), in the presence of varying state non-compete law strength and the ratio of long-term compensation to total compensation. The dependent variable is labor velocity. I use negative binomial count regressions due to the count nature of the dependent variable. Variables are defined in Appendix A (with identification of variables logged and log-transformed), and are winsorized at the 1% level. Year and Fama French 17 industry fixed effects are included for all regressions. Standard errors are robust to heteroskedasticity, and are clustered by firm. T-statistics are given in parentheses. Number of firm-year observations and adjusted r-squared are also included.

Panel A: Negative Binomial Regressions of Labor Velocity on O/K

		Interactions		
Variables	Model 1	Model 2	Model 3	Model 4
Intercept	-20.0216 ***	-16.8328 ***	-15.6527 ***	-0.1535 ***
	(-9.80)	(-9.26)	(-9.46)	(-9.16)
O/K	0.7312 ***	0.9172 ***	0.8025 ***	0.6955 ***
	(7.76)	(4.72)	(8.84)	(8.06)
Garm		0.0434		0.0430
		(1.42)		(1.47)
NoBind Ratio			-0.3068 ***	-0.3613 ***
			(-4.73)	(-2.98)
O/K x Garm		0.0379		
		(-1.16)		
O/K x NoBind Ratio			-0.1409 **	
			(-2.09)	
Garm x NoBind Ratio				0.0175
				(0.89)
1-Year CAPM	-0.4973 ***			
	(-6.62)			
Size	0.7844 ***	0.7448 ***	0.6846 ***	0.6590 ***
	(7.27)	(7.19)	(7.25)	(6.84)
Momentum	-0.3156 ***	-0.2982 ***	-0.2635 ***	-0.2407 ***
	(-3.67)	(-3.73)	(-3.17)	(-2.90)
Market / Book	-0.4222 ***	-0.4191 ***	-0.4067 ***	-0.3965 ***
	(-2.83)	(-2.92)	(-2.79)	(-2.71)
Employees	0.1784 *	0.2460	0.2440 ***	0.2708 ***
	(1.92)	(2.62)	(2.95)	(3.00)
Total Comp	0.0668	0.0371 ***	0.0886	0.0907
	(0.87)	(0.53)	(1.35)	(1.35)
Innovative Industries	0.7303 **			
	(2.34)			
Year Fixed	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes
Observations	7425	12194	7878	7684
Adj R^2	0.281	0.263	0.318	0.309

*,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

Table 4.7
Effect of O/K, Inventor Outflow, and Inventor Velocity on Firm Risk

This table presents abnormal returns analysis of organization capital, inventor labor outflows, and inventor labor velocity on 1-year and 3-year firm returns. I limit the sample to only firms that have ever filed a patent to give an even comparison between the three measures. The dependent variable is 1-year abnormal returns net of the risk-free rate in columns 1-2, and 3-year abnormal returns net of the risk-free rate in columns 3-5. Column 1 uses the Fama-MacBeth (1973) model, while the other columns use fixed effects panel models. Variables are defined in Appendix A (with identification of variables logged and log-transformed), and are winsorized at the 1% level. Year and Fama French 17 industry fixed effects are included for all regressions. Standard errors are robust to heteroskedasticity, and are clustered by firm. T-statistics are given in parentheses. Number of firm-year observations and adjusted r-squared (average r-squared for Fama-MacBeth (1973) regressions) are also included.

Panel A: Regressions of Abnormal Returns on O/K, Labor Flows, and Labor Velocity

	O/K		Labor Flows & Labor Velocity		
Variable	(Fama MacBeth) 1-Year Rets	(Fixed Effects) 1-Year Rets	(Fixed Effects) 3-Year Rets	(Fixed Effects) 3-Year Rets	(Fixed Effects) 3-Year Rets
Intercept	0.5314 **	5.4866 ***	13.2325 ***	15.0616 ***	13.2132 ***
	(1.97)	(31.40)	(9.56)	(33.00)	(9.60)
O/K	0.0292 ***	0.0379 ***	0.1146	0.0340	0.1145
	(3.31)	(3.19)	(1.05)	(1.15)	(1.06)
Outflow			0.0015 **		-0.0199 *
			(2.27)		(-1.73)
Velocity				0.0090 **	0.0003
				(2.12)	(0.04)
O/K x Outflow			0.0015 **		
			(2.35)		
O/K x Velocity				0.0022	
				(0.40)	
Outflow x Velocity					0.0015 *
					(1.78)
CAPM		-0.0026 ***	-0.0044 ***	-0.0038 ***	-0.0045 ***
		(-7.16)	(-3.34)	(-8.09)	(-3.36)
Size	-0.0154	-0.2588 ***	-0.5341 ***	-0.7308 ***	-0.5332 ***
	(-1.36)	(-26.76)	(-7.48)	(-28.70)	(-7.54)
Momentum	-0.0100	0.0099	-0.0478	0.0119	-0.0473
	(-0.29)	(1.45)	(-1.07)	(0.91)	(-1.06)
Market / Book	-0.0462 ***	-0.0172	-0.4433 ***	-0.0594 *	-0.4482 ***
	(-3.99)	(-1.32)	(-4.67)	(-1.76)	(-4.74)
Employees	0.0218	0.0583 ***	-0.2376 **	0.1228 ***	-0.2399 **
	(1.39)	(3.80)	(-2.09)	(2.71)	(-2.07)
Year Fixed	N/A	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes	Yes
R-squared	0.0910	0.0499	0.0111	0.0272	0.0111
No. Obs	37571	37571	4069	31234	4069

*,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

Table 4.8
O/K and Risk: The Effect of Legal and Compensatory Factors

This table presents abnormal returns analysis of the effect of organization capital, state non-compete law strength, and ratio of long-term compensation to total compensation on 1-year and 3-year firm returns. The dependent variable in panel A is 1-year abnormal returns net of the risk-free rate, while the dependent variable in panel B is 3-year abnormal returns net of the risk-free rate. In each panel, Column 1, 3, and 4 use a random effects panel model to account for the time-invariance of the Garmaise Index, while column 2 uses a fixed effects panel model. Variables are defined in Appendix A (with identification of variables logged and log-transformed), and are winsorized at the 1% level. Year and Fama French 17 industry fixed effects are included for all regressions. Standard errors are robust to heteroskedasticity, and are clustered by firm. T-statistics are given in parentheses. Number of firm-year observations and adjusted r-squared are also included.

Panel A: Panel Regressions of 1-Year Abnormal Returns on O/K, Legal, and Compensatory Factors

Variable	Model 1	Model 2	Model 3	Model 4
Intercept	0.9504 ***	7.9886 ***	0.7527 ***	0.7474 ***
	(12.61)	(21.85)	(7.44)	(7.39)
O/K	0.0499 ***	0.0709 ***	0.0519 ***	0.0420 ***
	(5.30)	(3.00)	(7.87)	(2.75)
Garm	0.0025		0.0083 ***	0.0093 ***
	(1.22)		(2.98)	(2.85)
NoBind Ratio		0.0134 *	0.0353 ***	0.0419 ***
		(1.70)	(2.61)	(2.70)
O/K x Garm	-0.0023			0.0023
	(-1.45)			(0.87)
O/K x NoBind Ratio		0.0053		0.0157
		(0.96)		(1.39)
Garm x NoBind Ratio			-0.0063 **	-0.0081 ***
			(-2.51)	(-2.79)
O/K x Garm x NoBind Ratio				-0.0038 *
				(-1.74)
1-Year CAPM	-0.0115 ***	-0.0067 ***	-0.0135 ***	-0.0135 ***
	(-13.89)	(-15.73)	(-3.38)	(-3.38)
Size	-0.0451 ***	-0.3708 ***	-0.0327 ***	-0.0327 ***
	(-9.86)	(-19.27)	(-5.68)	(-5.69)
Momentum	-0.0270 ***	0.0219	-0.0180	-0.0178
	(-2.86)	(1.54)	(-1.36)	(-1.35)
Market / Book	-0.0500 ***	-0.0511 **	-0.0804 ***	-0.0807 ***
	(-5.45)	(-2.05)	(-6.57)	(-6.58)
Total Comp	0.0340 ***	0.0269 ***	0.0229 ***	0.0231 ***
	(5.84)	(2.78)	(3.11)	(3.14)
Year Fixed	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes
Observations	19891	12065	11846	11846
Adj R^2	0.179	0.016	0.102	0.102

*,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

Panel B: Panel Regressions of 3-Year Abnormal Returns on O/K, Legal, and Compensatory Factors

Variable	Model 1	Model 2	Model 3	Model 4
Intercept	5.7639 ***	17.5606 ***	4.1337 ***	4.1586 ***
	(16.12)	(19.98)	(10.15)	(10.12)
O/K	0.1872 ***	0.0192	0.1447 ***	0.1929 ***
	(4.63)	(0.37)	(6.91)	(3.87)
Garm	0.0010		0.0085	0.0047
	(0.11)		(1.03)	(0.46)
NoBind Ratio		0.0366 ***	0.0170	0.0016
		(2.83)	(0.61)	(0.05)
O/K x Garm	-0.0125 *			-0.0076
	(-1.86)			(-0.91)
O/K x NoBind Ratio		-0.0035		-0.0318
		(-0.36)		(-1.35)
Garm x NoBind Ratio			0.0006	0.0023
			(0.11)	(0.41)
O/K x Garm x NoBind Ratio				0.0040
				(0.96)
3-Year CAPM	-1.6588 ***	-0.4192 ***	-0.8040 ***	-0.8058 ***
	(-7.28)	(-11.04)	(-5.82)	(-5.84)
Size	-0.2512 ***	-0.7925 ***	-0.1613 ***	-0.1614 ***
	(-13.81)	(-17.38)	(-7.83)	(-7.84)
Momentum	-0.0473 ***	0.0540 **	-0.0468 **	-0.0458 **
	(-2.82)	(2.26)	(-2.05)	(-2.01)
Market / Book	-0.2707 ***	-0.2438 ***	-0.3613 ***	-0.3630 ***
	(-8.71)	(-4.33)	(-9.31)	(-9.37)
Total Comp	0.0261 **	-0.0039	-0.0036	-0.0029
	(1.96)	(-0.21)	(-0.22)	(-0.17)
Year Fixed	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes
Observations	15562	10552	10363	10363
Adj R^2	0.095	0.022	0.098	0.098

*,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

Table 4.9

Instrumental Variable Regressions of Returns on the "Outside Option" for O/K

This table shows the results from two-stage least square regressions that control for the endogeneity of the relation between organization capital and firm returns, by isolating the portion of organization capital affecting firm risk via the "outside option". I use 3-year abnormal returns net of the risk-free rate as the dependent variable. I include three instrumental variables constructed from Compustat data from 1984-2012, identified as follows: SG&A ratio, staff expenses ratio, and employment ratio. Variables are defined in Appendix A (with identification of variables logged and log-transformed), and are winsorized at the 1% level. For each model, the first-stage regression estimates the model regressing O/K on the instrumental variables and the control variables. The second-stage regression estimates the regression of 3-year abnormal returns on the predicted O/K with other determinants of returns. Standard errors are robust to heteroskedasticity, and are clustered by firm. I also include year and 2-digit SIC industry fixed effects. P-values are reported for the first stage F-test and the Hansen's overidentification test.

Panel A: IV Regressions of Returns on O/K

	Model 1		Model 2		Model 3		Model 3	
	First Stage	Second Stage	First Stage	Second Stage	First Stage	Second Stage	First Stage	Second Stage
Intercept	0.8401 ***		0.6567 ***		1.9256 ***		1.6072 ***	
	(6.83)		(5.93)		(32.23)		(7.65)	
Predicted O/K		0.1302 ***		0.1328 ***		0.1092 ***		0.1950 **
		(3.68)		(3.90)		(9.42)		(2.52)
3-Year CAPM	0.7118 ***	2.0494 ***	0.7313 ***	2.0578 ***	0.4612 ***	-2.4130 ***	0.4657 ***	1.9208 ***
	(10.20)	(7.32)	(10.78)	(7.45)	(12.24)	(-12.64)	(4.26)	(6.75)
Size	0.0053	0.0048	0.0047	0.0090	-0.0357 ***	-0.0120 ***	-0.0416 ***	0.0087
	(1.02)	(0.73)	(0.96)	(1.49)	(-15.06)	(-3.22)	(-4.29)	(1.07)
Momentum	0.0220 *	-0.0341	0.0215 *	-0.0367	-0.0013	-0.0428 ***	-0.0234	-0.0309
	(1.84)	(-1.32)	(1.87)	(-1.49)	(-0.40)	(-4.98)	(-1.21)	(-1.18)
Market / Book	-0.0457 *	-0.3648 ***	-0.0471 **	-0.3676 ***	0.0016	-0.2526 ***	0.1999 ***	-0.3798 ***
	(-1.87)	(-8.29)	(-1.96)	(-8.59)	(0.21)	(-17.82)	(4.80)	(-8.12)
Instrumental Variable								
SG&A Ratio	-1.7197 ***		-1.7686 ***		-1.4292 ***			
	(-19.25)		(-21.19)		(-87.50)			
Staff Expenses Ratio	-0.1648 ***		-0.2410 ***				-0.2287 *	
	(-2.60)		(-3.52)				(-1.73)	
Employment Ratio	-0.3386 **				-0.2713 ***		-1.6950 ***	
	(-2.29)				(-9.10)		(-7.04)	
Industry Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9617	9617	10608	10608	66494	66494	9652	9652
Adj R^2	0.954	0.316	0.953	0.328	0.903	0.125	0.873	0.314
IV TESTS								
First Stage F-Test (p-value)	0.0000		0.0000		0.0000		0.0000	
Hansen's J overid (p-value)[a]	0.0864		0.0460		0.7981		0.1717	

*,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

[a]: I exclude industry fixed effects for this test. Results are robust to their inclusion.

Table 4.10
O/K and Risk: The Michigan Non-Compete Experiment

This table presents estimates from a difference-in-difference-in-difference regression of 1-year abnormal returns for firms affected by the exogenous change in Michigan non-compete laws in 1985. The dependent variable is 1-year firm returns net of the risk-free rate. Post is a dummy variable equal to 1 for the 1-year period of abnormal returns after the event transition period, and equal to zero for the abnormal returns 1 year before the event transition period. The event transition period includes the 3-year legal debate period of the non-compete law change (1985-1987), and the 3-year adjustment period (1988-1990) after the legal debate period. Treatment is an indicator variable with firms in Michigan equal to 1, and firms outside of Michigan equal to 0. Variables are defined in Appendix A (with identification of variables logged and log-transformed), and are winsorized at the 1% level. Fama French 17 industry fixed effects are included for all regressions. Standard errors are robust to heteroskedasticity, and are clustered by firm. T-statistics are given in parentheses. Number of firm-year observations and adjusted r-squared are also included.

Panel A: Diff-In-Diff-In-Diff Regressions of 1-Year Returns on O/K, based on the Michigan Non-Compete Law Change

	Full Matched Sample (O/K Quintile 1 - 5)		High O/K (O/K Quintile 4 & 5)		
	All	Non-Auto	All	Non-Auto	Non-Auto & Enf State
Intercept	0.0780	0.0659	-0.0856	-0.0849	0.0315
	(0.80)	(0.68)	(-1.10)	(-1.11)	(0.23)
Post	0.2755 ***	0.2687 ***	0.0052	-0.0076	-0.1674
	(3.92)	(3.79)	(0.04)	(-0.06)	(-0.65)
Treatment	0.0933	0.0639	0.0831	0.0852	0.0692
	(1.16)	(0.84)	(1.01)	(1.12)	(0.59)
O/K	-0.0111	-0.0057	0.0457	0.0416	0.0080
	(-0.15)	(-0.07)	(0.59)	(0.53)	(0.05)
Post x Treatment	0.3074 *	0.3484 **	0.3776	0.4820	0.7282 *
	(1.94)	(2.01)	(1.08)	(1.35)	(1.82)
Post x O/K	0.4301 ***	0.4292 ***	0.6720 ***	0.6761 ***	0.6418
	(3.03)	(3.02)	(3.45)	(3.46)	(1.57)
Treatment x O/K	-0.0953	-0.0594	-0.0729	-0.0790	-0.1336
	(-0.63)	(-0.41)	(-0.49)	(-0.55)	(-0.59)
Post x Treatment x O/K	-0.8868 ***	-0.8995 ***	-0.9498 **	-1.0260 **	-1.0740 **
	(-3.22)	(-3.15)	(-2.31)	(-2.46)	(-2.03)
Employees	0.0122	0.0199 *	0.0306 ***	0.0305 ***	0.0317 **
	(1.22)	(1.93)	(3.16)	(2.94)	(2.12)
Year Fixed	N/A	N/A	N/A	N/A	N/A
Industry Fixed	Yes	Yes	Yes	Yes	Yes
Observations	777	726	514	487	188
Adj R^2	0.269	0.280	0.407	0.411	0.206

*,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

Table 4.11
Headquarter Moves and Non-Compete Laws: The Effect on the "Outside Option"

This table presents estimates from a difference-in-difference-in-difference regression of 3-year abnormal returns for firms moving to a state with either more strict or more lenient non-compete laws, as scored by Garmaise (2011). The dependent variable is 3-year firm returns net of the risk-free rate. Post is an indicator variable equal to 1 for the 3-year period of abnormal returns after the event year, and equal to zero for the abnormal returns 3 years before the event year. Treatment is an indicator variable with firms moving to a more strict non-compete state equal to 1, and firms moving to a more lenient state equal to 0. Firms moving to states with the same Garmaise score are excluded. Variables are defined in Appendix A (with identification of variables logged and log-transformed), and are winsorized at the 1% level. Standard errors are robust to heteroskedasticity, and are clustered by firm. T-statistics are given in parentheses. Number of firm-year observations and adjusted r-squared are also included.

Panel A: Diff-In-Diff-In-Diff Regressions of 3-Year Returns on O/K, based on HQ Moves and the Garmaise (2011) Index

Variable	Model 1	Model 2
Intercept	2.1470 **	1.5744
	(2.00)	(1.18)
Post	0.1341	0.1967
	(0.29)	(0.41)
Treatment	0.6873	0.6675
	(1.42)	(1.38)
O/K	-0.0656	-0.0850
	(-0.27)	(-0.33)
Post x Treatment	-1.0043	-1.0533 *
	(-1.59)	(-1.66)
Post x O/K	0.2493	0.3116
	(0.82)	(0.96)
Treatment x O/K	0.4477	0.4756
	(1.30)	(1.34)
Post x Treatment x O/K	-0.7295 *	-0.7851 *
	(-1.68)	(-1.73)
CAPM	-0.8460	-0.6815
	(-0.43)	(-0.34)
Size	-0.0699 *	-0.0308
	(-1.68)	(-0.40)
Momentum	0.0534	0.0420
	(0.29)	(0.22)
Book / Market	-0.1610	-0.2233
	(-0.87)	(-1.04)
Employees		-0.0809
		(-0.65)
Year Fixed	Yes	Yes
Observations	106	104
Adj R^2	0.337	0.348

*,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

Appendix Table A.1: Variable definitions

Variables	Definition (*Data sources*)
Firm Classifications and Miscellaneous Variables	
Garm	Categorical variable ranging from 0 to 9 based on the state presence of noncompete law provisions, with a higher score indicating tougher non-compete laws. For this paper, I use a modified Garmaise index (which subtracts 9 from the original index) to allow for easier interpretation of interaction terms, so that a higher score indicates weaker non-compete laws, and higher "outside option" risk *(Source: Garmaise (2011))*
Innovind	Dummy variable equal to 1 for firms above the 50th percentile for the rank of innovativeness, zero otherwise. *(Source: Hirshliefer, Low, and Teoh (2012))*
SG&A Ratio	Ratio of the selling, general, and administrative expenses for a firm divided by total assets, divided by the average firm selling, general, and administrative expenses for a firm divided by total assets for the two-digit SIC industry. SGA Ratio = [(SGA/total assets) / (SGA average for the 2-digit SIC industry / Total assets average for the 2-digit SIC industry)]. I exclude the firm's SG&A/total assets ratio when calculating the industry ratio in the denominator.
Staff Expenses Ratio	Ratio of the selling, general, and administrative expenses for a firm divided by total assets, divided by the average firm selling, general, and administrative expenses for a firm divided by total assets for the two-digit SIC industry. SGA Ratio = [(SGA/total assets) / (SGA average for the 2-digit SIC industry / Total assets average for the 2-digit SIC industry)]. I exclude the firm's SG&A/total assets ratio when calculating the industry ratio in the denominator.
Employment Ratio	Ratio of the selling, general, and administrative expenses for a firm divided by total assets, divided by the average firm selling, general, and administrative expenses for a firm divided by total assets for the two-digit SIC industry. SGA Ratio = [(SGA/total assets) / (SGA average for the 2-digit SIC industry / Total assets average for the 2-digit SIC industry)]. I exclude the firm's SG&A/total assets ratio when calculating the industry ratio in the denominator.
Firm Characteristics	
Size	Log of (1 + market capitalization of the firm). *(Source: CRSP)*
Momentum	Prior 12-month return for a firm. *(Source: Jegadeesh and Titman (1993), CRSP)*
M/B Ratio	Log of (1 + market capitalization of the firm / book value of assets). *(Source: CRSP, Compustat)*
O/K	Log of organization capital. Selling, general, and administrative (SG&A) stock / total assets, adjusted to 2012 dollars using the CPI index, discounted using the perpetual inventory method with a 15% discount rate, as follows: SG&A stock = $SG\&A_t + (.85)(SG\&A_{t-1}) + (.7)(SG\&A_{t-2}) + (.55)(SG\&A_{t-3}) + (.4)(SG\&A_{t-4})$. *(Source: Compustat)*
1-Year Rets	1-year firm returns including dividends, net of the risk-free rate (1-year Treasury bills). *(Source: CRSP)*
3-Year Rets	3-year firm returns including dividends, net of the risk-free rate (geometric return of the past three (1-year returns minus 1- year Treasury bills)). *(Source: CRSP)*
Velocity	(Number of inventors leaving a firm in the prior 5 years) + (Number of inventors joining a firm in the prior 5 years). *(Source: NBER patent data project of Hall, Jaffe, and Trajtenberg (2001), the patent dataverse of Lai, D'Amore, and Fleming (2011), and the Kogan, Papanikolaou, Seru, and Stoffman (2012) patent data).*
Outflow	Net number of inventors leaving a firm in the prior 5 years. *(Source: NBER patent data project of Hall, Jaffe, and Trajtenberg (2001), the patent dataverse of Lai, D'Amore, and Fleming (2011), and the Kogan, Papanikolaou, Seru, and Stoffman (2012) patent data).*
Total Comp	Log of total compensation, defined as follows: (salary+bonus+other annual+restricted stock grants+LTIP payouts+all other+Black Scholes value of option grants+value of options exercised). *(Source: Execucomp).*
NoBind Ratio	Log transformation of the ratio of total compensation divided by forms of compensation that tend to "bind" employees to a firm, defined as follows: (salary+bonus+other annual+restricted stock grants+LTIP payouts+all other+Black Scholes value of option grants+value of options exercised) / (Black Scholes value of option grants+restricted stock grants+LTIP payouts). *(Source: Execucomp).*
1-Year CAPM	1-year value weighted market return net of 1-year risk free rate (from U.S. Treasuries). (*Source: Ken French's website).*
3-Year CAPM	3-year value weighted market return net of 3-year risk free rate (from U.S. Treasuries). (*Source: Ken French's website).*
Employees	Log of (1 + number of employees working for the firm). *(Source: Compustat)*
ROA	Return on Assets=annual firm market return / total assets. *(Source: CRSP, Compustat)*

Patent Filing Characteristics

Firmspec	Log transformation of firm specificity. The number of internal citations (from future firm patents) divided by the total citations received. *(Source: Marx Strumsky, and Fleming (2009), NBER patent data project of Hall, Jaffe, and Trajtenberg (2001)).*
Firmpatct	Log of (1 + number of patents per firm year). The total number of patents filed by the firm during the calendar year. *(Source: Marx Strumsky, and Fleming (2009), NBER patent data project of Hall, Jaffe, and Trajtenberg (2001)).*
Invidindconc	Inventor industry concentration of patents across technology classes. Herfindahl type measure of the degree of specialization of an inventor. *(Source: Marx Strumsky, and Fleming (2009), Hirshleifer, Hsu, and Li (2013), NBER patent data project of Hall, Jaffe, and Trajtenberg (2001)).*
Ipt	Log of (1 + inventor patent total). Total number of prior patents for the inventor. *(Source: Marx Strumsky, and Fleming (2009), NBER patent data project of Hall, Jaffe, and Trajtenberg (2001)).*
Tslp	Time since last patent. Total number of years since the last patent filing for the inventor. *(Source: Marx, Strumsky, and Fleming (2009), NBER patent data project of Hall, Jaffe, and Trajtenberg (2001)).*

Difference-in-Difference - Michigan Experiment

Postevent (1/0)	Indicator variable equal to 1 in the year 1990, 0 in the year 1984.
Treatment (1/0)	Indicator variable equal to 1 for firms headquartered in Michigan, 0 for firms headquartered outside of Michigan. (Source: Compustat)
Nonauto	Indicator variable equal to 0 for firms located in between 4-digit SIC code 3700 and 3799, 1 otherwise.
Enfstate	Indicator variable equal to 0 for the following not enforcing non-compete laws: Michigan, Alaska, California, Connecticut, Minnesota, Montana, North Dakota, Nevada, Oklahoma, Washington; 0 otherwise. *(Source: Marx, Strumsky, and Fleming (2009)).*

Difference-in-Difference - Headquarter Moves

Postevent (1/0)	Dummy variable equal to 1 for the 3rd year after a headquarter move, 0 for the 3rd year before a headquarter move. *(Source: 10-K searches)*
Treatment (1/0)	Dummy variable equal to 1 for firms moving to a state with non-compete laws 2 points stricter on the Garmaise index, 0 for firms moving to a state with non-compete laws 2 points less strict on the Garmaise index. *(Source: Garmaise (2011), 10-K searches)*

CHAPTER 5

CONCLUSION

This dissertation consists of three essays on investments and corporate finance. The first essay focuses on factors affecting market makers in the trading of securities, and finds that market makers can identify asymmetric trading via the PIN measure and abnormal volumes and adjust spreads accordingly. The second essay is a corporate finance article which empirically tests the theoretical predictions of Manso (2011) that the individual choice of management to innovate is motivated by a firm "tolerance for early failure", as innovations often struggle along their development paths. Ultimately, I find empirical support for many of the predictions of Manso. The third essay is a corporate finance article which empirically tests theories of why returns are higher in firms with high organization capital investments. Eisfeldt and Papanikolaou (2013) introduced the idea that the threat of the loss of "key talent" may increase risk for firms with high levels of organization capital (SG&A stock / assets). I add to this debate by testing the movement of inventors between firms, and find strong support for the theories of Eisfeldt and Papanikolaou.