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**NANYANG
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SINGAPORE

THREE ESSAYS ON FINANCE

YANG CHUYI

NANYANG BUSINESS SCHOOL

2020

THREE ESSAYS ON FINANCE

YANG CHUYI

Nanyang Business School

A thesis submitted to the Nanyang Technological University
in partial fulfilment of the requirement for the degree of
Doctor of Philosophy

2020

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Chapter 1

The contributions of the co-authors are as follows:

- I discovered the findings that the Monday effect is affected by the jackpot sizes on the preceding Saturday
- Prof Chuan Yang Hwang provided project direction
- I developed the hypothesis, collected jackpot data, conducted data analysis and prepared the manuscript under the supervision of Prof Chuan Yang Hwang
- Prof Chuan Yang Hwang revised the manuscript

Chapter 2 is presented at Nanyang Business School Seminar (Singapore, October 2017), 2017 Singapore Scholar Symposium (Singapore, November 2017), Sichuan University Department of Economics (Chengdu, December 2017), 6th East Lake International Forum for Outstanding Overseas Young Scholars (Wuhan, December 2017), Asian Finance Association Conference (Tokyo, June 2018)

The contributions of the co-authors are as follows:

- Assoc Prof Lei Zhang and Asst Prof Chongwu Xia provided project direction
- I developed the hypothesis, conducted data analysis and prepared the manuscript under the supervision of Assoc Prof Lei Zhang
- Asst Prof Chongwu Xia revised the manuscript

Chapter 3 is presented at 2017 Asia FMA PhD Consortium (Taipei, May 2017), 2017 Asian Meeting of the Econometric Society (Hong Kong, June 2017), 2017 Singapore Economic Review Conference (Singapore, August 2017), Jiangxi University of Finance and Economics (Nanchang, October 2018)

The contributions of the co-authors are as follows:

- Assoc Prof Lei Zhang provided securities class action lawsuit data and provided project direction
- I developed the hypothesis, conducted data analysis and prepared the manuscript under the supervision of Assoc Prof Lei Zhang
- Assoc Prof Barry Oliver revised the manuscript

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Summary

In Chapter 1, using large lottery jackpots on Saturday as repeated exogenous shocks to investor attention, we find that the Monday effect of market return and the Monday effect of anomalies only exist on Mondays with a large jackpot on the preceding Saturday. For example, the Monday effect of high idiosyncratic volatility stocks is a striking - 64 bps when there was a large Saturday jackpot but is negligible otherwise. This is consistent with the hypothesis that individual investors allocate the weekends to process information and decide on trading strategies. Large jackpots during the weekends distract individual investors' attention from the stock market, resulting in less buying relative to selling, lower return and larger stock co-movement on the following Monday. The jackpot effect is larger among stocks preferred by individual investors. Interestingly, we do not find similar jackpot effect on weekday drawings.

In Chapter 2, we study the real effects of foreign exchange hedging on corporate innovation. Under the *information asymmetry hypothesis*, corporate hedging reduces firm's information asymmetry, and alleviates manager's career concern from undervaluation and helps investors to better monitor the manager, which in turn increases innovation. Under the *market pressure hypothesis*, hedging imposes more short-term earnings pressure on managers because of mark-to-market hedge accounting, hence leads to lower innovation. Our results support the *information asymmetry hypothesis*. Hedged firms invest more heavily in innovative projects, generate more patents and have more patent citations. To address endogeneity concerns, we employ both difference-in-differences and instrumental variables regressions, and test for reverse causality explicitly.

In Chapter 3, we document a measure of law firm expertise that could predict the outcomes of future lawsuits conducted by the law firm, using securities class action lawsuits from 1996 to 2013. We use prior Dismissed Ratio as law firm expertise measure on a rolling basis, defined as ratio of number of dismissed cases to number of total cases conducted by the law firm in the past 5 years. It is found that law firms with lower prior Dismissed Ratio are more likely to be skilled law firms with less agency problem. Cases conducted by skilled law firms with less agency problem are more likely to be settled, have more negative cumulative abnormal return during the filing date, win larger settlement amount, result in larger probability of CEO turnover and are associated with larger short interest one week prior to the filing event. Skilled law firms contribute to better outcomes by exerting more effort in the litigation process, as evident by the longer Case Length from filing date to status date. In addition, market share of law firms increases after performing as skilled law firms and skilled law firms are less likely to disappear from the market in the future. Overall, predictive power and persistence of law firm expertise suggest law firm fixed effect in securities class action lawsuits. Robustness tests suggest existence of law firm expertise beyond case selection.

Chapter 1

Lottery Jackpots and the Monday Effect

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Lottery Jackpots and the Monday Effect

Abstract

Using large lottery jackpots on Saturday as repeated exogenous shocks to investor attention, we find that the Monday effect of market return and the Monday effect of anomalies only exist on Mondays with a large jackpot on the preceding Saturday. For example, the Monday effect of high idiosyncratic volatility stocks is a striking - 64 bps when there was a large Saturday jackpot but is negligible otherwise. This is consistent with the hypothesis that individual investors allocate the weekends to process information and decide on trading strategies. Large jackpots during the weekends distract individual investors' attention from the stock market, resulting in less buying relative to selling, lower return and larger stock co-movement on the following Monday. The jackpot effect is larger among stocks preferred by individual investors. Interestingly, we do not find similar jackpot effect on weekday drawings.

JEL Classification: G41, G12, G11

Keywords: Investor Attention, Monday Effect, Stock Market Anomalies

I. Introduction

The Monday effect, equity market return on Monday is lower than other days of the week and on average negative, has remained an intriguing anomaly for a long time in the U.S. and international markets¹. The most consistent and widely accepted explanation² is that the Monday effect is related to investors' trading behavior. As it takes time to process information, individual investors will process information during the weekends and trade on Monday for liquidity needs or rebalancing reasons (Osborne (1962), Miller (1988), Lakonishok and Maberly (1990), Abraham and Ikenberry (1994)). In contrast, institutional investors usually allocate Monday as strategic planning day (Osborne (1962)) and refrain from trading on Monday (Jain and Joh (1988), Lakonishok and Maberly (1990), Venezia and Shapira (2007), Ülkü and Rogers (2018)).

These papers also suggest that individual investors are more likely to sell (or less likely to buy) on Monday and depress prices³. However, the static proxies for individual investors' and institutional investors' trading activity based on trader-type classifications become less accurate in the recent period with electronic trading and order divisibility (Hvidkjaer (2008), Campbell,

¹ The Monday effect also exists in other asset class: treasury bill returns (Gibbons and Hess (1981)), federal funds rates (Griffiths and Winters (1995)), bonds return (Jordan and Jordan (1991)), gold price (Ball, Torous, and Tschoegl (1985)), and currency exchange rate (Coats (1981), McFarland, Pettit, and Sung (1982)). International evidence on the Monday effect is documented in Chang, Pinegar, and Ravichandran (1993), Dubois and Louvet (1996) and Jaffe and Westerfield (1985).

² Other explanations for the Monday effect lie in several areas: Monday effect as statistical errors (Sullivan, Timmermann, and White (2001)), settlement and clearing delays (Lakonishok and Levi (1982)), information flows of both macro (Chang, Pinegar, and Ravichandran (1998)) and firm-specific announcements (French (1980), Damodaran (1989)), and Monday blue (Rystrom and Benson (1989)).

³ There are mixed evidences of individual investors' trading behavior on Monday. For example, Ülkü and Rogers (2018) find increase in net buying from individual investors and decrease in net buying from institutional investors on Monday, using daily trading data from Korea Stock Exchange, Taiwan Stock Exchange and Stock Exchange of Thailand.

Ramodorai, Schwartz (2009)). To overcome this difficulty, we take advantage of the following insight. If the Monday effect is indeed driven by individual investors' trading pattern and if there are exogenous events that distract their attention to learning trading strategies during the weekends, then we would expect Monday return and trading activity to vary with distraction events. In this paper, we identify large Powerball jackpots⁴, as series of attention distraction events during the weekends; and show that they cause lower return on the following Mondays.

Attention is a scarce resource and paying attention requires effort (Kahneman (1973)). Limited investor attention will influence investor perceptions, resulting in neglect of information and under-reaction to news (Hirshleifer and Teoh (2003), Peng (2005), Peng and Xiong (2006), Hirshleifer, Lim and Teoh (2009)). Thus, limited attention is expected to have impact on both stock valuations and trading interest. In our setting, a large jackpot attracts attention through its large prize as well as widespread media coverage (Clotfelter and Cook (1989)), causing investors to pay less attention to the stock market in general. The major advantage of utilizing large jackpots as attention distracting events is that they are largely independent of the economic factors that may systematically affect our tests. This is because jackpots accumulate when there is no winners for a consecutive period and thus their occurrences can be treated as random events.

Gao and Lin (2015) are the first to recognize large jackpots as series of natural experiments of shocks to investor attention, and find that individual investors' trading activity decreases during large jackpot days in Taiwan. Using the same data, Huang, Huang and Lin (2019) further argue that investors will pay less attention to stocks listed on the Taiwan Stock Exchange during these days. Limited attention forces them to allocate relatively more attention to market information,

⁴ Jackpot size larger than or equal to the 70 percentile of our sample period, 114 million US dollars.

which, in turn, results in larger return co-movement as hypothesized in Peng and Xiong (2006), Veldkamp (2006) and Veldkamp and Wolfers (2007). In the U.S equity markets, Dorn, Dorn, and Sengmueller (2015) find less small trade participation when the combined future jackpot size of the multi-state lotteries (Powerball and Mega Millions) increases. Despite of these convincing evidence of the lottery impact on the trading activity of individual investors, none of the papers in the literature has been able to show that lottery jackpots have any impact on stocks returns so far.

In this paper, we connect the Monday effect literature with a seemingly unrelated literature on stock trading as gambling, and provide new perspectives to both strands of literature. Unlike earlier papers, we find that lottery jackpots significantly affect stock returns. In particular, we find return predictability in U.S. equal-weighted and value-weighted market return based on Powerball jackpot size on Saturday. More importantly, we discover that the Monday effect only exists when there was a large Saturday jackpot.⁵ The lottery impacts on Monday effect are significant, both economically and statistically. While the Monday return of the equal-weighted market is - 4 bps in our sample period, it is -21 (3) bps with (without) a large jackpot on the preceding Saturday.

According to the best of our knowledge, we are the first paper to document investor inattention as causal explanation behind the Monday effect. We propose the *investor inattention hypothesis* to explain these findings. Our hypothesis posits that a large Saturday jackpot would distract investors from learning trading strategies, as individual investors usually reserve the weekends to decide trading strategies and positions. Since buying requires more attention than selling, distraction effect from large jackpots will have asymmetric effect on buying and selling behavior

⁵ We define large jackpots as those with jackpot size larger than or equal to the 70 percentile of our sample period. We also use alternative definition for large jackpots, including above 50 percentile, above 75 percentile, and above 80 percentile of Saturday jackpot size. Our results remain qualitatively the same and economic significance increases with larger thresholds.

(Barber and Odean (2008)). Consistent with the hypothesis, we find less buying than selling from individual investors, lower market return and larger return co-movement on Monday following a large Saturday jackpot. Furthermore, the effects are stronger for liquid stocks, which is consistent with models of limits to arbitrage literature (Shleifer and Summers (1990), Shleifer and Vishny (1997), DeLong, Shleifer, Summers, and Waldman (1990a), (1990b)). According to these models, greater liquidity reflects intense trading activity of noise traders, who tend to be individual investors. In addition, we reveal the distraction effect of jackpots to be larger with bad news or negative return on Friday, as bad news and negative return on Friday further discourage the trading interest and the attention paid to the stock market over the weekends. This is consistent with “ostrich effect” that investors monitor investments less frequently in non-rising markets than rising markets (Karlsson, Loewenstein, and Seppi (2009)).

Our paper is similar to Gao and Lin (2015) and Huang, Huang and Lin (2019) in many aspects, but there are major differences. First, we extend their studies from the Taiwanese stock and lottery markets to the more established and much larger U.S. markets, thus our sample covers more firms with larger market capitalization, and over a much longer period. Second, unlike their papers, we show that there is a lottery jackpot impact on stocks returns, which, in turn, allows us to extend the study from market returns to return anomalies as discussed below. Third, and more importantly, we show that the lottery jackpot effect in the U.S. has a day-of-the-week pattern, which enables us to contribute to the Monday effect literature.

Our paper is also closely related to Birru (2018), who shows a surprising and strong day-of-the-week pattern on return anomalies. In particular, Birru (2018) uncovers the Monday effect of anomalies --- anomalies associated with speculative or hard-to-value stocks such as the abnormally low returns of stocks with high idiosyncratic volatility or distress risk concentrate on Monday.

Birru (2018) explains these results as investors' bad mood on Monday lowering the valuation of speculative stocks. We complement Birru (2018) by showing that investor inattention caused by large jackpots plays an important role in his findings. Since speculative stocks are harder to value and require more attention to study and learn, the inattention effect caused by Saturday jackpot drawings would be much stronger for these stocks. Indeed, we find that the Monday effect of several prominent anomalies is stronger than the Monday effect of market returns. Furthermore, it exists only when there was a large jackpot on the preceding Saturday. For example, the Monday effect of high idiosyncratic volatility stocks and high distress risk stocks are strikingly large (more than - 60 bps) when there was a large Saturday jackpot. In contrast, the Monday effect of the same stocks are insignificant and negligible when there was not. These results, together with *investor inattention hypothesis*, contribute significantly to the literature by showing that investor inattention plays an important role in the formation of major stock return anomalies.

Besides Powerball drawings on Saturday, there are other lottery drawings on weekdays: Powerball drawings on Wednesday, and Mega Millions drawings on Tuesday and Friday. Interestingly, we find there is no jackpot effect associated with the weekday drawings as we found with Saturday drawings. This asymmetry between weekend jackpots and weekday jackpots suggests that unlike over the weekend, individual investors usually don't have time to learn and study trading strategies and positions during the weekdays. Thus, distraction from large jackpots on weekdays have minimal impact on investors' trading behavior.

In addition to lottery jackpots, negative Friday return and sports events over the weekends also distract investors from learning trading strategies during the weekends. We study the joint effect of negative Friday return and two popular sports events, Super Bowl and Kentucky Derby, on Monday return in the United States from 1967 to 2002. We find lower Monday return following

both negative Friday return and sports events, which explains most of the Monday effect in earlier period. This extends our *investor inattention hypothesis* to other investor attention distraction events in a much earlier sample period, further corroborating the causal evidence that investor inattention is the driving force behind the Monday effect.

The rest of the paper is organized as follows: Section II develops hypothesis. Section III describes sample and data in detail. Section IV presents the main results on the Monday effect. Section V explores the return co-movement and Section VI explores trading activity. Section VII studies weekday drawings. Section VIII studies sports events and the Monday effect in earlier sample periods. Section IX concludes.

II. Hypothesis Development

In this paper, we propose *investor inattention hypothesis* to explain the Monday effect. Osborne (1962), Miller (1988), Lakonishok and Maberly (1990), Abraham and Ikenberry (1994) highlight the role of individual investors' trading pattern in explaining the Monday effect. As it takes time to process information, individual investors will process information during the weekends and trade on Monday. Due to limited attention (Kahneman (1973)), a large jackpot drawing will distract individual investors from learning trading strategies during the weekends. In addition, we expect the jackpot effect to be larger among stocks with intense trading from noise traders, who tend to be individual investors and have a preference for lottery-like stocks such as those with high idiosyncratic volatility or positive skewness (Barberis and Huang (2008), Kumar (2009), Bali, Cakici, and Whitelaw (2011), Green and Hwang (2012)). According to limits to arbitrage literature (Shleifer and Summers (1990), Shleifer and Vishny (1997)), liquidity is provided by noise traders who often possess wrong beliefs or are overconfident about their information. Consistent with this, Hwang, Titman and Yi (2019) show that lottery-related anomalies are much stronger in liquid

stocks. Thus, in this paper we choose liquidity to proxy for the trading intensity of noise traders and hence of individual investors.

We are also motivated by Gao and Lin (2015), and Huang, Huang, and Lin (2019) from the investor attention literature. Gao and Lin (2015) document lower individual trading activity during large jackpot days in Taiwan. They argue that both trading and gambling are fun and exciting activities, and thus investors would be distracted from stock market and allocate more attention to lottery gambling on those days. Huang, Huang, and Lin (2019) further find that such distractions have resulted in a larger return co-movement of Taiwanese stocks on large jackpot days. This is because given limited attention, investors will pay more attention to aggregate (i.e., market) shocks instead of firm specific shocks (Peng and Xiong (2006), Veldkamp (2006) and Veldkamp and Wolfers (2007)).

According to Barber and Odean (2008), attention affects buying and selling behavior of individual investors asymmetrically. Investors choose from thousands of stocks when buying stocks, whereas they sell from a few stocks that they already owned and seldom short sell. We hence hypothesize that a large jackpot during the weekend distracts investors from learning trading strategies, which will result in relative less buying than selling on the following Monday, as buying requires more attention.

Accordingly, we propose the *investor inattention hypothesis* formally as below.

Investor Inattention Hypothesis: Individual investors get distracted by lottery drawings with large jackpot pool on Saturday, and spend less time studying trading strategies during the weekends. As buying requires more attention than selling, investors will buy less relative to sell on the following Monday, resulting in lower market return. Furthermore, when attention is limited, investors would

pay relatively more attention to market information than individual stock information, which would increase the co-movement in the stock market. This hypothesis generates four testable implications:

1. Both the Monday effect of market return and the Monday effect of anomalies are much stronger following a large jackpot on Saturday.
2. Return co-movement on Monday would be higher following a large jackpot on the preceding Saturday.
3. The jackpot effects predicted above are stronger in liquid stocks preferred by individual investors.
4. Trading activity, particularly buying, on Monday would be lower following a large jackpot on the preceding Saturday.

III. Data

Powerball is one of the most popular multi-state lotteries in the United States⁶. We have collected a daily history of jackpots and national-level sales for each drawing of Powerball game and Mega Millions game⁷ from January 2003 to December 2018. Powerball drawings happen at 10:59 p.m. Eastern Time on Wednesday and Saturday, including holidays. Mega Millions drawings happen

⁶ Lottery games are widely played in the United States. According to Gallup Survey in June 2016, 49% of U.S. adults reported buying lottery tickets and 64% reported gambling in any forms in the past year of the survey, which makes lottery tickets the most popular form of gambling in the United States. In addition, 53% of high income group (above \$90,000), 40% of low income group (under \$36,000), 56% of middle income group (between \$36,000 and \$89,999) have reported buying lottery in the past year of the survey. As of the fiscal year of 2014, the total spending on lottery tickets is over \$70 billion, which is larger than the combined spending on books, video games, movie tickets and sporting events tickets. Source: Derek Thompson, Lotteries: America's \$70 Billion Shame, THE ATLANTIC (May 11, 2015), <https://www.theatlantic.com/business/archive/2015/05/lotteries-americas-70-billion-shame/392870/>

⁷ An agreement to cross-sell Mega Millions and Powerball in American lottery jurisdictions was reached by The Mega Millions consortium and Multi-State Lottery Association (MUSL) on October 13, 2009. The expansion was effective on January 31, 2010, after which 23 existing Powerball member states began selling Mega Millions tickets and 10 existing Mega Millions member states began selling Powerball tickets.

at 11 p.m. Eastern Time on Tuesday and Friday, including holidays. The news media will announce the jackpot each morning following the previous drawing. Therefore, people would know the advertised jackpot amount on jackpot drawing day t when they trade on day t (Dorn, Dorn, and Sengmueller (2015)), if day t is a trading day and a jackpot drawing day.

Jackpot sizes of Powerball and Mega Millions should be time-series uncorrelated with each other, since the hit of a jackpot is a random event and large jackpots arise due to a series of no-hit events. We define jackpot size based on jackpot size of both Mega Millions and Powerball: jackpot size equals to the Mega Millions jackpot size on Tuesday and Friday, and equals to the Powerball jackpot size on Wednesday and Saturday. Large Jackpot Dummy on Tuesday or Friday equals to 1 if jackpot size of Mega Millions on Tuesday or Friday is larger than or equal to 70 percentile of Mega Millions jackpot size in our sample period. Large Jackpot Dummy on Wednesday or Saturday equals to 1 if jackpot size of Powerball is larger than or equal to 70 percentile of Powerball jackpot size in our sample period.

We adopt CRSP daily market indexes, equal-weighted market return index and value-weighted market return index, as proxy for market return. We calculate daily Close-to-Close, Open-to-Close and Close-to-Open return from S&P 500 prices. Individual investors' trading behavior is identified through TAQ data.

IV. Results

i. Summary Statistics

We tabulate summary statistics of equal-weighted market index return and value-weighted market index return by days of the week in Panel A of Table 1. Our sample period is from January 2003 to December 2018, consistent with availability of lottery jackpot data. For Mondays from January

2003 to December 2018, the average equal-weighted market return is -4 bps and average value-weighted market return is -1 bps. In contrast to negative average return on Monday, average equal-weighted market return and value-weighted market return are positive for Tuesday, Wednesday, Thursday and Friday. We also provide summary statistics of total trading volume as sum of trading volume of all stocks and total dollar trading volume as sum of dollar trading volume of all stocks by days of the week. On average, total trading volume on Monday is 3830 millions of shares traded, and total dollar volume on Monday is 122,000 million US dollars.

In Panel B, we tabulate summary statistics of jackpot size by days of the week and Large/Non-large Jackpot Dummy. Large Jackpot Dummy on Tuesday or Friday equals to 1 if jackpot size on Tuesday or Friday is larger than or equal to 70 percentile of Mega Millions jackpot amount (\$89 million). Large Jackpot Dummy on Wednesday or Saturday equals to 1 if jackpot size on Wednesday or Saturday is larger than or equal to 70 percentile of Powerball jackpot amount (\$114 million). Non-large Jackpot Dummy equals to 1 when Large Jackpot Dummy equals to 0. The largest jackpot on Saturday during the sample period reaches \$947.9 million.

[Insert Table 1 Here]

ii. The Monday Effect a Weekend Jackpot Effect?

In Table 2, we confirm the existence of the Monday effect in our sample. In Column (1) and (2), we regress equal-weighted return and value-weighted market return on Monday, Tuesday, Thursday and Friday dummy, with Wednesday as benchmark. We control for Before holiday dummy and After holiday dummy, as individual investors increase trades before or after holidays and weekends (Lakonishok and Maberly (1990), Dorn, Dorn, and Sengmueller (2015)). We estimate Newey-West standard errors, allowing maximum lags up to 5 lags. The significantly

negative coefficient of the Monday dummy in Column (1) and the insignificant coefficient in Column (2) indicate that the Monday effect exists in the equal-weighted return index but not in value-weighted return index during our sample period. This is consistent with prior literature that smaller stocks have more significant Monday effect while the Monday effect of larger stocks decrease over the years (Kamara (1997)).

[Insert Table 2 Here]

Table 3 reports the baseline results of this paper where we perform the same regressions as in Table 2 except that we do it separately on Large Saturday Jackpot and Non-large Saturday Jackpot subsamples. For every trading day in week w , we classify it into Large Saturday Jackpot and Non-large Saturday Jackpot subsample based on whether there was a large Saturday Jackpot in week $w-1$. A Powerball jackpot on Saturday is deemed as Large if it ranks among the top 70 percentile of all Powerball jackpots in our sample period, and Non-large otherwise. The results of equal-weighted market return are reported in Column (1) and (2) and those of value-weighted market return are in Column (3) and Column (4). Strikingly, we find the Monday effect only exists in the subsample of Large Saturday Jackpot⁸. Relative to benchmark (Wednesday), equal-weighted market return is 30 bps lower and value-weighted market return is 27 bps lower on Monday in the Large Saturday Jackpot subsample. In contrast, Monday return is not statistically different from other days of the week in the Non-large Saturday Jackpot subsample.

As Monday return is affected by the non-trading period during the weekends, Rogalski (1984) decomposes S&P500 and Dow Jones Industrial Average close-to-close return into trading day

⁸ We use alternative cut-off thresholds for Large Jackpot Dummy, such as top 50, 75 and 80 percentile. Our results remain qualitatively the same, and is not driven by the thresholds for Large Jackpot definition.

returns and non-trading day returns, and shows that negative Monday returns are concentrated in non-trading period from Friday close to Monday open. Similar to Rogalski (1984), we also decompose S&P500 close-to-close return into non-trading period (close-to-open) return and trading period (open-to-close), except that we perform the analyses separately on Large Saturday Jackpot and Non-large Saturday Jackpot subsamples. These results are reported in Panel B of Table 3. We observe that the Monday effect only exists in Large Saturday Jackpot subsample, when market return is calculated from S&P500 prices. Furthermore, the effect is mainly restricted in the trading period as indicated by the significant coefficients of Monday dummy in Column (5) Open-to-Close return and insignificant coefficients of Monday dummy in Column (3) Close-to-Open respectively, opposite to the findings of Rogalski (1984).

We further test the heterogeneous jackpot effect among different liquidity groups in panel C. We focus on the test of the third prediction of the *investor inattention hypothesis* – the jackpot effect is larger among liquid stocks dominated by noise traders (Shleifer and Summers (1990), Shleifer and Vishny (1997)). We separate stocks based on daily share turnover ratio in the previous quarter end, and classify stocks as liquid (illiquid) stocks if share turnover ratio is larger (smaller) than or equal to 70th (30th) percentile threshold. Consistent with our hypothesis, we observe the jackpot effect to be largest among liquid stocks and there is monotonic increase of jackpot effect when liquidity measure increases. Equal-weighted return of stocks on Monday in the liquid group, middle group, and illiquid group is 42 bps, 29 bps and 23 bps lower than other days of the week respectively. In contrast, the Monday effect is absent in neither groups when there were absent of large Saturday jackpots.

[Insert Table 3 Here]

In sum, the results in Table 3 indicate that Monday effect is essentially a Saturday (weekend) jackpot effect postulated in the *investor inattention hypothesis*, and its effect concentrates in Monday trading hours. In addition to attention distract from large Saturday jackpots, bad earnings news may adversely affect the trading interest and the attention paid to stock market by individual investors, which may in turn amplify the jackpot effect described in the Table 3. We therefore study the effect of Saturday jackpots on Monday return when there was negative return and bad earnings announcement news on the preceding Friday.

iii. Friday Earnings News, Friday Return and the Monday Effect

Information release on Friday and over the weekend has been proposed to explain the Monday effect. Gennotte and Trueman (1996) show that managers have the incentive to release bad news after trading hours, which is also consistent the findings of DellaVigna and Pollet (2009) that earnings announcement on Friday has lower immediate response and higher delayed response due to less investor attention on Friday. To make sure our baseline results are not driven by the delayed response to news releases on Friday and over the weekend, we do the following analyses. We first compute standardized unexpected earnings (SUE) surprises for each earnings announcement, based on IBES reported analyst forecasts and actuals as in Livnat and Mendenhall (2006). For each combined period of Friday and the following weekend, we first count the total number of firms with positive SUE and the total number of firms with negative SUE for earning news announced during that particular period. For each combined period, we calculate the bad news to total news ratio and classify it as Bad news period if the ratio is above the sample mean, and good news period otherwise. Finally, we modify the regressions in Panel A of Table 3 by further separating the Monday dummy into Monday dummy that follows bad news Friday period (Monday_Bad News Friday) and that follows good news Friday period (Monday_Good News Friday). Column (1) of

Table 4 reveals that Monday with large Saturday jackpots has 37 (26) bps lower equal-weighted return when there are more bad (good) news on the preceding Friday and the weekend, suggesting that bad news on Friday exacerbates the effect of weekend jackpots on Monday return but doesn't drive the Monday effect. Furthermore, Column (2) indicates that in the absence of large Saturday jackpots, there is no Monday effect even for Monday that follows a bad news Friday period. Column (3) and Column (4) deliver the same message when we examine the value-weighted market return. Our finding lends support to Damodaran (1989) that small proportion of around 3.4% of the Monday effect could be explained by earnings announcement and dividend announcement on Friday.

[Insert Table 4 Here]

Abraham and Ikenberry (1994) find that negative Monday return is driven by Friday's return, as Monday's return is on average -0.61% when Friday's return is negative, while Monday's return is on average 0.11% when Friday's return is positive during their sample period. They further document that following a positive Friday, early morning trading of Monday does not have large price decline. Hence, we perform similar analyses as in Table 4, except that we replace bad (good) news Friday with negative (positive) return Friday in Table 5. The results in Table 5 are similar to Table 4 in that Negative Friday return exacerbates but does not drive the Monday effect as there is no significant Monday effect in the absence of Saturday jackpot even when there was negative Friday return as shown in Column (2) and Column (4). The Monday return following a large Saturday jackpot and a negative Friday return is noteworthy in magnitude. It is lower than other weekdays by 58 bps, which is striking considering the average equally-weighted daily market return on Monday is -4 bps during our sample period, and suggesting a profitable trading strategy. It is also consistent with *investor inattention hypothesis* and suggests that the effect of the

distraction from large Saturday jackpots is more severe when investors' trading interest and attention paid to stock market are already low due to bad news and negative return on Friday. This is consistent with "ostrich effect" that investors monitor investments less frequently in non-rising markets than rising markets (Karlsson, Loewenstein, and Seppi (2009)).

[Insert Table 5 Here]

iv. The Monday Effect of Anomalies

According to our *investor inattention hypothesis*, if individual investors' inattention during the weekends are driving the Monday effect, then we shall expect the effect of Saturday jackpots to be stronger among stocks that are hard to value and are preferred by individual investors. Birru (2018) documents a striking day-of-the-week effect in many prominent anomalies. In particular, he shows that profits derived from the long leg of these anomaly-based long-short trading strategies concentrate on Friday, but he also shows a much larger profit derived by taking a short position in speculative and hard-to-value stocks concretes on Monday, a phenomenon we call the Monday effect of anomalies. Birru (2018) attributes the low returns associated with these speculative and hard-to-value stocks to the low valuations caused by bad mood on Monday (Wright and Bower (1992)). Having shown that a large Saturday jackpot plays a critical role in explaining the Monday effect of market return, we are interested in learning if a large Saturday jackpot has similar effect on the Monday effect of anomalies. We first validate findings in Birru (2018) using two anomalies (IVOL and distress risk) that have the strongest Monday effect in our sample period. Both high IVOL and high distress risk are associated with hard-to-value and speculative firms.

Following Kumar (2009), IVOL at the end of month t is the residual from fitting Carhart four-factor model using daily return of the previous 6 months, from $t-6$ to $t-1$. A stock is classified as

high (low) IVOL for trading days in month $t+1$, if its IVOL ranks in the top (bottom) quintile at the end of month t . We also use the 12-month logit regression coefficients from Table IV in Campbell, Hilscher, Szilagyi (2008) to calculate the distress probability at the end of December in each year t . A stock is classified as high (low) Distress risk stocks for trading days in year $t+1$, if distressed probability of the stock is in the top (bottom) quintile of distressed probability in the December of year t .

In Table 6 Panel A, we report value-weighted excess return and alpha for high IVOL and high Distress stocks adjusted by CAPM, Fama-French three-factor model and Carhart four-factor model respectively. We calculate the return and alphas separately on Monday and non-Monday (rest of the days). Consistent with Birru (2018), we find that short-leg return of both anomalies is profitable on Monday but not on the rest of the days. In Panel B, we further separate Monday studied in Panel A into Monday with Large Saturday jackpot and Monday with Non-large Saturday Jackpot subsamples. And we find that the Monday effect of anomalies exist only in the subgroup of Monday with Large Saturday Jackpot⁹. In particular, the excess return of high IVOL and high Distress risk are on average -44 bps and -43 bps respectively on Monday with Large Saturday jackpot but are insignificant on Monday with Non-Large Saturday jackpot.

Assuming the risk of a stock does not vary systematically within the day of the week, a more powerful test to detect the Monday effect of anomalies is to avoid risk-adjustment and run value-weighted excess regressions of high IVOL and high Distress risk portfolios on the day-of-the-week dummies as shown in Panel C of Table 6, similar to the regression as in Table 2. Form these

⁹ In Birru (2018), long-short portfolio of IVOL earns on average 22.6 bps on Monday from July 1963 to December 2013. During our sample period, long-short portfolio of IVOL and Distress earns on average 29 bps on Monday with large jackpots, compared with insignificant 9 bps on Monday with non-large jackpots.

regressions, we observe a clear Monday effect for high IVOL stocks and high Distress risk stocks. When we run the same regression separately on Large Saturday Jackpot and Non-large Saturday Jackpot subsamples in Panel D, the Monday effect for both anomalies becomes stronger in the Large Saturday Jackpot subsample. Furthermore, the Monday effect of anomalies only exists in this subsample and absent in Non-large Saturday Jackpot subsample¹⁰. The magnitude of the Monday effect for high IVOL and high distress risk stocks are strikingly large, in excess of 60 bps, suggesting a profitable trading strategy. In sum, these results are not only consistent with the first testable implication of *investor inattention hypothesis* that the Monday effect is larger among stocks that are hard to value in nature and require more investor attention, but also suggest Monday effect of anomalies, like the Monday effect of market return, could be a manifestation of weekend jackpot effect.

[Insert Table 6 Here]

V. Return Co-movement and Saturday Jackpots

In this section, we test the second prediction of *investor inattention hypothesis* that there would be an increase in return co-movement in the stock market on Monday following a large jackpot on the preceding Saturday.

For each stock in our sample, we calculate its return co-movement by the day-of-the-week and Large Saturday Jackpot dummies. Consistent with our prior definition, Large Saturday Jackpot dummy equals to 1 if Powerball's jackpot on Saturday is larger than or equal to the 70 percentile of Powerball jackpot. Non-large Saturday Jackpot dummy equals to 1 when Large Saturday

¹⁰ In unreported results, we also find that low future return of stocks with high maximum daily return over the past month (Bali, Cakici, and Whitelaw (2011)), low price (Birru and Wang (2016)), young age (Ritter (1991)) and far from 52-week high (George and Hwang (2004)) only exists on Monday following a large Saturday jackpot.

Jackpot dummy equals to 0. For trading days in week w , we classify into Large Saturday Jackpot and Non-large Saturday Jackpot groups based on Large Saturday Jackpot dummy and Non-large Saturday Jackpot dummy on the Saturday of week $w-1$. Return co-movement is calculated as the adjusted R-square from the market model regression (Barberis, Shleifer and Wurgler (2005)), and as time series Pearson correlation of stock excess returns and market excess returns (Peng and Xiong (2006), Antón and Polk (2014)). For each stock in the portfolios defined by Large Saturday Jackpot dummy and day-of-the-week dummy, we require at least 20 observations for the regression and correlation estimation. The mean and median estimate in each portfolios are reported in Panel A of Table 7. Compared with Mondays without large Saturday jackpots, Mondays with large Saturday jackpots have significantly larger return co-movement. This is consistent with our second prediction of *investor inattention hypothesis* that return co-movement on Monday, would be higher following a large jackpot on the preceding Saturday. In addition, we observe the co-movement increase due to large Saturday jackpot is larger on Monday than on other weekdays.

As explained earlier in the section of hypothesis development, we use high liquidity to proxy for the trading intensity of nosier traders and individual investors. We separate stocks based on share turnover ratio in the previous quarter end, and classify stocks as liquid (illiquid) stocks if share turnover ratio is larger (smaller) than or equal to 70th (30th) percentile threshold. We repeat our tests in Panel A but separately for liquid and illiquid stocks and report the results in Panel B and Panel C respectively. We can clearly see that the jackpot effect on the co-movement is much larger on Monday than other weekdays, and the effect is larger liquid stocks, consistent with the third prediction of the *investor inattention hypothesis*. For example, the average increase in adjusted R-square of Monday return is 0.0695 for liquid stocks, compared with 0.0367 for that of

other weekday returns. The difference 0.0328 is significant at 1% level. The corresponding figures for the illiquid stocks are 0.0298, 0.0135, and 0.0163 respectively.

[Insert Table 7 Here]

VI. Trading Activity and Saturday Jackpots

In this section, we focus on the test of the fourth prediction of the *investor inattention hypothesis* -- distraction from large Saturday jackpots would reduce the trading activity, particularly buying of individual investors. We use odd-lot trades (trades of fewer than 100 shares) as proxy for individual investors' trading behavior (Ritter (1988), Lakonishok and Maberly (1990)). For the sample period from 2003–2012, we follow Lee and Ready (1991) to sign trades as buyer or seller initiated using TAQ Trade and Quote data. With the rise of algorithm trading, trade-size partition becomes less accurate in the recent period. From 2013 to 2018, we follow Boehmer, Jones, Zhang, and Zhang (2019) to classify marketable odd-lot retail trades as either buy or sell using TAQ Millisecond Trade and Quote data. For each trading day t from 2003-2018, we aggregate daily buy volume for each stock i traded on NYSE/AMEX/NASDAQ, as Odd-Lot Buy Volume on day t . Similarly, we aggregate daily sell volume for each stock i traded on NYSE/AMEX/NASDAQ, as Odd-Lot Sell Volume on day t . We calculate daily measures of odd-lot order imbalance using buy and sell volume, as proxy for asymmetric buying and selling activities of individual investors. O'Hara, Yao, and Ye (2014) suggest using volume-based or dollar-volume-based measures for order imbalance to reduce bias arising from missing odd lots in TAQ data.

$$Order\ Imbalance_t = \frac{\sum_i Odd - Lot\ Buy\ Volume_{i,t} - \sum_i Odd - Lot\ Sell\ Volume_{i,t}}{\sum_i Odd - Lot\ Buy\ Volume_{i,t} + \sum_i Odd - Lot\ Sell\ Volume_{i,t}}$$

In Table 8 Column (1), we run the order imbalance regressions on weekday dummies and an interactive term of Monday dummy and Large Saturday jackpot dummy so that the coefficient of the interactive term, *Monday_Large Saturday Jackpot*, captures the effect of large Saturday jackpots on order imbalance of the following Monday. We also control for yearly time dummies for the time-varying transaction cost in all trading activity regressions (Choe and Hansch (2005)). The significantly negative coefficient on Monday indicates that individual investors tend to buy less relative to sell on Mondays following large Saturday jackpots. Interestingly, we do not observe significant asymmetric buying and selling behavior on Mondays without large Saturday jackpots, which is consistent with our main return result that the Monday effect only exists following large Saturday jackpots. This is consistent with the fourth prediction of *investor inattention hypothesis* that a large Saturday jackpot distracts individual investors' attention over the weekends when investors normally spend time and attention studying trading strategies. As buying require more attention than selling (Barber and Odean (2008)), a large Saturday jackpot asymmetrically affects buying and selling behavior of individual investors, resulting in further lower buying than selling on the following Monday. Furthermore, as negative Friday return is likely to trigger selling behavior of individual investors, we further study the interaction effect of large Saturday jackpot with negative Friday return in Column (2). We create Negative Friday Return dummy and Positive Friday Return dummy for week w , based on whether the return of respective market index on the preceding Friday is negative or positive in week $w-1$. We interact Negative Friday Return dummy with Monday dummy and Large Saturday Jackpot dummy as *Monday_Negative Friday Return_Large Saturday Jackpot*. However, we do not observe any additional order imbalance arising from negative Friday return, as shown by the insignificant coefficient of *Monday_Negative Friday Return_Large Saturday Jackpot*. In Column (3), we separately study the interaction effect

of Positive/Negative Friday return dummy with Large/Non-Large Saturday Jackpot dummy. Compared with other days of the week, there is relative less buying than less on Mondays with Large Jackpots, and the magnitude is largest (0.038) when there was negative Friday return and large Saturday jackpot among the four groups. Therefore, we provide individual investors' reduction in buying relative to selling as the link between large Saturday jackpots and lower Monday return.

[Insert Table 8 Here]

VII. Weekend Jackpot vs. Weekday Jackpot

As *investor inattention hypothesis* is designed to explain the Monday effect, we have so far focus on the distraction and inattention caused by the weekend (Saturday) jackpot. In this section, we investigate if there is a similar effect caused by the weekday jackpots. For drawings on Tuesday, Wednesday and Friday, we study the effect of jackpots on market indexes on the same trading day and exclude any holidays. For drawings on Saturday, we study the effect on market return and trading activity on the following Monday. Large Jackpots are events where the jackpot size of Tuesday or Friday Mega Millions or the jackpot size of Wednesday or Saturday Powerball are above the 70 percentiles of the respective Mega Millions and Powerball jackpot size in our sample. In Table 9, we modify the specification of the trading activity regressions in Table 8 to test if there is weekday jackpot effect on return. Specifically, we regress equal-weighted market return and value-weighted market return on interaction of Monday dummy with Large Saturday Jackpot dummy, interaction of Tuesday/Wednesday/Friday dummy with Large Tuesday/Wednesday/Friday Jackpot dummy, day-of-the-week dummies, Before holiday and After holiday dummies. We find that weekday jackpots, including Wednesday Powerball, have no effect on the contemporaneous weekday return as indicated by the insignificant coefficients on various

interaction terms between weekday dummies and large weekday jackpot dummies. In contrast, the Monday effect caused by the large Saturday jackpots we have observed earlier in Table 3 remains strong in Table 9. This asymmetry in effects between weekend and weekday jackpots does not reflect the difference in the type of jackpot, where Mega Millions are exclusively weekday jackpots. Instead, it reflects the significant effect of Saturday Powerball that falls on the weekends, and the insignificant weekday jackpots that also includes the Wednesday Powerball. The lack of effect from weekday jackpots is also consistent with the *investor inattention hypothesis*. While investors normally reserve weekends for studying stocks' trading strategies, they need to work and cannot afford to do so during weekdays. As a result, even though individual investors may also be distracted by large jackpots on weekdays, such distraction may not affect the attention nor the effort that they spend on studying stocks' trading strategies, as they rarely do so on weekdays even without distraction.

In addition, the asymmetric effect could help us separate gambling sentiment and mood change explanation from investor attention explanation. Chen, Kumar and Zhang (2018) find that gambling sentiment proxied by Internet search volume predicts abnormal return of lottery-like stocks positively in the short-run due to increased investor demand. Edmans, Garcia, and Norli (2007) link sport sentiment to stock return. Soccer outcomes could trigger sudden changes in investor mood, and market declines after losses in the soccer outcomes. The effect is stronger in smaller stocks and robust in other sports events, such as cricket, rugby, and basketball games. In our setting, if change in gambling sentiment or mood is induced by disappointment of most investors for not winning the large jackpot, we should observe the jackpot effect on return for both

weekend jackpots and weekday jackpots. The fact that we only observe aggregate return predictability from Saturday jackpots lends further support to *investor inattention hypothesis*.¹¹

[Insert Table 9 Here]

VIII. Sports Events, Friday Return and the Monday Effect: Evidence from 1967

The earliest studies of the Monday effect in the equity stock market include French (1980) who studies S&P 500 index from January 1953 to December 1977, and Gibbons and Hess (1981) who study both S&P 500 index and CRSP market indexes from July 1962 to December 1978. Keim and Stambaugh (1984) discover negative Monday return for S&P composite back to 1928 and rule out measurement errors as explanation.

We further test *investor inattention hypothesis* using negative Friday return and sports events over the weekends in the earlier period before lottery jackpot data is available. Negative Friday return will in the first place distract investors from the stock market. According to “ostrich effect”, investors monitor investments less frequently in non-rising markets than rising markets (Karlsson, Loewenstein, and Seppi (2009)). Therefore, we examine whether Friday negative return is enough to explain the Monday effects in the earlier period from 1967 to 2002. We define Negative Friday Return dummy for week w , which equals to 1 if the return of respective market index on the preceding Friday is negative in week $w-1$. We first validate the existence of Monday effect in earlier sample period in Column (1) and (4) of Table 10 for equal-weighted and value-weighted market return respectively. Compared with the Monday effect from 2003 to 2018 (11 bps lower)

¹¹ In unreported results, we also find the co-movement increase associated with large jackpot is much larger on Monday than on other weekdays. These results are inconsistent with mood change explanation as the mood change and valuation change alone should not cause co-movement to change, let alone causing the change to display the week-of-the-day pattern.

in Table 2, the magnitude of the Monday effect from 1967 to 2002 (24 bps lower) is twice as large for equal-weighted market return, which is possibly due to a greater influence of individual investors in the earlier period as there has been a steady increase in the institutional investors over the years. In Column (2) and (5) of Table 10, we regress equal-weighted and value-weighted market return on Monday dummy with Negative Friday return, Monday dummy and other days-of-the-week dummies. The difference in equal-weighted market return between Monday with negative Friday return and other Mondays is as large as 69 bps. Equal-weighted market return on Monday is 73 bps and 4.1 bps lower than other days of the week when the previous Friday return is negative and non-negative respectively. In addition, Monday effect for value-weighted market return only exists with negative Friday return, which is 46 bps lower than other days. Consistent with Abraham and Ikenberry (1994), we find that negative Monday return is largely driven by Friday's return in our sample period from 1967 to 2002. Abraham and Ikenberry (1994) argue that lower Monday return arises from individual investors' selling behavior following bad news on Friday. Different from Abraham and Ikenberry (1994), our results suggest that lower Monday return following negative Friday return is also contributed by less buying from individual investors who are distracted from the stock market. This is consistent with "ostrich effect" that investors monitor the market less frequently following negative Friday return, which results in less trading on Monday. Similar to negative Friday return as distraction events, large Saturday jackpots will also distract individual investors from learning the stock market and result in decline in trading volume dominated by noise traders as shown in Table 8.

As further support for investor inattention explanation, additional distraction such as sports events further reduce attention that investors spend on researching on the stock market, which in turn further lower the Monday return on market. We therefore study the effect of popular sports

events during the weekends on the Monday effect to corroborate our *investor inattention hypothesis*. If investor inattention caused by large Powerball jackpots on Saturday is driving the Monday effect, then sports events during the weekends that also distract investor attention will impact market return on the following Monday. Due to unavailability of the jackpot data from 1967 to 2002, we validate our *investor inattention hypothesis* using two popular sports events (Super Bowl and Kentucky Derby) in the United States from 1967 to 2002. The Super Bowl is an annual championship game of the National Football League (NFL) held on Sunday between mid-January and early February, starting from 1967. The Kentucky Derby is an annual horse race event held on the first Saturday of May, starting from 1875. We collect each event date of Super Bowl and Kentucky Derby from January 1967 to December 2002, and define a Sports Event dummy based on the dates of both events. Sports Event dummy equals to 1 on the Monday of week w if there was a sports event (Super Bowl or Kentucky Derby) over the weekends of week $w-1$.

In Column (3) and (6), we jointly study the investor attention distraction effect from negative Friday return and sports events. We interact Sports Event dummy with Negative Friday Return dummy and Monday dummy as Monday_Negative Friday Return_Sports Event dummy to study the interaction effect. In Column (3), we regress equal-weighted market return on Monday dummy with Negative Friday return and Sports Event, Monday dummy with Negative Friday Return, Monday dummy and other days-of-the-week dummies. Consistent with results in Column (2), lower Monday return concentrates on Mondays following negative Friday return. Furthermore, with the presence of sports events and negative Friday return, the Monday return is 34 bps further lower than Monday with negative Friday return and without sports events. For Monday following sports events and negative Friday return, the equal-weighted return is a strikingly 105.6 (67.6+33.9) bps lower than other days of the week. Similarly, for value-weighted market return in

Column (6), Monday effect only exists following negative Friday return. Therefore, results of sports events further corroborate our *investor inattention hypothesis* that similar to large jackpot drawings, sports events over the weekends will also distract individual investors from learning trading strategies, resulting in lower Monday return.

[Insert Table 10 Here]

We directly examine the impact of negative Friday return and sports events on investor attention by measuring return co-movement. Based on existence of sports events and the sign of Friday return in week $w-1$, we classify Monday in week w into following groups: Monday with Negative Friday Return and Sports Event, Monday with Negative Friday Return and all Monday. We calculate firm-level co-movement by each of the group. We require at least 20 observations for each firm in each group to reduce effects of outliers. Comparing Monday with negative Friday return to all Monday, we observe an increase in return co-movement with negative Friday return. Mean co-movement measured using adjusted R-square (correlation) is 0.0577 (0.1906) on Monday and 0.0748 (0.2206) on Monday with negative Friday return. This is consistent with our hypothesis that negative Friday return distract investors from learning the stock market, resulting in more attention allocated to market information instead of firm-specific information. Furthermore, conditional on negative Friday return, return co-movement on Monday with sports events is significantly larger than other Monday. Return co-movement is largest in the group with sports events and negative Friday return: mean co-movement measured using adjusted R-square is 0.115 and mean co-movement measured using correlation is 0.3197. This suggests that both negative Friday return and sports events distract investor attention from the stock market, consequently, investors will allocate more attention to market information instead of firm-specific information. A sports event over the weekends following negative Friday return will have additional distraction

effect, which is consistent with the results in Table 10 that Monday return is the lowest in this scenario. Therefore, we provide robust evidence of investor inattention as driving force behind the Monday effect using negative Friday return and sports events from 1967 to 2002, when our lottery jackpot data is not available.

[Insert Table 11 Here]

IX. Conclusion

We use the setting of large jackpots on Saturday that distract investor attention to provide causal evidence on the Monday effect, the puzzling phenomenon that Monday has lower return than other days. We find that the Monday effect exists only when there was a large jackpot on the preceding Saturday. We propose *investor inattention hypothesis* to explain this finding--- individual investors normally reserve weekends for learning trading strategies and information processing, a large jackpot drawing on Saturday will distract them from the stock market, resulting in less buying than selling activities and return decline on Monday. Other evidences such as increase in return co-movement on Monday following large Saturday jackpots, with stronger effect for liquids stocks, are also consist with *investor inattention hypothesis*.

We also find investor inattention is closely related to the Monday effect of anomalies, first discovered by Birru (2018) who find that anomalies associated with speculative or hard-to-value stocks such as the low future returns of stocks with high idiosyncratic volatility or distress risk only occur on Monday. We show that these anomalies, just like the Monday effect of market returns, also exist only on Monday following large Saturday jackpots. These results suggest that investor inattention is likely the key driver behind many major return anomalies in the literature.

To the best of our knowledge, we are the first paper to document aggregate market return predictability of lottery jackpots in the literature. We owe this success to separating the weekend jackpot from weekday jackpot. We also extend distraction effect of lottery jackpots to sports events and negative Friday return, further corroborating our *investor inattention hypothesis* in earlier sample period. Whether this applies to stocks return and jackpots in other countries remains interesting future research.

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Table 1 Summary Statistics

In this table, we report summary statistics of market return and market trading activity by days of the week from January 2003 to December 2018 in Panel A. We report mean, median, standard deviation, minimum and maximum of market indexes return, total trading volume, and total dollar trading volume, by days of the week in Panel A. Equal-Weighted Market Return is the equal-weighted return including dividends. Value-Weighted Market Return is the value-weighted return including dividends. Total trading volume is the sum of trading volume of all stocks. Total dollar volume is the sum of dollar trading volume of all stocks. Return is reported in percentage, total trading volume is reported in millions of shares traded and total dollar volume is reported in millions of dollar. In Panel B, we tabulate the summary statistics of jackpot size by days of the week and Large Jackpot Dummy for trading days from January 2003 to December 2018. Large Jackpot Dummy on Tuesday or Friday equals to 1 if jackpot size on Tuesday or Friday is larger than or equal to 70 percentile of Mega Millions jackpot amount (\$89 million). Large Jackpot Dummy on Wednesday or Saturday equals to 1 if jackpot size is larger than or equal to 70 percentile of Powerball jackpot amount (\$114 million). Non-large Jackpot Dummy equals to 1 when Large Jackpot Dummy equals to 0.

Panel A Market Return, Total Trading Volume, and Total Dollar Volume by Days of the Week

	Obs	Mean	Median	Std.Dev.	Min	Max
Monday						
Equal-Weighted Market Return (in Percentage)	755	-0.035	0.043	1.23	-7.824	10.742
Value-Weighted Market Return (in Percentage)	755	-0.014	0.014	1.3	-8.937	11.488
Total Trading Volume (in Millions of Shares Traded)	755	3830	3520	1180	1420	10900
Total Dollar Volume (in Million)	755	122000	122000	35500	42700	298000
Tuesday						
Equal-Weighted Market Return (in Percentage)	825	0.082	0.088	1.02	-5.151	6.263
Value-Weighted Market Return (in Percentage)	825	0.091	0.098	1.16	-5.792	9.526
Total Trading Volume (in Millions of Shares Traded)	825	4080	3800	1250	1440	10300
Total Dollar Volume (in Million)	825	129000	132000	36100	48700	304000
Wednesday						
Equal-Weighted Market Return (in Percentage)	828	0.078	0.154	1.04	-7.078	5.211
Value-Weighted Market Return (in Percentage)	828	0.052	0.085	1.12	-8.977	4.685
Total Trading Volume (in Millions of Shares Traded)	828	4170	3910	1270	1140	9940
Total Dollar Volume (in Million)	828	132000	134000	37600	25900	291000
Thursday						
Equal-Weighted Market Return (in Percentage)	812	0.054	0.117	1.07	-6.704	5.127
Value-Weighted Market Return (in Percentage)	812	0.042	0.079	1.17	-7.273	6.798
Total Trading Volume (in Millions of Shares Traded)	812	4200	3900	1380	1350	12200
Total Dollar Volume (in Million)	812	133000	135000	39200	35800	320000
Friday						
Equal-Weighted Market Return (in Percentage)	807	0.097	0.162	0.87	-3.96	4.956
Value-Weighted Market Return (in Percentage)	807	0.029	0.107	0.97	-4.364	6.11
Total Trading Volume (in Millions of Shares Traded)	807	4150	3800	1520	895	12200
Total Dollar Volume (in Million)	807	133000	131000	47100	18000	338000

Panel B Jackpot Size (in Million) by Days of the Week and Jackpot Dummy

Jackpot Dummy	Obs	Mean	Median	Std.Dev.	Min	Max
Non-large Saturday Jackpot	537	53.99	50	28.19	10	113
Large Saturday Jackpot	218	207.55	179.5	104.68	114	947.9
Non-large Tuesday Jackpot	581	37.77	33	22.56	10	88
Large Tuesday Jackpot	244	179.73	144.5	127.87	89	1537
Non-large Wednesday Jackpot	583	53.14	50	28.22	10	112
Large Wednesday Jackpot	245	210.06	177	124.10	114	1500
Non-large Friday Jackpot	564	38.80	34	22.64	10	88
Large Friday Jackpot	243	179.56	146	103.82	89	1000

Table 2 The Monday Effect

In Panel A, we verify the long-existing Monday effect (where Monday return is on average lower than other days of the week) using market return indexes from 2003 January to 2018 December. The dependent variables are market return indexes in CRSP. In Column (1), Equal-Weighted Market Return is the equal-weighted return including dividends. In Column (2), Value-Weighted Market Return is the value-weighted return including dividends. In Column (1) and (2), we regress return of market indexes on Monday, Tuesday, Thursday and Friday dummy, with Wednesday as benchmark. We control for Before holiday and After holiday dummies. We estimate Newey-West standard errors, allowing maximum lags up to 5 lags. ***, ** and * represent significance levels at 1%, 5% and 10% respectively with t-statistics given in parentheses.

	(1) Equal-Weighted Market Return	(2) Value-Weighted Market Return
Monday	-0.113** (-2.00)	-0.066 (-1.07)
Tuesday	-0.002 (-0.05)	0.032 (0.56)
Thursday	-0.025 (-0.50)	-0.010 (-0.18)
Friday	0.001 (0.02)	-0.033 (-0.63)
Before holiday	0.220*** (2.76)	0.119 (1.47)
After holiday	0.127 (1.31)	0.103 (1.00)
Constant	0.071* (1.95)	0.048 (1.21)
Observations	4,027	4,027

Table 3 The Monday Effect a Weekend Jackpot Effect?

This table studies the effect of Saturday jackpots on Monday return in the subsample of Large and Non-large Saturday Jackpot respectively. Large Saturday Jackpot dummy equals to 1 if Powerball's jackpot on Saturday is larger than or equal to the 70 percentile of Powerball jackpot. Non-large Saturday Jackpot dummy equals to 1 when Large Saturday Jackpot dummy equals to 0. For trading days in week w , we classify into Large Saturday Jackpot and Non-large Saturday Jackpot groups based on Large Saturday Jackpot dummy and Non-large Saturday Jackpot dummy on the Saturday of week $w-1$.

In Panel A, we perform subsample analysis on equal-weighted and value-weighted market return. Large Saturday jackpot subsample is in Column (1) and (3). Non-large Saturday Jackpot subsample is in Column (2) and (4). The dependent variables are market return indexes in CRSP. In Column (1) and (2), Equal-Weighted Market Return is the equal-weighted return including dividends. In Column (3) and (4), Value-Weighted Market Return is the value-weighted return including dividends.

In Panel B, we use alternative measure of stock market return. In Column (1) and (2), we calculate close-to-close return from S&P 500 stock prices. In Column (3) and (4), we calculate close-to-open return from S&P 500 stock prices. In Column (5) and (6), we calculate open-to-close return from S&P 500 stock prices.

In Panel C, we study the effect of jackpots on return of stocks within different liquidity groups. We separate stocks based on share turnover ratio in the previous quarter end, and classify stocks as liquid (illiquid) stocks if share turnover ratio is larger (smaller) than or equal to 70th (30th) percentile threshold. We calculate equal-weighted return for liquid, middle group and illiquid stocks respectively. We regress the return of stocks in each liquidity group on Monday dummy and day-of-the-week dummies, when there was a large Saturday jackpot in Column (1)-(3). Similarly, we perform similar analyses in Column (4)-(6) when there was a non-large Saturday jackpot.

For all regressions in this table, we control for Before holiday, After holiday dummies. We estimate Newey-West standard errors, allowing maximum lags up to 5 lags. ***, ** and * represent significance levels at 1%, 5% and 10% respectively with t-statistics given in parentheses.

Panel A Subsample Analysis on Equal-Weighted and Value-Weighted Market Return

	(1) Equal-Weighted Market Return	(2) Equal-Weighted Market Return	(3) Value-Weighted Market Return	(4) Value-Weighted Market Return
	Large Saturday Jackpot	Non-large Saturday Jackpot	Large Saturday Jackpot	Non-large Saturday Jackpot
Monday	-0.303*** (-3.18)	-0.034 (-0.49)	-0.273** (-2.57)	0.019 (0.26)
Tuesday	-0.037 (-0.40)	0.014 (0.25)	0.026 (0.24)	0.038 (0.55)
Thursday	-0.058 (-0.61)	-0.015 (-0.26)	-0.053 (-0.50)	0.002 (0.04)
Friday	-0.049 (-0.55)	0.021 (0.38)	-0.085 (-0.87)	-0.011 (-0.18)
Before holiday	0.321** (2.12)	0.176* (1.89)	0.178 (1.09)	0.092 (1.00)
After holiday	0.134 (0.59)	0.099 (0.97)	0.129 (0.50)	0.056 (0.54)
Constant	0.093 (1.49)	0.062 (1.40)	0.082 (1.20)	0.034 (0.70)
Observations	1,178	2,847	1,178	2,847

Panel B Subsample Analysis on S&P Close-to-Close, Close-to-Open and Open-to-Close Return

	(1)	(2)	(3)	(4)	(5)	(6)
	Close-to-Close		Close-to-Open		Open-to-Close	
	Large Saturday Jackpot	Non-large Saturday Jackpot	Large Saturday Jackpot	Non-large Saturday Jackpot	Large Saturday Jackpot	Non-large Saturday Jackpot
Monday	-0.237** (-2.22)	0.045 (0.60)	0.012 (0.58)	0.013 (1.27)	-0.249** (-2.49)	0.031 (0.44)
Tuesday	0.049 (0.45)	0.048 (0.68)	0.002 (0.08)	0.003 (0.35)	0.048 (0.45)	0.044 (0.65)
Thursday	-0.040 (-0.37)	0.012 (0.18)	-0.013 (-0.66)	-0.002 (-0.25)	-0.027 (-0.27)	0.015 (0.22)
Friday	-0.079 (-0.82)	-0.014 (-0.22)	-0.005 (-0.22)	0.003 (0.30)	-0.074 (-0.83)	-0.017 (-0.27)
Before holiday	0.129 (0.77)	0.068 (0.74)	-0.015 (-0.44)	-0.002 (-0.19)	0.144 (0.96)	0.071 (0.79)
After holiday	0.143 (0.55)	0.053 (0.51)	-0.024 (-0.66)	-0.001 (-0.07)	0.165 (0.68)	0.054 (0.57)
Constant	0.061 (0.88)	0.017 (0.36)	0.011 (0.99)	-0.001 (-0.18)	0.049 (0.74)	0.018 (0.39)
Observations	1,178	2,846	1,178	2,846	1,178	2,846

Panel C Subsample Analysis by Different Liquidity Groups

	(1)	(2)	(3)	(4)	(5)	(6)
		Large Saturday Jackpot		Non-large Saturday Jackpot		
	Illiquid	Middle	Liquid	Illiquid	Middle	Liquid
Monday	-0.229*** (-3.08)	-0.289** (-2.57)	-0.420*** (-3.05)	-0.052 (-1.16)	-0.025 (-0.30)	-0.056 (-0.57)
Tuesday	-0.032 (-0.44)	-0.008 (-0.06)	-0.036 (-0.25)	-0.006 (-0.14)	0.043 (0.59)	0.017 (0.19)
Thursday	0.015 (0.21)	-0.010 (-0.08)	-0.070 (-0.50)	-0.008 (-0.19)	-0.009 (-0.12)	-0.030 (-0.33)
Friday	0.038 (0.55)	-0.053 (-0.48)	-0.124 (-0.96)	0.053 (1.40)	0.019 (0.27)	-0.037 (-0.44)
Before holiday	0.283** (2.36)	0.273 (1.44)	0.448** (2.00)	0.215*** (2.92)	0.153 (1.28)	0.198 (1.46)
After holiday	0.011 (0.07)	0.167 (0.56)	0.220 (0.62)	0.066 (0.76)	0.065 (0.55)	0.104 (0.71)
Constant	0.074 (1.47)	0.078 (0.98)	0.117 (1.25)	0.078** (2.54)	0.068 (1.25)	0.074 (1.13)
Observations	1,178	1,178	1,178	2,847	2,847	2,847

Table 4 Friday Earnings News and the Monday Effect

In this table, we study interaction effect between Saturday jackpot and earnings announcement on Friday and weekends in the subsample of Large and Non-large Saturday Jackpot. We compute standardized unexpected earnings (SUE) surprises for each earnings announcement, based on IBES reported analyst forecasts and actuals as in Livnat and Mendenhall (2006). For each earnings announcement day that falls on Friday, Saturday or Sunday, we count the total number of firms with SUE larger than 0 as number of good news and count the total number of firms with SUE smaller than 0 as number of bad news. We then calculate percentage of bad news as number of bad news/(number of good news + number of bad news). If the percentage of bad news on Friday and weekends is larger than or equal to mean, then we classify the following Monday as a day with bad news and define Bad News dummy = 1; otherwise, it is a day with good news and define Good News dummy = 1. For each Monday, we interact Bad News dummy/Good News dummy with Monday dummy to study the interaction effect. For trading days in week w , we classify into Large Saturday Jackpot and Non-large Saturday Jackpot groups based on Large Saturday Jackpot dummy and Non-large Saturday Jackpot dummy on the Saturday of week $w-1$. Large Saturday jackpot subsample is in Column (1) and (3). Non-large Saturday Jackpot subsample is in Column (2) and (4). In Column (1) and (2), Equal-Weighted Market Return is the equal-weighted return including dividends. In Column (3) and (4), Value-Weighted Market Return is the value-weighted return including dividends. We control for Before holiday and After holiday dummies. We estimate Newey-West standard errors, allowing maximum lags up to 5 lags. ***, ** and * represent significance levels at 1%, 5% and 10% respectively with t-statistics given in parentheses.

	(1) Equal-Weighted Market Return	(2) Non-large Saturday Jackpot	(3) Value-Weighted Market Return Large Saturday Jackpot	(4) Non-large Saturday Jackpot
Monday_ Bed News Friday	-0.365** (-2.28)	0.098 (1.04)	-0.388** (-2.15)	0.160 (1.57)
Monday_ Good News Friday	-0.259** (-2.53)	-0.120 (-1.52)	-0.191* (-1.74)	-0.072 (-0.85)
Tuesday	-0.037 (-0.40)	0.014 (0.25)	0.026 (0.24)	0.038 (0.55)
Thursday	-0.058 (-0.61)	-0.015 (-0.26)	-0.053 (-0.50)	0.002 (0.04)
Friday	-0.049 (-0.55)	0.021 (0.38)	-0.085 (-0.87)	-0.011 (-0.17)
Before holiday	0.320** (2.10)	0.173* (1.86)	0.176 (1.07)	0.089 (0.97)
After holiday	0.137 (0.60)	0.099 (0.96)	0.134 (0.52)	0.055 (0.53)
Constant	0.093 (1.49)	0.062 (1.41)	0.082 (1.20)	0.034 (0.71)
Observations	1,178	2,847	1,178	2,847

Table 5 Friday Return and the Monday Effect

Negative Friday return is an explanation for the Monday effect (Abraham and Ikenberry, 1994). In this table, we separately study the effect of Saturday jackpot on Monday return when the return of respective market index on the preceding Friday is positive or negative. We interact Positive/Negative Friday Return dummy with Monday dummy in the subsample of Large and Non-large Saturday jackpot respectively. For trading days in week w , we classify into Large Saturday Jackpot and Non-large Saturday Jackpot groups based on Large Saturday Jackpot dummy and Non-large Saturday Jackpot dummy on the Saturday of week $w-1$ respectively. Large Saturday Jackpot subsample is in Column (1) and (3). Non-large Saturday Jackpot subsample is in Column (2) and (4). In Column (1) and (2), Equal-Weighted Market Return is the equal-weighted return including dividends. In Column (3) and (4), Value-Weighted Market Return is the value-weighted return including dividends. We control for Before holiday and After holiday dummies. We estimate Newey-West standard errors, allowing maximum lags up to 5 lags. ***, ** and * represent significance levels at 1%, 5% and 10% respectively with t-statistics given in parentheses.

	(1) Equal-Weighted Market Return	(2) Non-Large Saturday Jackpot	(3) Value-Weighted Market Return	(4) Non-Large Saturday Jackpot
Monday_ Negative Friday Return	-0.579*** (-3.45)	-0.172 (-1.60)	-0.369** (-2.10)	0.062 (0.55)
Monday_ Positive Friday Return	-0.098 (-1.06)	0.051 (0.69)	-0.190* (-1.85)	-0.011 (-0.14)
Tuesday	-0.037 (-0.39)	0.015 (0.25)	0.026 (0.24)	0.038 (0.55)
Thursday	-0.058 (-0.61)	-0.015 (-0.26)	-0.053 (-0.50)	0.002 (0.04)
Friday	-0.049 (-0.56)	0.021 (0.38)	-0.085 (-0.88)	-0.011 (-0.18)
Before holiday	0.328** (2.19)	0.177* (1.90)	0.181 (1.11)	0.093 (1.01)
After holiday	0.133 (0.57)	0.096 (0.94)	0.133 (0.51)	0.056 (0.54)
Constant	0.093 (1.49)	0.062 (1.40)	0.082 (1.20)	0.034 (0.70)
Observations	1,178	2,847	1,178	2,847

Table 6 The Monday Effect of Anomalies

In this table, we focus on the stocks that are difficult to value and therefore require more investor attention. We use stocks with high idiosyncratic volatility (Ivol) and high distressed risk probability (Distress) as examples of hard-to-value stocks. Consistent with Kumar (2009), idiosyncratic volatility at the end of month t is the residual from fitting four-factor model using daily return of the previous 6 months, from $t-6$ to $t-1$. Stocks are classified as high (low) Ivol stocks for trading day d in month $t+1$, if Ivol of the stock is in the top (bottom) quintile of idiosyncratic volatility. Distressed risk probability is measured following Campbell, Hilscher, Szilagyi (2008) Table IV predictive return for 12 months. We calculate distressed risk at the end of December in each year t . Stocks are classified as high (low) Distress stocks for trading day d in year $t+1$, if distressed probability of the stock is in the top (bottom) quintile of distressed probability in the December of year t .

In Panel A, we calculate excess return and alphas of short legs of the anomalies, adjusted by CAPM, Fama-French three-factor model, Carhart four-factor model, on Monday and other days of the week separately. In Panel B, we calculate excess return and alphas of short legs of the anomalies, adjusted by CAPM, Fama-French three-factor model, Carhart four-factor model, on Monday with Large Saturday Jackpot and Non-large Saturday Jackpot respectively.

In Panel C, we validate findings in Birru (2018) that profits of the anomalies with short leg as speculative leg concentrate on Monday. We regress time-series of value-weighted excess return of the short legs on day-of-the-week dummies. In Panel D, we study the joint effect of large jackpots and day-of-the-week dummies. We regress time-series of value-weighted excess return of the short leg on days of the week dummy in the subsample of Large Saturday Jackpot and Non-large Saturday jackpot respectively. For trading days in week w , we classify into Large Saturday Jackpot and Non-large Saturday Jackpot groups based on Large Saturday Jackpot dummy and Non-large Saturday Jackpot dummy on the Saturday of week $w-1$. Large Saturday jackpot subsample is in Column (1) and (3). Non-large Saturday jackpot subsample is in Column (2) and (4).

We estimate Newey-West standard errors, allowing maximum lags up to 5 lags. ***, ** and * represent significance levels at 1%, 5% and 10% respectively with t -statistics given in parentheses.

Panel A Alpha of Short Legs of Anomalies by Days of the Week

Short Leg of Anomalies								
Anomaly	Monday				Tuesday through Friday			
	Excess	CAPM	FF3	Carhart	Excess	CAPM	FF3	Carhart
Ivol	-0.14	-0.123	-0.101	-0.065	0.07	0.049	0.035	0.031
t-statistics	-1.77	-2.96	-2.72	-1.87	1.30	1.49	1.21	1.08
p-value	0.08	0.00	0.01	0.06	0.19	0.14	0.23	0.28
Distress	-0.263	-0.127	-0.128	-0.078	0.026	0.002	-0.008	-0.016
t-statistics	-2.34	-2.71	-3.19	-2.25	0.46	0.08	-0.30	-0.68
p-value	0.02	0.01	0.00	0.02	0.65	0.94	0.76	0.50

Panel B Alpha of Short Legs of Anomalies on Monday by Large Saturday Jackpot Dummy

Short Leg of Anomalies								
Anomaly	Monday Large Jackpot				Monday Non-large Jackpot			
	Excess	CAPM	FF3	Carhart	Excess	CAPM	FF3	Carhart
Ivol	-0.438	-0.178	-0.13	-0.095	-0.019	-0.102	-0.08	-0.046
t-statistics	-3.00	-2.32	-1.96	-1.49	-0.21	-2.04	-1.80	-1.08
p-value	0.00	0.02	0.05	0.14	0.84	0.04	0.07	0.28
Distress	-0.429	-0.143	-0.132	-0.088	-0.014	-0.1	-0.068	-0.028
t-statistics	-2.83	-2.21	-2.36	-1.77	-0.14	-2.18	-1.96	-0.93
p-value	0.01	0.03	0.02	0.08	0.89	0.03	0.05	0.35

Panel C Regression of Short Legs of Anomalies on Days of the Week

	(1)	(2)
	Short Leg of Anomalies	
	High Ivol	High Distress
Monday	-0.217** (-2.20)	-0.223** (-2.25)
Tuesday	-0.034 (-0.36)	0.019 (0.20)
Thursday	-0.053 (-0.57)	-0.034 (-0.36)
Friday	-0.037 (-0.45)	-0.086 (-1.01)
Before Holiday	0.376*** (2.93)	0.274* (1.69)
After Holiday	0.307* (1.65)	0.149 (0.81)
Constant	0.062 (0.94)	0.085 (1.32)
Observations	4,027	4,027

Panel D Regression of Short Legs of Anomalies on Days of the Week and Jackpot Dummy

	(1)	(2)	(3)	(4)
	Short Leg of Anomalies			
	High Ivol		High Distress	
	Large Saturday Jackpot	Non-large Saturday Jackpot	Large Saturday Jackpot	Non-large Saturday Jackpot
Monday	-0.636*** (-3.62)	-0.044 (-0.37)	-0.609*** (-3.35)	-0.063 (-0.54)
Tuesday	-0.098 (-0.56)	-0.001 (-0.01)	0.008 (0.04)	0.033 (0.29)
Thursday	-0.162 (-0.88)	-0.017 (-0.16)	-0.102 (-0.53)	-0.015 (-0.15)
Friday	-0.192 (-1.27)	0.026 (0.26)	-0.198 (-1.19)	-0.041 (-0.41)
Before holiday	0.610** (2.00)	0.278** (2.18)	0.580 (1.36)	0.144 (1.02)
After holiday	0.230 (0.51)	0.274 (1.44)	-0.066 (-0.15)	0.161 (0.85)
Constant	0.189 (1.60)	0.010 (0.12)	0.183 (1.62)	0.046 (0.59)
Observations	1,178	2,847	1,178	2,847

Table 7 Return Co-movement and Saturday Jackpots

In this table, we study the effect of large jackpots on market attention by measuring co-movement of all stocks, liquid stocks and illiquid stocks. We separate stocks based on share turnover ratio in the previous quarter end, and classify stocks as liquid (illiquid) stocks if share turnover ratio is larger (smaller) than or equal to 70th (30th) percentile threshold. Following Barberis, Shleifer and Wurgler (2005), we measure co-movement as the adjusted R-Square from the market model regressions. Following Peng and Xiong (2006) and Antón and Polk (2014), we measure co-movement as the time series Pearson correlation of stock excess returns and market excess returns. Large Saturday Jackpot dummy equals to 1 if Powerball's jackpot on Saturday is larger than or equal to the 70 percentile of Powerball jackpot. Non-large Saturday Jackpot dummy equals to 1 when Large Saturday Jackpot dummy equals to 0. For trading days in week *w*, we classify into Large Saturday Jackpot and Non-large Saturday Jackpot groups based on Large Saturday Jackpot dummy and Non-large Saturday Jackpot dummy on the Saturday of week *w*-1. We calculate firm-level co-movement by Large Saturday Jackpot dummy and day-of-the-week dummy. We require at least 20 observations for each firm in each portfolio defined by Large Saturday Jackpot dummy and day-of-the-week dummy to reduce effects of outliers. In Panel A, we calculate mean and median co-movement of all stocks by Large Saturday Jackpot dummy on Monday and other weekday. In Panel B, we calculate mean and median co-movement of liquid stocks by Large Saturday Jackpot dummy on Monday and other weekday. In Panel C, we calculate mean and median co-movement of illiquid stocks by Large Saturday Jackpot dummy on Monday and other weekday. We further test the difference between mean and median co-movement between Large Saturday Jackpot subsample and Non-Large Saturday Jackpot subsample in all panels.

Panel A Co-movement of All Stocks on Monday and Other Weekdays

adjusted R-Square					
Monday Return		Large Saturday Jackpot	Non-Large Saturday Jackpot	Difference	(p value)
	Mean	0.2255	0.1884	0.0371	<.0001
Other Weekday Return	Median	0.1977	0.152	0.0457	<.0001
	Mean	0.1551	0.1421	0.013	<.0001
	Median	0.1275	0.1094	0.0181	0.0004
Correlation					
Monday Return		Large Saturday Jackpot	Non-Large Saturday Jackpot	Difference	(p value)
	Mean	0.4081	0.3595	0.0486	<.0001
Other Weekday Return	Median	0.4404	0.3685	0.0719	<.0001
	Mean	0.3287	0.3062	0.0225	<.0001
	Median	0.3456	0.3084	0.0372	<.0001

Panel B Co-movement of Liquid Stocks on Monday and Other Weekdays

adjusted R-Square					
Monday Return Liquid Stocks		Large Saturday Jackpot	Non-Large Saturday Jackpot	Difference	(p value)
	Mean	0.3026	0.2331	0.0695	<.0001
	Median	0.2822	0.1991	0.0831	<.0001
Other Weekday Return Liquid Stocks		Large Saturday Jackpot	Non-Large Saturday Jackpot	Difference	(p value)
	Mean	0.2006	0.1639	0.0367	<.0001
	Median	0.1755	0.1368	0.0387	<.0001
Correlation					
Monday Return Liquid Stocks		Large Saturday Jackpot	Non-Large Saturday Jackpot	Difference	(p value)
	Mean	0.5008	0.4255	0.0753	<0.0001
	Median	0.529	0.439	0.09	<0.0001
Other Weekday Return Liquid Stocks		Large Saturday Jackpot	Non-Large Saturday Jackpot	Difference	(p value)
	Mean	0.3959	0.3451	0.0508	<.0001
	Median	0.4111	0.3508	0.0603	<.0001

Panel C Co-movement of Illiquid Stocks on Monday and Other Weekdays

adjusted R-Square					
Monday Return Illiquid Stocks		Large Saturday Jackpot	Non-Large Saturday Jackpot	Difference	(p value)
	Mean	0.1376	0.1078	0.0298	<.0001
	Median	0.0834	0.0401	0.0433	<.0001
Other Weekday Return Illiquid Stocks		Large Saturday Jackpot	Non-Large Saturday Jackpot	Difference	(p value)
	Mean	0.0988	0.1123	0.0135	<.0001
	Median	0.0436	0.0367	0.0069	0.4465
Correlation					
Monday Return Illiquid Stocks		Large Saturday Jackpot	Non-Large Saturday Jackpot	Difference	(p value)
	Mean	0.2987	0.2454	0.0533	<0.0001
	Median	0.2916	0.2014	0.0902	<0.0001
Other Weekday Return Illiquid Stocks		Large Saturday Jackpot	Non-Large Saturday Jackpot	Difference	(p value)
	Mean	0.2563	0.2366	0.0197	<.0001
	Median	0.2102	0.1809	0.0293	<.0001

Table 8 Trading Activity and Saturday Jackpots

In this table, we study the effect of Saturday jackpots on individual investors' trading activity proxied by odd-lot order imbalance. We calculate odd-lot order imbalance as (aggregate daily odd-lot buy volume – aggregate daily odd-lot sell volume) / (aggregate daily odd-lot buy volume + aggregate daily odd-lot sell volume). For the sample period from 2003– 2012, we follow Lee and Ready (1991) to sign trades as buyer or seller initiated using TAQ Trade and Quote data. With the rise of algorithm trading, trade-size partition becomes less accurate in the recent period. From 2013 to 2018, we follow Boehmer, Jones, Zhang, and Zhang (2019) to classify marketable odd-lot retail trades as either buy or sell using TAQ Millisecond Trade and Quote data.

We create Negative Friday Return dummy and Positive Friday Return dummy for week w , based on whether the return of respective market index on the preceding Friday is negative or positive in week $w-1$. We interact Negative Friday Return dummy with Monday dummy and Large Saturday Jackpot dummy as Monday_Negative Friday Return_Large Saturday Jackpot. We interact Positive Friday Return dummy with Monday dummy and Large Saturday Jackpot dummy as Monday_Positive Friday Return_Large Saturday Jackpot. We interact Negative Friday Return dummy with Monday dummy and Non-Large Saturday Jackpot dummy as Monday_Negative Friday Return_Non-Large Saturday Jackpot. We interact Positive Friday Return dummy with Monday dummy and Non-Large Saturday Jackpot dummy as Monday_Positive Friday Return_Non-Large Saturday Jackpot.

In Column (1), we regress odd-lot order imbalance on Monday with Large Saturday Jackpot dummy, Monday dummy, and other days-of-the-week dummies. In Column (2), we regress odd-lot order imbalance on Monday with Large Saturday Jackpot dummy, Monday with Negative Friday return and Large Saturday Jackpot dummy, Monday dummy, and other days-of-the-week dummies. In Column (3), we regress odd-lot order imbalance on Monday with Negative Friday return and Large Saturday Jackpot dummy, Monday with Positive Friday return and Large Saturday Jackpot dummy, Monday with Negative Friday Return and Non-Large Saturday Jackpot dummy, Monday with Positive Friday Return and Non-Large Saturday Jackpot dummy and other days-of-the-week dummies.

We control for Before holiday, After holiday dummies. We additionally control for year fixed effect to control for time-varying transaction costs. We estimate Newey-West standard errors, allowing maximum lags up to 5 lags in return regressions. ***, ** and * represent significance levels at 1%, 5% and 10% respectively with t-statistics given in parentheses.

	(1)	(2)	(3)
	Odd-lot Order Imbalance		
Monday_Large Saturday Jackpot	-0.031*** (-3.01)	-0.027** (-2.12)	
Monday_ Negative Friday Return_Large Saturday Jackpot		-0.009 (-0.57)	-0.038*** (-2.93)
Monday_ Positive Friday Return _Large Saturday Jackpot			-0.029** (-2.47)
Monday_ Negative Friday Return_Non-Large Saturday Jackpot			-0.018* (-1.69)
Monday_ Positive Friday Return _Non-Large Saturday Jackpot			0.008 (0.93)
Monday	-0.002 (-0.22)	-0.002 (-0.22)	
Tuesday	0.005 (0.72)	0.005 (0.72)	0.005 (0.72)
Thursday	-0.002 (-0.29)	-0.002 (-0.29)	-0.002 (-0.29)
Friday	0.010 (1.44)	0.010 (1.44)	0.010 (1.44)
Before holiday	0.003 (0.29)	0.003 (0.29)	0.003 (0.30)
After holiday	0.002 (0.18)	0.002 (0.18)	0.002 (0.16)
Constant	-0.013 (-1.37)	-0.013 (-1.38)	0.027*** (5.50)
Observations	4,025	4,025	4,025

Table 9 Weekend Jackpots vs. Weekday Jackpots

We study the effect of Saturday jackpot and weekday jackpot on market return. Large Jackpot Dummy on Tuesday or Friday equals to 1 if jackpot size on Tuesday or Friday is larger than or equal to 70 percentile of Mega Millions jackpot amount. Large Jackpot Dummy on Wednesday or Saturday equals to 1 if jackpot size is larger than or equal to 70 percentile of Powerball jackpot amount. We regress equal-weighted and value-weighted return on interaction of Monday dummy with Large Saturday Jackpot dummy, interaction of Tuesday/Wednesday/Friday dummy with Large Tuesday/Wednesday/Friday Jackpot dummy. We control for Before holiday and After holiday dummies. We estimate Newey-West standard errors, allowing maximum lags up to 5 lags. ***, ** and * represent significance levels at 1%, 5% and 10% respectively with t-statistics given in parentheses.

	(1) Equal-Weighted Market Return	(2) Value-Weighted Market Return
Monday_Large Saturday Jackpot	-0.236** (-2.43)	-0.241** (-2.30)
Tuesday_Large Tuesday Jackpot	-0.041 (-0.54)	-0.092 (-1.11)
Wednesday_Large Wednesday Jackpot	-0.043 (-0.56)	-0.033 (-0.40)
Friday_Large Friday Jackpot	0.053 (0.84)	0.084 (1.17)
Monday	-0.019 (-0.29)	0.014 (0.20)
Tuesday	0.036 (0.64)	0.070 (1.10)
Wednesday	0.038 (0.67)	0.020 (0.31)
Friday	0.011 (0.21)	-0.047 (-0.80)
Before holiday	0.218*** (2.76)	0.117 (1.46)
After holiday	0.122 (1.26)	0.099 (0.95)
Constant	0.046 (1.21)	0.037 (0.92)
Observations	4,027	4,027

Table 10 Friday Return, Sports Events and the Monday Effect

This table studies the effect of Friday return and weekend sports events, Super Bowl and Kentucky Derby, on Monday return from January 1967 to December 2002. We define a Sports Event dummy, which equals to 1 on the Monday of week w if there was a sports event (Super Bowl or Kentucky Derby) over the weekends of week $w-1$. We create Negative Friday Return dummy and Positive Friday Return dummy for week w , based on whether the return of respective market index on the preceding Friday is negative or positive in week $w-1$. We interact Negative Friday Return dummy with Monday dummy as Monday_ Negative Friday Return. We interact Negative Friday Return dummy with Monday dummy and Sports Event dummy as Monday_ Negative Friday Return_Sports Event. In Column (1), we regress equal-weighted market return on Monday dummy, and other days-of-the-week dummies. In Column (2), we regress equal-weighted market return on Monday with Negative Friday return dummy, Monday dummy, and other days-of-the-week dummies. In Column (3), we regress equal-weighted market return on Monday with Negative Friday return and Sports Event dummy, Monday with Negative Friday Return dummy, Monday dummy and other days-of-the-week dummies. In Column (4) - (6), we study value-weighted market return. We estimate Newey-West standard errors, allowing maximum lags up to 5 lags. ***, ** and * represent significance levels at 1%, 5% and 10% respectively with t-statistics given in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
	Equal-Weighted Market Return			Value-Weighted Market Return		
Monday_ Negative Friday Return_Sports Event			-0.339** (-2.30)			-0.082 (-0.44)
Monday_ Negative Friday Return		-0.689*** (-13.22)	-0.676*** (-12.64)		-0.460*** (-8.51)	-0.456*** (-8.28)
Monday	-0.239*** (-9.33)	-0.041* (-1.74)	-0.041* (-1.74)	-0.161*** (-4.80)	0.035 (1.06)	0.035 (1.06)
Tuesday	-0.139*** (-6.59)	-0.139*** (-6.59)	-0.139*** (-6.58)	-0.071** (-2.50)	-0.071** (-2.50)	-0.071** (-2.50)
Thursday	0.008 (0.38)	0.008 (0.38)	0.008 (0.38)	-0.050* (-1.78)	-0.050* (-1.78)	-0.050* (-1.78)
Friday	0.113*** (5.13)	0.113*** (5.13)	0.113*** (5.13)	-0.016 (-0.54)	-0.016 (-0.54)	-0.016 (-0.54)
Constant	0.133*** (7.78)	0.133*** (7.78)	0.133*** (7.78)	0.102*** (4.92)	0.102*** (4.92)	0.102*** (4.92)
Observations	9,061	9,061	9,061	9,061	9,061	9,061

Table 11 Return Co-movement and Sports Events

In this table, we study the effect of weekend sports events on market attention by measuring co-movement of all stocks on Monday from January 1967 to December 2002. Following Barberis, Shleifer and Wurgler (2005), we measure co-movement as the adjusted R-Square from the market model regressions. Following Peng and Xiong (2006) and Antón and Polk (2014), we measure co-movement as the time series Pearson correlation of stock excess returns and market excess returns. Negative Friday Return equals to 1 on the Monday in week w , if return on Friday in week $w-1$ is negative. Negative Friday Return with Sports Event dummy equals to 1 on the Monday in week w , if return on Friday in week $w-1$ is negative and there are sports events over the weekend of week $w-1$. We calculate firm-level co-movement in each of the groups. We require at least 20 observations for each firm in each group to reduce effects of outliers. We further test the difference of mean/median co-movement between Mondays with negative Friday return and all Mondays, as well as the difference between Mondays with negative Friday return and sports events and Mondays with negative Friday return.

Adj-Rsquare					
Monday Return	Negative Friday Return		All Monday	Difference	P value
	Mean	0.0748			
	Median	0.0357	0.02434	0.01136	<0.0001
Monday Return	Negative Friday Return with Sports Event		Negative Friday Return	Difference	P value
	Mean	0.115			
	Median	0.07439	0.0357	0.03869	<.0001
Correlation					
Monday Return	Negative Friday Return		All Monday	Difference	P value
	Mean	0.2206			
	Median	0.2108	0.1691	0.0417	<0.0001
Monday Return	Negative Friday Return with Sports Event		Negative Friday Return	Difference	P value
	Mean	0.3197			
	Median	0.3355	0.2108	0.1247	<.0001

Chapter 2

Foreign Exchange Hedging and Corporate Innovation

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Abstract

We study the real effects of foreign exchange hedging on corporate innovation. Under the *information asymmetry hypothesis*, corporate hedging reduces firm's information asymmetry, and alleviates manager's career concern from undervaluation and helps investors to better monitor the manager, which in turn increases innovation. Under the *market pressure hypothesis*, hedging imposes more short-term earnings pressure on managers because of mark-to-market hedge accounting, hence leads to lower innovation. Our results support the *information asymmetry hypothesis*. Hedged firms invest more heavily in innovative projects, generate more patents and have more patent citations. To address endogeneity concerns, we employ both difference-in-differences and instrumental variables regressions, and test for reverse causality explicitly.

1. Introduction

According to Bank for International Settlements (2017), notional amount of outstanding foreign exchange derivatives arrives at \$77 trillion as of June 2017. Dominating the currency derivative usage is corporate hedging (DeMarzo and Duffie, 1995). However, in the frictionless world of Modigliani and Miller (1958), hedging should be irrelevant, as shareholders possess the requisite tools and information to create their desired risk profile. This contradiction leads to the long-debated question: Does corporate hedging matter? Existing literature provides various explanations on why firms hedge. These explanations include managerial risk aversion (Stulz, 1984), information asymmetry (DeMarzo and Duffie, 1991, 1995; Breeden and Viswanathan, 2015), tax convexity (Mayers and Smith, 1982; Smith and Stulz, 1985), financial distress and debt capacity (Nance, Smith, and Smithson, 1993), and underinvestment problem (Shapiro and Titman, 1986; Stulz, 1990; Froot, Scharfstein, and Stein, 1993).

Empirically, existing studies have largely focused on capital market implications of corporate hedging. For example, Carter, Rogers, and Simkins (2006), Allayannis and Weston (2001), Perez-Gonzalez and Yun (2013), and Gilje and Taillard (2017) find that corporate hedging increases firm value. Graham and Rogers (2002) and Campello, Lin, Ma, and Zhou (2011) document that corporate hedging improves debt capacity. On the contrary, Tufano (1996) and Jin and Jorin (2006) test the relationship between hedging and firm value within specific industries, and fail to find significant results. In this paper, we take one step further and examines whether corporate hedging affects firms' real activities. In particular, we study how foreign exchange (FX) hedging affects corporate innovation.¹²

¹² We acknowledge that there are other types of financial uncertainty such as interest rate risk. We focus on FX hedging because the usage of currency derivatives is mainly for hedging purpose against FX risk (Allayannis and Weston,

Ex-ante, it is unclear whether corporate hedging increases or decreases firms' innovation activities. On one hand, corporate hedging is shown to reduce the information asymmetry between the firms and the outside investors. When firms have proprietary information that could not be shared with investors, investors could neither hedge the risk nor do they know how to hedge (DeMarzo and Duffie, 1991). In this case, firms could hedge on investors' behalf so that investors are less concerned with information asymmetry. DeMarzo and Duffie (1995) further show that hedging could help to signal managerial ability and enhance the informational content of corporate earnings. Similarly, Breeden and Viswanathan (2015) argue that hedging can be a strategy used to enhance learning process about managerial ability. Consistent with the theoretical works, DaDalt, Gay, and Nam (2002) empirically validate the role of hedging in reducing noise from macroeconomic factors and hence information uncertainty. Moreover, Manconi, Massa, and Zhang (2017) show that corporate hedging reduces information asymmetry and increases stock price informativeness, by documenting the eroded information advantage of informed traders after hedging. The role of corporate hedging on reducing information asymmetry has two implications for firm innovation.

First, innovation is a long-term process with significant uncertainty, and requires information privacy due to its strategic importance (Hall, Jaffe and Trajtenberg, 2005; Caggese, 2012). The lack of full disclosure on innovation investments hinders effective communication between managers and outside investors, and increases information asymmetry (Bhattacharya and Ritter, 1983; Anton and Yao, 2002). Therefore, innovative firms tend to be undervalued by investors (Diamond and Verrecchia, 1991). The undervaluation leads to higher take-over threat to the firms and higher career concern to the managers, managers are consequently induced to be more myopic

2001; Brown, 2001), while interest rate derivatives usage have been found to be more likely for the purpose of speculation and earnings management (Faulkender, 2005; Chernenko and Faulkender, 2011).

and tend to reduce innovation activities (Stein, 1988, 1989). In short, reduction of information asymmetry between the firm and investors alleviates manager's career concern from undervaluation, and allows manager to better allocate resources to long term value enhancing activities such as innovation. Second, reduction of information asymmetry allows the market to play a more active role in monitoring managers when they pursue innovation activities that are informationally opaque in nature (e.g., Holmstrom and Tirole, 1993; Faure-Grimaud and Gromb, 2004). In addition, higher stock price informativeness may also facilitate managers to better learn about the value of their growth opportunities and engage in more value-increasing innovation activities (Foucault and Gehrig, 2008). This will increase the firm's innovation efficiency.¹³

Therefore, given that information environment is key to corporate innovation, and corporate hedging reduces a firm's information asymmetry, we hypothesize that hedging boosts innovation. We term this argument the *information asymmetry hypothesis*.¹⁴

On the other hand, innovation process is subject to capital market pressure which might lead to managerial myopia and long-term value sacrifice (Bhojraj and Libby, 2005; He and Tian, 2013). The survey by Graham, Harvey, and Rajgopal (2005) finds that due to market pressure, CFOs tend to sacrifice long-term value by means like cutting R&D expenditure to meet short-term profit targets. Corporate hedging can increase firms' short-term earnings pressure as a result of mark-to-market requirement for hedge accounting. In this case, firms have to recognize the loss from derivatives hedging position immediately, but may not be able to recognize the gain from the underlying asset due to accounting conservatism requirement. Therefore, hedging increases short-

¹³ Similar arguments have been used by Blanco and Wehrheim (2017) to develop the hypothesis that options trading affect firm innovation.

¹⁴ Alternatively, hedging can spur innovation through its role in lower cost of capital. However, this alternative argument cannot explain our findings that hedging also improves innovation efficiency. We discuss this issue in detail in Section 6.3

term earnings pressure. As a result, hedging reduces firms' long-term investment and hinders corporate innovation. We term this alternative argument the *market pressure hypothesis*.

Corporate hedging can be negatively associated with innovation for other reasons. First, the purpose of financial derivatives usage could be for speculation (Faulkender, 2005). In this scenario, hedging is a signal of managerial myopia and therefore correlated with lower level of innovation. Second, hedging as a mean of risk management, can also be a signal of managerial risk aversion (Stulz, 1984) and leads to lower innovation. Third, the accounting literature has some findings that hedging can increase firm's financial reporting opacity (Campbell, 2015; Donohoe, 2015; Chang, Donohoe, and Sougiannis, 2016; Campbell, D'Adduzio, Downes, and Utke, 2017), which predicts lower innovation.

To test the relationship between corporate hedging and innovation, we focus on the usage of foreign exchange derivatives (*FX hedge*) to measure corporate hedging activities, because the usage of currency derivatives is mainly for hedging purpose against FX risk (Allayannis and Weston, 2001; Brown, 2001). We rely on the number of patents and forward citation of patents at firm level to measure innovation outputs. We find that FX hedging leads to higher innovation investments and outputs in the baseline regression, supporting the *information asymmetry hypothesis*. While our identification strategy relies on the dummy variable *FX hedge*, we conduct a battery of analyses to examine how the extent of *FX hedge*'s potential benefit affects firm's innovation. We show that the effect of *FX hedge* are stronger for firms facing higher FX hedging needs (as measured by *FX risk exposure*, *international competition*, and *FX volatility*). Our results are robust to negative binomial regression, and subsample regressions accounting for the patent data truncation bias and accounting rule change.

Endogeneity is a major concern to our findings. It is possible that our results are driven by some firm unobservable characteristics that simultaneously affect firm's hedging decision and innovation. For example, firms with higher opacity and volatility may have higher propensity to utilize FX hedging, while these characteristics are also associated with higher innovation activities. It is also possible that the causality between hedging and innovation goes the opposite direction. For example, higher innovation outputs might be related to higher innovation inputs and risk, leading to stronger incentive to hedge. To address the endogeneity problem, we first conduct a change regression to rule out the effect of time invariant unobservable variables. We also perform propensity score matching (PSM) to find a control firm for each firm that initiates *FX hedge*, and conduct a difference-in-differences (DiD) analysis. The results show that relative to the control firms, the treatment firms (those initiate *FX hedge*) are associated with higher innovation outputs after the initiation. Next, we take advantage of the institutional feature of corporate tax code in U.S. firms and use tax convexity as an instrumental variable (IV) to FX hedging. The results from two-stage IV Heckman treatment regression holds qualitatively similar with baseline results. Moreover, we explicitly address the reverse causality concern by categorizing each firm-year into four types: remain-unhedged firms, quit-hedging firms, start-hedging firms, and continue-hedging firms, and test whether innovation affects hedging decisions. Empirically, there is no evidence to reject the hypotheses that decision to begin/quit hedging is unaffected by innovation, at conventional levels of significance.

To provide further support to the *information asymmetry hypothesis*, we conduct moderation analyses using *analyst forecast dispersion*, *breadth of ownership*, and *PIN* to measure information asymmetry. Consistent with the *information asymmetry hypothesis*, we find that the effect of *FX hedge* is stronger for firms with higher information asymmetry. Next, we conduct a battery of

analyses to examine how FX hedge affects firm's myopic behavior. Specifically, we find that *FX hedge* increases firm's long term investment, and curbs manager's real earnings management. We also find that effect of *FX hedge* is stronger when managers have higher career concern (or are more likely to be myopic facing information asymmetry).

In the additional analyses, we first we address the competing *market pressure hypothesis*. Though we find that the *market pressure hypothesis* plays a role in affecting corporate innovation, the effect is dominated by *information asymmetry hypothesis*. Next we find that *FX hedge* increases innovation efficiency, which is consistent with our *information asymmetry* hypothesis, and inconsistent with the alternative explanation of cost of capital channel. Finally, we further investigate the cost of capital channel. We show that though *FX hedge* decreases firm's cost of capital which in turn increases innovation outputs, the channel only explains a marginal portion of the effect of *FX hedge* on innovation.

Our paper contributes to the literature in three ways. First, we contribute to the strand of literature on corporate hedging. Froot, Scharfstein, and Stein (1993) argue that one benefit of hedging is alleviating underinvestment problem. DeMarzo and Duffie (1995) provide a theoretical basis for the information asymmetry reduction role of corporate hedging, by arguing that hedging allows investors to learn better about the management ability and project quality from firm's earnings. Empirically, some findings support that corporate hedging increases firm value (Carter et al., 2006; Allayannis and Weston, 2001; Perez-Gonzalez and Yun, 2013; Gilje and Taillard, 2017). Related to firm innovation, Géczy, Minton, and Schrand (1997) document a positive relation between currency hedging and growth opportunity in Fortune 500 firms. Petersen and Thiagarajan (2000) show that the choice of hedging is influenced by abilities to adjust operating costs, requirement of investment capital as well as managerial incentives and compensation.

Campello et al. (2011) show that hedging allows firm to enjoy lower borrowing cost and less investment restrictions. By focusing on innovation, we can not only separate the short-term and long-term investment, but also examine the outcome of investment. We hence contribute to the fundamental question of whether hedging matters, by documenting a real effect of hedging on firm innovation outputs and efficiency.

Second, we contribute to the literature on motivating firm innovation, especially on the information environment side. Manso (2011) argues that motivating innovation requires tolerance of short-term failure and reward for long-term success, which provides the theoretical basis of how information environment can shape innovation. He and Tian (2013) reveal the negative effect of analyst coverage on firm innovation, as a result of reduced tolerance for failure and exacerbated managerial myopia. Dai, Shen, and Zhang (2017) find that innovation is impeded by media coverage. Similarly, Agarwal, Vashishtha and Venkatachalam (2018) find that mutual fund transparency exacerbates managerial myopia and leads to a decline in innovation. Blanco and Wehrheim (2017), on the other hand, find that options trading can enhance price efficiency and therefore boost innovation. We add to this line of research by showing that hedging reduces firm's information asymmetry, hence alleviates manager's career concern from undervaluation, and helps investors to better monitor the manager, leading to higher innovation.

Third, we contribute to the debate on whether the purpose of derivatives usage by non-financial firms is for hedging against risks or for speculating of underlying asset's movements. Innovation provides an ideal setting as it is a long-term process that should be differently affected by derivatives usage according to its purpose. Allayannis and Weston (2001) find that the purpose of using currency derivatives is generally to reduce FX risk exposure instead of speculation. Faulkender (2005) and Chernenko and Faulkender (2011) argue that interest rate derivatives usage

is more likely for speculating on interest rate movements and facilitating earnings management. Consistently, DaDalt et al. (2002) find that the informational role of hedging is primarily driven by currency derivatives and weakly extends to interest rate derivatives. We document that firms with FX hedging are associated with more innovations, which supports the view that the usage of FX derivatives is generally for hedging purposes.

The rest of the paper is organized as follows: Section 2 describes sample and data in details. Section 3 presents the main results. Section 4 addresses endogeneity concern. Section 5 explores the economic channel. Section 6 provides additional analyses. Section 7 concludes.

2. Sample and Data

We start our sample with all non-financial firms in the Compustat and CRSP merged database with available hedging information. We hand collect the hedging information for these firms based on their 10-K and 10-Q filings as in Manconi et al. (2017). Next, we compute firm characteristics from Compustat, CRSP and Thomson Reuter's 13F databases, and exclude firms with missing values.

To gauge the innovation outputs, we construct measures from the patent database by Kogan, Papanikolaou, Seru, and Stoffman (2017), which covers all U.S. patent documents from Google Patents and NBER database up to 2010. We use application year as time placer and end the innovation output data until 2006, since excluding 3 to 4 years is necessary to minimize patent data truncation bias (Dass, Nanda, and Xiao, 2017)¹⁵. The similar database has been widely used

¹⁵ Our results are qualitatively similar if we extend our sample to year 2007 or 2008.

in previous innovation studies (Moser and Voena, 2012; Moser, Voena, and Waldinger, 2014; Bernstein, 2015; Dong, Hirshleifer, and Teoh, 2016).

Specifically, two measures of innovation outputs are used for a given firm in each year: number of patents (*LnPatent*), and forward citation (*LnCitation*) adjusted using fixed effect approach as in Hall, Jaffe, and Trajtenberg (2001). Consistent with innovation literature, we take the natural logarithm of innovation outputs (Hall et al., 2001; Kogan et al., 2017). *LnPatent* is the natural logarithm of $(1 + Patent\ Number)$, where *Patent Number* is the number of patents finally granted. *LnCitation* is the natural logarithm of $(1 + Citation)$, where *Citation* is the sum of adjusted citation for all patents applied in a given firm-year. For each patent citation, we scale the raw citation by the mean citation of the same technological class and application year. *LnCitation* gauges the importance of patents with forward patent citation, and indicates the scientific value of patent quality. The citation of patents is an important complement to the patent number measure (Griliches, Pakes, and Hall, 1987; Trajtenberg, 1990; Hall et al., 2001). Following literature (Tian and Wang, 2011; Atanassov, 2013; Hsu, Tian and Xu, 2014), we take a two-year gap between innovation output measures and independent variables due to the long-term nature of innovative activities.

Following literature (Nance et al., 1993; Allayannis and Weston, 2001; Purnanandam, 2008; Campello et al., 2011), we focus on firm's usage of relevant derivatives to measure corporate hedging activities.¹⁶ To measure FX hedging, we search firms' 10-K and 10-Q filings using keywords provided by Manconi et al. (2017).¹⁷ For those filings containing the keywords, we

¹⁶ The Financial Accounting Standards Board (FASB) (1998) Statement of Financial Accounting Standards (SFAS) 133 (effective on 2000), requires all derivatives to be carried at fair value, instead of notional value. For this reason, Graham and Rogers (2002) note that the fair value information reported under SFAS 133 is limited and warn against using the fair value information to study corporate hedging.

¹⁷ Specifically, we search for the following keywords: "foreign exchange forward", "forward foreign exchange", "foreign exchange rate forward", "currency forward", "currency rate forward", "foreign exchange option", "currency

manually check the filings to eliminate misclassifications. The *FX hedge* is then defined to be 1 if the firm uses FX hedging in year t , and 0 otherwise.

We also include several control variables in our test. *Size* is firm's size measured by logged total asset and we expect larger firms to have more innovation outputs (Hall and Ziedonis, 2001). We use net property, plant, and equipment scaled by prior fiscal year's total asset (*PPE*) to control for capital intensity, as capital intensity will influence firm's innovation activities (Hall and Ziedonis, 2001). *M/B* is firm's market to book ratio, a proxy for firm's growth opportunities. In addition, we also control for sales growth (*Sales Growth*). We control for the firm age (*Age*) measured by the number of years since its initial appearance in CRSP database, as firm in the different life cycle might have different innovation capacity. Institutional ownership (*Institutional ownership*) is controlled for its influence on firm innovation (Aghion, Van Reenen, and Zingales, 2013). Other controls include firm's return on asset (*ROA*), leverage (*Leverage*), cash holding (*Cash Holding*), stock return (*Return*), Amihud's illiquidity (*Illiquidity*), stock volatility (*Return Volatility*), Herfindahl index (*HHI*), and square of Herfindahl index (*HHI_sq*). *Foreign Income* is firm's foreign income exposure, and is included to control for firms' propensity to utilize foreign exchange rate hedge (Manconi et al., 2017). The variable definitions are listed in Appendix 1.

Finally, we recognize that there are firms that do not conduct FX hedging because they don't face significant ex ante FX exposure, such firms are not proper counterfactuals in our tests. We therefore follow Graham and Rogers (2002) and Campello et al. (2011), to exclude firms without ex ante FX risk exposures using the following procedures:

option", "foreign exchange rate option", "currency rate option", "foreign exchange future", "currency rate future", "foreign exchange swap", "currency swap", "foreign exchange rate swap", "currency rate swap", "foreign exchange cap", "currency cap", "foreign exchange rate cap", "currency rate cap", "foreign exchange collar", "currency collar", "foreign exchange rate collar", "currency rate collar", "foreign exchange floor", "currency floor", "foreign exchange rate floor" and "currency rate floor". We also filter out filings containing phrases such as "we (the company) do not (does not) have (utilize, enter) any foreign exchange derivatives."

First, similar with Campello et al. (2011), we check whether firms explicitly discuss FX risks in their 10-K and 10-Q filings based on keywords. The list of keywords includes “currency risk”, “currency rate risk”, “exchange risk”, “exchange rate risk”, “foreign exchange risk”, and “foreign exchange rate risk”.

Second, we follow Graham and Rogers (2002) and Campello et al. (2011), and check whether firms disclose positive values of foreign currency adjustment, exchange rate effect, foreign income taxes, or deferred foreign taxes in their annual Compustat files, or disclose foreign assets, sales, or income in the Compustat Geographic segment files.

Last, we follow Aggarwal and Harper (2010) and Jorion (1991) to calculate FX risk exposures. For each firm in each year, we pool firm-month observations for the past five years and we regress stock returns on changes in exchange rate between US dollar against currencies of major US trading partners (the Trade Weighted US dollar index TWEXB from the Federal Reserve Bank at St Louis), and market return. The regression coefficient on exchange rate changes is taken as a proxy for FX risk exposure. The coefficients are replaced with zero if not significant at 10% significance level.

Following these procedures, we end up deleting 3,766 observations that 1) have no discussion on FX risks; 2) do not have positive foreign related items; 3) do not have statistically significant measures of ex-ante FX risk exposure. The final sample consists of 32,194 firm-year observations from 1998 to 2006 (or from 1994 to 2004 in terms of independent variables).

Table 1 Panel A provides the summary statistics for the variables used in our main analysis. In our sample, 13.7% of the firm-year observations use FX hedging, which is consistent with Campello et al. (2011) and Manconi et al. (2017). On average, 27.1% of the firms have nonzero number of patents, consistent with innovation literature that majority of the firms report zero

innovation outputs (e.g., Tian and Wang, 2011; He and Tian, 2013). The distribution of control variables are all consistent with previous studies.

[Table 1 about here]

Table 1 Panel B and C provide the distribution of hedging firms across industries¹⁸ and years. The “Chemicals and Allied Products” industry has the highest proportion of hedging firms, while the “Wholesale, Retail Services” industry has the lowest proportion. On the time dimension, there is a trend of increase in the proportion of firms that engage in FX Hedging.

3. Main Results

3.1. Pooled OLS Baseline Regression

We start by testing whether *FX hedge* cause managers to increase investment on innovation using the following regression:

$$R\&D/Assets_{i,t+1/i,t+2} = \alpha_0 + \alpha_1 FX_hedge_{i,t} + \sum \alpha_k Controls_{i,t} + \varepsilon_{i,t+2} \quad (1)$$

R&D/Assets is the ratio of R&D expenditures divided by lagged total assets. If the R&D expenditure is missing, we follow Hirshleifer, Low, and Teoh (2012), He and Tian (2013), and Blanco and Wehrheim (2017), and replace the missing values with zero.¹⁹ *FX hedge* is a dummy variable that equals to 1 if the firm hedges against FX risk and 0 otherwise. We control for various firms characteristics that are likely to influence innovation input and FX hedging decision. We also include year fixed effect to control for the time trend at aggregate level and industry fixed effects to account for the heterogeneous innovative nature of different industries. The hedging

¹⁸ The industry classification we use here is Fama-French 12 industry, for the simplicity of illustration. In our regressions, we employ 2-digit SIC code for industry classification.

¹⁹ In the internet appendix, we restrict our sample to nonmissing R&D observations, and find qualitatively similar results.

literature (Allayannis and Ofek, 2001; Manconi et al., 2017) generally includes industry fixed effects instead of firm fixed effects, as firm's hedging activities do not vary much across years.²⁰ To address the concern that our results are driven by unobservable firm characteristics, we include lagged *R&D/Assets* as additional control variables.²¹ The results are reported in Table 2 Panel A. In columns (1) and (2), we use the *R&D/Asset* measured at year $t+1$, while in columns (3) and (4), we use the *R&D/Asset* measured at year $t+2$.

[Table 2 about here]

The coefficients of *FX hedge* are all positive and statistically significant at 1% significance level. Compared with the non-hedgers, firms that hedge against FX risk invest 0.004 to 0.011 more in R&D depending on model specifications. Compared with the mean level of *R&D/Assets* (0.061), the effect is also economically significant.

Since missing R&D expenditures doesn't necessarily imply the firm lacks innovation activities (Koh and Reeb, 2015), and innovation output is more relevant to our research question, we therefore focus on innovation outputs. To test the relationship between FX hedging and innovation outcomes, we run the following OLS regression:

$$Innovation_Output_{i,t+2} = \alpha_0 + \alpha_1 FX_hedge_{i,t} + \sum \alpha_k Controls_{i,t} + \varepsilon_{i,t+2} \quad (2)$$

where the innovation output is measured by two variables at firm-year level: *LnPatent* (natural logarithm of (1+ number of patents)), and *LnCitation* (natural logarithm of (1+ forward adjusted citation)). To address the concern that our results are driven by unobservable firm characteristics,

²⁰ In fact, the results from firm fixed effect model will be unreliable if the regressor doesn't have much time series variation (Zhou, 2001).

²¹ There are also innovation studies that do not include firm fixed effects when the variables of interest do not have much time series variation (Hall et al., 2005; Hirshleifer, Low, and Teoh, 2012). In particular, Blundell, Griffith, and Van Reenen (1999) and Blanco and Wehrheim (2017) control for the pre-sample mean of innovation outputs to control for unobservable firm characteristics. In unreported results, we use the similar approach and find robust results.

we control for lagged *LnPatent* or *LnCitation* correspondingly. The results are reported in Table 2 Panel B.

Consistent with previous findings, our results show that innovation output increases with size (He and Tian, 2013), market-to-book ratio (Dong et al., 2016), cash holding, illiquidity (He and Tian, 2013), and volatility. Innovation output is found to be negatively associated with leverage (Tian and Wang, 2014), sales growth and prior stock return.

More importantly, Table 2 Panel B shows that FX hedging boosts innovation output in both measures in all specifications. The coefficients of *FX hedge* are all significantly positive at 1% significance level. Compared with the non-hedgers, firms that hedge against FX risk generate 10.2% - 14.8% more patents, receive 11.5% -16.2% more adjusted citations depending on model specifications.

3.2. Potential Benefit of FX hedge

A drawback of our identification strategy is that we rely on a dummy variable to measure FX hedging, and can't provide information about how the extent of FX hedging affects firm's innovation outputs. Due to data limitation,²² it's difficult to construct a measure for the extent of FX hedging. We therefore indirectly examine how the extent of *FX hedge*'s potential benefit affects firm's innovation. Specifically, we proxy firm's FX hedging needs by *FX exposure*, *International competition*, and *FX volatility*. Presumably, firms with higher FX hedging needs potentially benefit more from FX hedge. In Table 3, we test whether the effect of *FX hedge* is stronger for firms with higher hedging needs.

²² It's difficult to quantify both the dollar amount of firms' FX exposures due to the lack of theoretical background. It's also difficult to measure the notional amount of FX derivatives that firms use to hedge FX risk, since the SFAS 133 requires derivatives to be carried at fair value, as opposed to notional value.

[Table 3 about here]

In Table 3 Panel A, we use *FX exposure* to measure FX hedging needs. *FX exposure* is computed as defined in Section 2. The coefficients of the interaction term between *FX hedge* and *High FX exposure* (a dummy variable that equals to 1 if *FX exposure* is higher than the median level, and 0 otherwise) are positive and statistically significant in all specifications. Compared to firms with low *FX exposure*, the effect of *FX hedge* is 0.080 to 0.115 stronger in firms with high *FX exposure*.

In Table 3 Panel B, we use *International competition* to measure FX hedging needs. For each 4-digit SIC industry, *international competition* is measured as the fraction of non-US sales (measured in US dollars) among total sales. We obtain sales data of international companies from the Compustat Global database. The coefficients of the interaction term between *FX hedge* and *High international competition* (a dummy variable that equals to 1 if *International competition* is higher than the median level, and 0 otherwise) are positive and statistically significant in all specifications. Compared to firms with low *International competition*, the effect of *FX hedge* is 0.109 to 0.158 stronger in firms with high *International competition*.

In Table 3 Panel C, we use *FX volatility* to measure FX hedging needs. For each year, FX volatility is computed as the standard deviation of monthly TWEXB (the exchange rate of US dollar against currencies of major US trading partners). The coefficients of the interaction term between *FX hedge* and *High FX volatility* (a dummy variable that equals to 1 if *FX volatility* is higher than the median level, and 0 otherwise) are positive and statistically significant in all specifications. Compared to years of low *FX volatility*, the effect of *FX hedge* is 0.030 to 0.060 stronger in years of high *FX volatility*.

Taken together, the results all consistently show that the effect of *FX hedge* is stronger when the potential benefit of *FX hedge* is larger.

3.3. Robustness Checks

In our main specification, we employ OLS regressions with logged innovation outputs as dependent variables. In this subsection, we use the negative binomial regression with the unlogged *Patent* and *Citation* as dependent variables, to check whether our findings are robust to the alternative model specification. The results are reported in Table 4 Panel A. The coefficients of *FX hedge* are positive and statistically significant in columns (1)-(4), suggesting that our results are robust to alternative model specification.

[Table 4 about here]

In addition, the lag between patent application and patent grant leads to truncation bias (Dass et al., 2017). In the main specification, we cut off our sample four years before 2010 to minimize truncation bias. In the subsection, we further cut off our sample to 1998-2004 to check whether our results still hold. The results are reported in Table 4 Panel B. The coefficients of *FX hedge* are positive and statistically significant in columns (1)-(4), suggesting that our results are robust to truncation bias.

Last, during the sample period of our study, there is a regime switch in hedge accounting. In 2000, the FASB Statement of Financial Accounting Standards (SFAS) 133 became effective. SFAS 133 requires all derivatives to be carried at fair value, instead of notional amount. As a result, the hedging information reported under SFAS 133 is limited (Graham and Rogers, 2002). In turn, this change in hedging accounting could potentially lower the effect of hedging on innovation. In this subsection, we examine whether the effect of hedging still exists after SFAS133.

In Table 4 Panel C, we restrain the sample period to post SFAS133 period, and test whether hedging affects innovation. The coefficients of *FX hedge* are positive and statistically significant in columns (1)-(4). Though the economic magnitudes of the effects are lower than in Table 2 Panel B (where the whole sample is used), they are still economically significant. Compared with the firms that do not hedge, the hedging firms have 9.0% - 9.1% (9.2% - 9.4%) higher patents (citations).

3. Endogeneity Concerns

While the above findings support our argument that FX hedging leads to more innovation outputs, it is possible that our results are driven by some unobservable firm characteristics that simultaneously affect firm's hedging decision and innovation. For example, firms with higher opacity and volatility may have higher propensity to utilize FX hedging, while these characteristics are also associated with higher innovation activities. It is also possible that the causality between hedging and innovation goes the opposite direction. For example, higher innovation outputs might be related to higher innovation inputs and risk, leading to stronger incentive to hedge. In this section, we address the above concerns using several tests.

4.1. Change Level Regression

In this subsection, we conduct a change level regression to control for the potential time-invariant omitted variables. Specifically, we compute the change of innovation outputs from year $t+2$ to $t+1$, and the change of independent variables from year t to $t-1$, so that the time-invariant portion is cancelled. We then run the following regression:

$$\Delta Innovation_Output_{i,t+2} = \alpha_0 + \alpha_1 \Delta FX_hedge_{i,t} + \sum \alpha_k \Delta Controls_{i,t} + \varepsilon_{i,t+2} \quad (3)$$

where $\Delta Innovation$ is measured by $\Delta LnPatent$ and $\Delta LnCitation$. Here we don't include the lagged innovation outputs, as the specification has already cancelled the time invariant firm variables. The results are reported in Table 5.

[Table 5 about here]

The coefficients of ΔFX_hedge are positive and statistically significant at 5% or lower significance levels, suggesting that our results are robust to the endogeneity concern related to time invariant omitted variables.

4.2. Difference-in-Differences Analysis

Following Guay (1999) and Chang et al. (2016), we take advantage of firms' initiation of FX hedging and conduct a difference-in-differences analysis. Specifically, we identify firms that initiate FX hedging in the sample period. For each of the first-time users, we match it with a similar firm that never uses FX hedging throughout the sample period, with a caliber of 0.05. We are able to identify 298 pairs of firms. By constructing a control group that is otherwise similar to the hedging firms, we can draw causal inferences in the non-experimental settings (Rosenbaum and Rubin, 1983).

Specifically, we regress the following model to obtain propensity scores:

$$Pr(Initiation_{i,t}) = \theta_0 + \sum \theta_K Y_{i,t} + \varepsilon_{i,t} \quad (4)$$

where the control variables includes firm size, market-to-book, foreign income, leverage, institutional ownership, cash holding, sales growth, prior return, stock illiquidity, return volatility, Herfindahl index and its square. We also include year and industry fixed effects.

We first check the covariate balance in Table 6 Panel A. No significant difference in control variables is found between the treatment and control groups. Based on the paired firms, we then run the following regression using two years window around the initiation:

$$Innovation_Outputs_{i,t+1} = \psi_0 + \psi_1 Initiation + \psi_2 Post + \psi_3 Initiation \times Post + \gamma X_{i,t} + \varepsilon_{i,t} \quad (5)$$

where *Initiation* is an indicator that equals to 1 for first-time users (i.e., the treatment group) and 0 otherwise. *Post* is an indicator that equals to 1 if the observation is the year of initiation, and 0 otherwise. We are interested in the interaction term between *Initiation* and *Post*, which captures the innovation differences between first-time users and non-users. The results are reported in Table 6 Panel B. In columns (1) and (3), we include year and industry fixed effects. Since in the DiD regression, we are more interested in the interaction term *Initiation* $\times$ *Post*, we drop the *Initiation* dummy, and include year and firm fixed effects to control for the time invariant firm characteristics in columns (2) and (4). We find that the coefficients of *Initiation* $\times$ *Post* are significantly positive in all the columns, further confirming the causal effect of FX hedging on innovation.

[Table 6 about here]

4.3. Instrumental Variable Approach

Though the above methods help to address endogeneity concerns related to time-invariant unobservable omitted variables, it is still possible that there exist time-variant omitted variables that affect both hedging decisions and innovation outcomes. To mitigate this concern, we conduct

a two-stage residual inclusion (Hausman, 1978) analysis in this subsection.²³ Specifically, following existing studies (Smith and Stulz, 1985; Campello et al., 2011; Manconi et al., 2017), we use corporate income tax convexity as an instrumental variable. Corporate income tax convexity is a result of institutional feature of the U.S. corporate tax code, and is weakly associated with firm innovation.²⁴ Hedging, however, can reduce the firm's expected tax liability through lowering taxable income variability, and is directly related to tax convexity.

Following Campello et al (2011) and Manconi et al (2017), we use the following equation to define effective tax convexity:

$$\begin{aligned} Convexity_{it} = & 4.88 + 0.019TIVol_{it} - 5.5TICorr_{it} - 1.28DITC_{it} + 3.29DNOL_{it} + 7.15DSmallNeg_{it} \\ & + 1.60DSmallPos_{it} - 4.77DNOL_{it} \times DSmallNeg_{it} - 1.93DNOL_{it} \times DSmallPos_{it} \quad (6) \end{aligned}$$

The tax convexity measure is essentially the expected average tax savings from 5% reduction in taxable income volatility (Graham and Smith, 1999)²⁵. *TIVol* denotes the volatility of taxable income, calculated on a rolling basis using all available historical annual data up to the year *t*. *TICorr* denotes taxable income's serial correlation, calculated on a rolling basis using all available historical annual data up to the year *t*. *DITC* is a dummy variable indicating investment tax credits. *DNOL* is a dummy variable indicating net operating losses. *DSmallNeg/DSmallPos* is a dummy variable indicating small negative/positive taxable income.

Following the two-stage residual inclusion regression (Hausman, 1978), we first estimate a Logit model using *FX hedge* as dependent variable and *Convexity* as independent variable with all

²³ Our results are robust if we use treatment regression model.

²⁴ One exception is Gentry & Hubbard (2004), who show that the household tax convexity deters people from entrepreneurial activities. If the similar effect exists in corporate innovation, it will only introduce downward bias to our findings, i.e., our findings would otherwise be stronger.

²⁵ The tax savings include tax-loss carrybacks, carryforwards, investment tax credits (ITCs), and the alternative minimum tax (AMT).

controls used in the baseline regressions. From the Logit regression, we compute the residual and include the residual as additional controls and then re-estimate our baseline regressions. The two-stage residual inclusion has been used by various studies to address endogeneity (e.g., Terza, Basu, and Rahouz, 2008; Chen, Hong, Jiang, and Kubik, 2012). We present the results in Table 7.

[Table 7 about here]

Columns (1) and (2) in Table 7 Panel A report the first stage of IV regression. Consistent with previous literature (Dionne and Garand, 2003; Campello et al., 2011; Manconi et al., 2017), the results show that tax convexity positively influences firm's hedging decision. Columns (3) and (4) report the second stage results. We find that the coefficients of *FX hedge* are positive and highly significant, which lends strong support to the *information asymmetry hypothesis*.

We then re-run the same regression in Table 7 Panel B with different definitions of tax convexity. Specifically, we exclude taxable income volatility from convexity calculation to avoid the potential correlation between income volatility and innovation. Our results remain robust.

Finally, to further alleviate the concern that the firm's tax convexity is related to innovation activities per se, we employ the state level tax convexity as an IV. The state level tax convexity is hard to manipulate by the firm, and serves as a valid IV. The results are reported in Table 7 Panel C. We find that the state level tax convexity is significantly related to firm's hedging activities, and our results that *FX hedge* boosts innovation are robust.

4.4. Reverse Causality

It is possible that firms hedge to mitigate the potential high earnings volatility caused by innovation activities. In this case, the causality between hedging and innovation goes the opposite to our hypothesis. To address the concern, we analyze the effect of prior innovation in year t on FX

hedging policy change (from year t to year $t+1$). Specifically, we create two dummy variables: *Begin Hedging* is a dummy variable that equals to 1 if firm does not hedge in year t but starts hedging in year $t+1$, and 0 otherwise; *Quit Hedging* is a dummy variable that equals to 1 if firm hedges in year t but does not hedge in year $t+1$, and 0 otherwise. The results are reported in Table 8.

[Table 8 about here]

In columns (1) and (2), we test whether innovation affects firm's decision to begin FX hedging, using *LnPatent* and *LnCitation* respectively. In columns (3) and (4), we test whether innovation affects firm's decision to quit FX hedging, using *LnPatent* and *LnCitation* respectively. In all specifications, none of the coefficients of innovation measures are significant. Therefore, we provide evidence that reverse causality could not explain the positive effect of FX hedging on innovation outputs.

5. Economic Channels

5.1. Information Asymmetry

Our *information asymmetry hypothesis* hinges on the information asymmetry reduction role of FX hedging, hence we expect the effects between hedging and innovation to be stronger for firms with higher information asymmetry. In this subsection, we conduct cross sectional analyses based on information asymmetry. Specifically, we use analyst forecast dispersion (Diether, Malloy, and Scherbina, 2002), breadth of investor ownership (Chen et al., 2002) and probability of informed trading *PIN* (Easley, Hvidkjaer, and O'Hara, 2002) to measure information asymmetry. For each variable, we define a dummy variable that equals to 1 if it is greater than the median level, and 0

otherwise. We then interact the dummy variables with *FX hedge* to test how the effect of *FX hedge* varies. The results are reported in Table 9.

[Table 9 about here]

In Table 9 Panel A, we use analyst forecast dispersion to measure information asymmetry. Analyst forecast dispersion is defined as the standard deviation of analyst EPS forecasts, divided by previous-month stock price. Larger analyst forecast dispersion indicates higher information asymmetry. In Table 9 Panel A, the coefficients of the interaction *FX hedge* $\times$ *High dispersion* are positive and statistically significant at 5% significance level in all the columns, suggesting that the effect of FX hedging on innovation is stronger for firms with larger analyst forecast dispersion. In terms of economic significance, compared with firms with lower analyst forecast dispersion, firms with higher dispersion enjoy 9.7 % - 10.8% more increase in patent number, and 3.0% - 5.2 % more increase in patent citation after FX hedging.

In Table 9 Panel B we use ownership breadth to measure information asymmetry. Chen et al. (2002) argue that breadth of ownership measures the number of institutional investors that are willing to hold a particular stock and implies lower disagreement in valuation among investors. As a result, higher ownership breadth is associated with less information asymmetry. In Table 9 Panel B, the coefficients of the interaction *FX hedge* $\times$ *High breadth* are negative and statistically significant at 5% or lower significance levels in all the columns, suggesting that the effect of FX hedging on innovation is stronger for firms with lower breadth of ownership, or higher information asymmetry. In terms of economic significance, compared with firms with lower breadth of ownership, firms with higher breadth have 10.2 % - 12.3% less increase in patent number, and 11.5% - 13.4 % less increase in patent citation after FX hedging.

In Table 9 Panel C we use the *PIN* to measure information asymmetry. Higher *PIN* indicates higher information asymmetry. The coefficients of the interaction *FX hedge* $\times$ *High PIN* are positive and statistically significant at 1% significance level in all the columns, suggesting that the effect of FX hedging on innovation is stronger for firms with higher *PIN*. In terms of economic significance, compared with firms with lower *PIN*, firms with higher *PIN* have 11.6 % - 14.4% more increase in patent number, and 17.6% - 20.5 % more increase in patent citation after FX hedging.

Taken together, we find consistent results that the effect of FX hedging on innovation is stronger for firms facing higher information asymmetry, lending further support to our *information asymmetry hypothesis*.

5.2. Myopic Behaviors

An important part of the *information asymmetry hypothesis* is that hedging alleviates manager's career concern from undervaluation, and helps the investors to better monitor manager in long term investment. In this subsection, we investigate whether the above argument is true. Specifically, we first test whether hedging increases firm's long term investment. The long-term investment is defined as the R&D expenditures divided by the sum of R&D expenditures and capital expenditure. We regress the long-term investment on *FX hedge* and report the results in Table 10 Panel A. In columns (1) and (2), we use the long term investment at year $t+1$ as dependent variables, while in columns (3) and (4), we use the long term investment at year $t+2$.

[Table 10 about here]

The coefficients of *FX hedge* are positive and significant at 1% significance level in all the columns, suggesting that FX hedging increases long-term investment.

To provide further evidence on the effect of hedging on manager's myopic behavior, we examine manager's real earnings management behavior. In Table 10 Panel B, we test how *FX hedge* affects firm's propensity of cutting R&D expense to manipulate earnings. According to Bushee (1998), managers tend to cut R&D for earnings management purpose, which is a myopic behavior and have real damage to the firm's long-term value. Following Bushee (1998), we define an indicator variable *SD dummy*, which equals to 1 if the firm's earning is lower than last year by an amount manageable through cutting R&D, and 0 otherwise. *SD dummy* essentially measures the feasibility of achieving desirable earnings target through cutting R&D. Distance from earnings goal relative to last year's R&D (*Distance*) is defined as the ratio of change in pre-tax and pre-R&D earnings to previous year's R&D expense. *Distance* reflects the portion of R&D expense that needs to be cut to generate an increase in earnings. Dependent variable (*CUT RD*) is an indicator that equals to 1 if a firm cuts R&D expense relative to last year, and 0 otherwise. We interact *FX hedge* and *SD dummy* to examine how FX hedging affects manager's decision to manipulate earnings. The results are reported in Table 10 Panel B. The coefficients of *FX hedge* $\times$ *SD dummy* are negative and significant at 1% significance level, suggesting that hedging firms are less likely to engage in real earnings manipulation than those without hedging. The results are consistent with the argument that FX hedging alleviates manager's career concern from undervaluation, and reduces manager's myopic behaviors.

Next, we follow Blanco and Wehrheim (2017), and use *Market competition* and *CEO entrenchment* to measure manager's career concern. If FX hedging boosts innovation through the reduction of career concern from undervaluation, we should observe the effect of hedging to be stronger in firms with more concerned managers. In Table 10 Panel C, we use the *HHI* to measure the market competition firms facing. *High market competition* is a dummy variable that equals to

1 if the *HHI* is lower than the median level, and 0 otherwise. Higher market competition indicates higher career concern to the managers, because competition reduces the probability of success and increases reputation risk (Blanco and Wehrheim, 2017). We find that the coefficients of the interaction *FX hedge* $\times$ *High market competition* are positive and significant in all the columns, suggesting that the effect of FX hedging on innovation is stronger for firms facing higher market competition. In Table 10 Panel D, we use the *G-index* (Gompers, Ishii, and Metrick, 2003) to measure CEO's entrenchment. Higher G-index indicates more restrictions on shareholder rights (higher CEO entrenchment), or lower career concern to the CEO. *High CEO entrenchment* is a dummy variable that equals to 1 if the *G-index* is higher than the median level, and 0 otherwise. We find that the coefficients of the interaction *FX hedge* $\times$ *High CEO entrenchment* are negative and significant in all the columns, suggesting that the effect of FX hedging on innovation is stronger for firms with less entrenched CEOs. Taken together, the results are consistent with the expectation that the effect of FX hedging is stronger when managers have higher career concern.

6. Additional Analyses

6.1. Accounting Conservatism

Our alternative *market pressure hypothesis* argues that mark-to-market hedge accounting requires firms to recognize the loss from derivative hedging position immediately, but firms may not be able to recognize the gain from the underlying asset immediately because of accounting conservatism practices. Therefore, the mark-to-market requirement of hedge accounting can increase hedging firms' short-term earnings pressure and dampens innovation. In this subsection, we test whether accounting conservatism influences the effect of hedging on innovation.

In Table 11, we define a dummy variable *High conservatism* that equals to 1 if the accounting conservatism is higher than the median level, and 0 otherwise. Accounting conservatism is defined as the C_Score following Khan and Watts (2009). We find that the coefficients of the interaction $FX\ hedge \times High\ conservatism$ are negative and significant at 1% significance level in all the columns, indicating that the *market pressure hypothesis* plays a role. However, if we sum the coefficients of *FX hedge* and $FX\ hedge \times High\ conservatism$, they all appear to be positive, suggesting that the *information asymmetry hypothesis* dominates the *market pressure hypothesis* even for the high accounting conservatism firms.

[Table 11 about here]

6.2. Innovation Efficiency

So far, we have found that *FX hedge* increases the innovation outputs. However, since Table 2 shows that *FX hedge* also increases firm's R&D expenditures, we do not know whether the effect of *FX hedge* on innovation comes from the increased investment in innovation or improvement on innovation efficiency. The question is important in our setting because our *information asymmetry hypothesis* implies that *FX hedge* should also increase firm's innovation efficiency, in addition to innovation outputs. First, if FX hedging reduces the information asymmetry of the firm and alleviates the manager's career concern of undervaluation, the manager should be able to pursue projects that are riskier but with higher NPV. Second, if the reduction of information asymmetry helps investors to better monitor the manager, it should also help the manager to better allocate the resources and improve innovation efficiency (Blanco and Wehrheim, 2017).

In this subsection, we examine whether *FX hedge* improves innovation efficiency. First, we follow Hirshleifer et al. (2012), and add the lagged R&D/Assets as an additional control in our regression,²⁶ so that we can interpret the coefficient of *FX hedge* as the effect on innovation efficiency. The results are reported in Table 12 Panel A. The coefficients of *FX hedge* are positive and statistically significant at 1% significance level in all the columns, suggesting that FX hedging increases firm's innovation efficiency. In addition, the magnitudes of coefficients are slightly lower than those in Table 2 Panel B, suggesting that the effect of FX hedging on innovation outputs are mainly from the improved innovation efficiency, instead of increased R&D expenditures.

[Table 12 about here]

To further test the relation between FX hedging and innovation efficiency, we employ a set of innovation efficiency measures. First, we test the effect of FX hedging on *Generality* and *Originality* of patents, following Trajtenberg, Henderson, and Jaffe (1997) and Hall et al. (2001). *Generality* reflects the range of fields for citations received by a patent, and *Originality* reflects the range of fields for citations made by a patent. Both *Generality* and *Originality* are measures of the fundamental importance of innovation (Lerner and Seru, 2015). In Table 12 Panel B, we present the results with *Generality* as dependent variable in column (1) and *Originality* in column (2). For each regression, we also include the corresponding lagged efficiency measure, to control for unobservable firm characteristics. The results show that FX hedging increases *Generality* and *Originality* at 5% or lower significance levels. These results suggest that hedging improves the fundamental importance of innovation activities.

Next, in column (3) of Table 13 Panel B, we reply on *Citation per Patent* to test the effect of FX hedging on innovation efficiency. In column (4) of Table 13 Panel B, we reports the results

²⁶ The results are qualitatively similar if we use the contemporary *R&D/Assets*.

on economic value of innovation (*Economic Value*). *Economic Value* is based on filtered stock price reaction to patents two days after the patent issuance day, and captures the private economic value of patent (Kogan et al., 2017). In column (5) of Table 13 Panel B, we use *Research Quotient* as a measure of innovation efficiency. *Research Quotient* is defined as the firm-specific output elasticity of R&D and provides complementary information on the efficiency of R&D investment (Knott, 2008).²⁷ In all the specifications, the coefficients of *FX hedge* are positive and statistically significant at conventional significance levels, consistent with the argument that FX hedging improves innovation efficiency.

6.3. Alternative explanation: Cost of Capital

An alternative explanation to our findings is that FX hedging reduces firm's cost of capital, and in turn increases firm's long term investment such as R&D expenditures. While most of our findings so far can be explained by this argument, it cannot explain our findings on innovation efficiency. On the contrary, the cost of capital argument may even imply a negative effect of FX hedging on innovation efficiency. This is because a lower cost of capital allows firms to invest in innovation projects that otherwise would have negative NPV. Nonetheless, in this subsection, we explicitly discuss the cost of capital channel.

First, we test whether FX hedging decreases firm's cost of capital. Following Li and Mohanram (2014), we measure the implied cost of capital (*ICC*) as the predicted earnings divided by the stock price using Gordon and Gordon (1997) model. The results are reported in Table 13 Panel A. In columns (1) and (2) we use the *ICC* at year $t+1$ as the dependent variable, while in

²⁷ Research quotients are estimated from firm's production function, holding inputs and elasticities constant. It reflects the percentage increase in revenues with a 1% increase in R&D investment.

columns (3) and (4) we use the *ICC* at year $t+2$. The results show that FX hedging in general reduces implied cost of capital one year and two years after FX hedging.

[Table 13 about here]

Since FX hedging indeed lowers firm's cost of capital, we next test whether our findings can be explained by the reduction in the cost of capital. In Panel B of Table 13, we add *ICC* as an additional control to test the relation between FX hedge and innovation outputs. We find that the coefficients of *FX hedge* are still positive and statistically significant at 1% significance level in all the columns. Compared with the results in Table 2 Panel B, the magnitudes of the coefficients are slightly lower, but are still economically significant. FX hedging increases firm's patent by 9.0% - 13.6%, and citation by 9.1% to 13.5%. Therefore, the cost of capital argument can at most explain a marginal part of our findings.

7. Conclusions

In this study, we study the real effects of FX hedging on corporate innovation. We test two competing hypotheses. Under the *information asymmetry hypothesis*, FX hedging reduces firm's information asymmetry, which alleviates manager's career concern from undervaluation and helps investors to better monitor the manager, in turn, FX hedging increases innovation. Under the *market pressure hypothesis*, hedging imposes higher short-term earnings pressure on managers because of mark-to-market hedge accounting, hence leads to lower innovation.

Our results support the *information asymmetry hypothesis*. We establish a positive causal effect between FX hedging and corporate innovation. Further, we find that the effect is stronger for firms with larger hedging needs or higher potential benefits from FX hedging. Our results are

robust to different model specification, and different sample periods accounting for patent data truncation bias and hedge accounting rule change. We also carefully address the endogeneity concerns by employing change regression, DiD regression and IV regression. We also explicitly test for reverse causality. Consistent with the *information asymmetry hypothesis*, we find that hedging effect is stronger for firms with higher information asymmetry. We also show that FX hedging effectively curbs manager's myopic behavior and focus more on long term investment.

Our paper contributes to the hedging literature by documenting an unexplored real impact of FX hedging. We also add to the literature on the relation between information environment and innovation. Finally, we provide additional insight to the debate on whether firm trading currency derivatives for speculative or hedging purpose in the ideal setting of innovation.

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Appendix: Variable Definitions

FX hedge: Indicator variable that equals to 1 if a given firm engages in foreign exchange hedging in a given year. Corporate hedging information is obtained from 10-K and 10-Q filings by hand-collection. Hand-collection process is following the keyword search procedure, following Manconi, Massa and Zhang (2017).

Firm Innovation Measures: Using patent database from Kogan et al. (2017), we construct firm-level innovation measure for each year with application date as time placer. Two measures of innovation outputs are used for a given firm in each year: number of patents (Patent), and adjusted citation (Citation) using fixed effect approach as in Hall et al. (2001). We take the natural logarithm of (1+ innovation output measures) due to the right skewness of these variables (Hall et al. (2001); Kogan et al. (2017)). Patent Number is the number of patents applied in a firm-year and finally granted, which denotes the firm's success in obtaining patents. For each patent citation, we adjust by scaling the mean citation of the same technological class and application year. Citation for each firm-year observation is the sum of adjusted citation for all patents applied in the firm-year. The citation of patents is an important complement to the patent number measure (Griliches et al. (1987), Trajtenberg (1990), Hall et al. (2001)).

Patent Generality/Originality: Following Trajtenberg et al. (1997) and Hall et al. (2001) and using 2011 version patent data of Kogan et al. (2017), generality of a patent is measured as one minus the Herfindahl concentration index for citation received by the patent in technological classes. A larger value of generality indicates that the patent will more likely to have a broader impact in a various fields. Originality of a patent is measured as one minus the Herfindahl concentration index for citation made by the patent in technological classes. A larger value of originality implies that the patent cites previous patents with a wind range of fields.

Citation per Patent: For each firm-year observation, we construct citation per patent as total adjusted citation divided by total number of patent number.

Economic Value of Patent: Following Kogan et al. (2017), stock-market based value of patents for a given firm in a given year, calculated based on stock price reaction of a three-day announcement window $[t, t+2]$ around issuance date of a patent. Forward patent citations measure the scientific value of innovation whereas stock-market based value of patents reflect the patent's private economic value.

R&D: Research and Development Expense, defined as Compustat Item (XRD) from Income Statement/ lag book assets (AT).

CAPEX: Capital expenditure, defined as Compustat Item (CAPX) Capital Expenditures/ lag book assets (AT)

Size: natural logarithm of Compustat Item book assets (AT).

M/B: Market to book ratio, defined as market value of assets/book assets, book assets is Compustat item (AT), where the market value of assets is calculated as: stock price (PRCC_F) * shares outstanding (CSHO) + short term debt (DLC) + long term debt (DLTT) + preferred stock liquidation value (PSTKL) – deferred taxes and investment tax credits (TXDITC).

Leverage: total debt/book assets (AT), where the total debt is Compustat Item long term debt (DLTT) + Compustat Item short term debt (DLC).

Cash: cash holding, defined as cash and short-term investments (CHE)/book assets (AT)

Growth: sales growth, defined as (current year sales (SALE) - prior year sales) / prior year sales

Foreign Income: Pretax Income Foreign (PIFO) / lag book assets (AT)

Age: Number of years since firm's initial appearance in the CRSP database

ROA: Operating Income Before Depreciation (OIBDP)/lag book assets (AT)

PPE: Property, Plant and Equipment - Total (Net) (PPENT)/ lag book assets (AT)

Tax convexity: Tax convexity index of a firm is defined following Graham and Smith ((1999)) and Campello, Lin, Ma and Zou (2011)

$$\text{Convexity}_{it} = 4.88 + 0.019TIVol_{it} - 5.50TICorr_{it} - 1.28DITC_{it} + 3.29DNOL_{it} + 7.15 \\ DSmallNeg_{it} + 1.60DSmallPos_{it} - 4.77DNOL_{it} \times DSmallNeg_{it} - 1.93 DNOL_{it} \times DSmallPos_{it}$$

Where *TIVol* denotes volatility of taxable income, calculated on a rolling basis using all available historical annual data up to the year of interest. Taxable income = operating income after depreciation (OIADP) + nonoperating income (UNOPINC) - interest and related expense (XINT) - [income taxes - deferred (TXDI)/top income tax rate] + [extraordinary items and discontinued operations (XIDO)/(1 - top income tax rate)] + special items (SPI)

TICorr denotes taxable income's serial correlation, calculated on a rolling basis using all available historical annual data up to the year of interest.

DITC is a dummy variable describing investment tax credits.

DNOL is a dummy variable describing net operating losses.

DSmallNeg/DSmallPos is a dummy variable describing small negative/positive taxable income. *DSmallNeg/DSmallPos* = 1 if taxable income is between -\$500,000 and \$0/\$0 and \$500,000.

Return: prior return, defined as cumulative raw return over the previous 12 months.

Illiquidity: Amihud illiquidity, average of the daily ratio of absolute stock return to dollar volume.

Volatility: return volatility, defined as the standard deviation of monthly stock returns in a year.

Inst: institutional ownership, defined as number of shares held by all of the institutional investors divided by the total number of shares outstanding, from Thompson Reuters 13F database.

Implied cost of capital: We follow the Li and Mohanram (2014) residual income model to estimate the implied cost of equity. It is the discount rate used to compute the present stock price from the expected future cash flows. To avoid the data availability issue with analysts' earnings forecasts, we follow the cross-sectional regression method to estimate the expected earnings, based on the residual income valuation. Specifically, following Li and Mohanram (2014), we estimate one-year ahead earnings as follows:

$$E_{t+1}=x_0+x_1NegE_t+x_2E_t+x_3NegE \times E_t+x_4B_t+x_5TACC_t+\varepsilon,$$

where E_{t+1} is the earnings in year t , $NegE$ is a dummy indicator for negative earnings, B_t is the book value of equity, and $TACC_t$ is the total accruals. Earnings are computed as the earnings before special and extraordinary items per share ((IB-SPI)/CSHO). $NegE$ equals 1 for firms with negative earnings and 0 otherwise. Book value of equity is computed as the book value of common stocks divided by the number of shares outstanding (CEQ/CSHO). Total accruals are computed as in Richardson et al. (2005), i.e., the sum of the change in non-cash working capital ($WC=(ACT-CHE)-(LCT-DLC)$), divided by CSHO), the change in net non-current operating assets ($NCO=(AT-ACT-IVAO)-(LT-LCT-DLTT)$), divided by CSHO) and the change in net financial assets ($FIN=(IVST+IVAO)-(DLTT+DLC+PSTK)$), divided by CSHO). To minimize the survivorship bias, we use the previous 5 years data to run pool regressions to estimate the coefficients and then compute the predicted earnings one-year ahead. Next, we use the Gordon and Gordon (1997) model to estimate the implied cost of equity as the predicted earnings divided by the stock price. We assume a 3-month reporting lag. That is, we match the stock price at the end of June of year t with the predicted earnings computed from firms with fiscal year ending between April of year $t-1$ and March of year t . We set negative estimates to missing.

Breadth of ownership: Following Chen et al. (2002), breadth of ownership is the number of mutual funds holding the stock in a firm-quarter, divided by the total number of mutual funds in that quarter. Firm-year definition is the yearly average across four quarters. Mutual fund ownership is obtained from the Thomson Reuters 13F database and only active U.S. domestic equity mutual funds are considered.

Analyst forecast dispersion: In a firm-month, standard deviation of analyst one-year EPS forecasts/stock price at the end of previous month. Firm-year analyst forecast dispersion is the average of monthly value, weighted by analyst coverage. Analyst forecasts are from I/B/E/S database.

SA index: Financial constraint measure based on firm size and age, following Hadlock and Pierce (2010).

Distance: The ratio of change in pre-tax and pre-R&D earnings to previous year's R&D expense, which reflects the portion of R&D expense that needs to be cut in order to manage a positive change in earnings, as in Bushee (1998).

Research quotient: Data item blup_lxrd from WRDS Research Quotient database, representing the firm-specific output elasticity of R&D investment (Knott (2008)).

HHI: Herfindahl index based on four-digit SIC code.

Table 1 Summary Statistics

This table presents the summary statistics of main variables used in our analyses. Using patent database from Kogan et al. (2017), we construct firm-level innovation measure for each year with application date as time placer. Patent Number is the number of patents applied in a firm-year and finally granted, which denotes the firm's success in obtaining patents. For each patent citation, we adjust by scaling the mean citation of the same technological class and application year. Citation for each firm-year observation is the sum of adjusted citation for all patents applied in the firm-year. Citation per patent is measured as total adjusted citation divided by total number of patent number. We take the natural logarithm of (1+ innovation output measures) due to the right skewness of these variables. *FX hedge* is an indicator variable that equals to 1 if a given firm engages in foreign exchange hedging in a given year, obtained from 10-K and 10-Q filings by hand-collection. The detailed definitions of control variables are provided in the appendix. The innovation variables are measured from 1998 to 2006, while the independent and control variables are lagged by two years, i.e., from 1996 to 2004. Panel A summarizes the main variables used in our analyses, Panel B and C describe the distributions of FX hedging across industries and years respectively.

Panel A: Summary Statistics of Main Variables

Variable	N	Mean	Median	Std
LnPatent	32,194	0.525	0.000	1.076
LnCitation	32,194	0.454	0.000	1.083
Patent	32,194	9.254	0.000	90.738
Citation	32,194	9.610	0.000	92.485
R&D/Assets	32,194	0.061	0.000	0.185
FX hedge	32,194	0.137	0.000	0.344
Size	32,194	5.214	5.064	1.934
M/B	32,194	1.887	1.212	1.961
Foreign income	32,194	0.086	0.000	0.306
Leverage	32,194	0.220	0.178	0.215
PPE	32,194	3.633	3.443	1.340
ROA	32,194	0.044	0.112	0.320
Age	32,194	23.388	18.000	14.755
Cash	32,194	0.197	0.093	0.232
CAPEX	32,194	0.077	0.045	0.104
Growth	32,194	0.282	0.096	0.888
Inst	32,194	0.376	0.341	0.274
Return	32,194	0.144	0.016	0.725
Illiquidity	32,194	0.517	0.230	0.652
Volatility	32,194	0.040	0.035	0.023
HHI	32,194	0.184	0.077	0.266
HHI_sq	32,194	0.104	0.006	0.259

Panel B: FX Hedging of Firms by Industry

Fama-French 12 Industry Classification	Hedger	Non-hedger	Total
Consumer NonDurables	382	1703	2085
Consumer Durables	197	749	946
Manufacturing	936	3191	4127
Oil, Gas, and Coal Extraction and Production	102	1192	1294
Chemicals and Allied Products	243	520	763
Business Equipment	1336	6876	8212
Telephone and Television Transmission	111	949	1060
Utilities	80	676	756
Wholesale, Retail Services	272	3519	3791
Healthcare, Medical Equipment, and Drug	387	3613	4000
Other -- Mines, Construction, etc.	373	4787	5160

Panel C: FX Hedging of Firms by Year

Year	Hedger	Non-hedger	Total
1996	256	2983	3239
1997	351	3078	3429
1998	446	3117	3563
1999	479	3539	4018
2000	520	3520	4040
2001	563	3142	3705
2002	590	2961	3551
2003	596	2732	3328
2004	618	2703	3321

Table 2 Baseline Regression

This table presents the baseline OLS regressions of innovation on FX hedging and the sample consists of firms with available FX hedging information from 1996 to 2006 and innovation data from 1998 to 2008. In Panel A, the dependent variable is *R&D/Assets*, computed as the ratio of R&D expenses divided by lagged total asset. The missing value of R&D expense is replaced by zero. In columns (1) and (2) we use the *R&D/Asset* measured at year $t+1$, while in columns (3) and (4), we use the *R&D/Asset* measured at year $t+2$. Columns (1) and (3) include year fixed effect, and columns (2) and (4) include year and industry fixed effects. In Panel B, two measures of innovation outputs are used for a given firm in each year: number of patents (Patent), and adjusted citation (Citation) using fixed effect approach as in Hall et al. (2001). Patent Number is the number of patents applied in a firm-year and finally granted, which denotes the firm's success in obtaining patents. For each patent citation, we adjust by scaling the mean citation of the same technological class and application year. Citation for each firm-year observation is the sum of adjusted citation for all patents applied in the firm-year. We take the natural logarithm of (1+ innovation output measures) due to the right skewness of these variables. Columns (1) and (2) test the effect of FX hedging on *LnPatent*, while columns (3) and (4) test on *LnCitation*. *FX hedge* is an indicator variable that equals to 1 if a given firm engages in foreign exchange hedging in a given year, obtained from 10-K and 10-Q filings by hand-collection, and zero otherwise. All specifications include year fixed effects, while columns (2) and (4) also include industry fixed effects (2-digit SIC code). We cluster the standard errors at the firm level. ***, ** and * represent significance levels at 1%, 5% and 10% respectively with t-statistics given in brackets.

Panel A: R&D Expenditures

	R&D/Assets _{t+1}		R&D/Assets _{t+2}	
	(1)	(2)	(3)	(4)
FX hedge _t	0.011*** [6.74]	0.006*** [3.81]	0.008*** [4.94]	0.004*** [2.82]
Size _t	-0.008*** [-11.26]	-0.007*** [-9.27]	-0.006*** [-6.97]	-0.004*** [-5.48]
M/B _t	0.010*** [11.12]	0.009*** [10.49]	0.010*** [9.63]	0.009*** [9.06]
Foreign income _t	0.002 [1.53]	-0.001 [-0.86]	0.002 [1.35]	-0.001 [-0.45]
Leverage _t	-0.000 [-0.04]	-0.001 [-0.13]	0.003 [0.51]	0.001 [0.23]
PPE _t	0.004*** [5.05]	0.004*** [4.11]	0.003*** [4.87]	0.003*** [3.30]
ROA _t	-0.077*** [-14.52]	-0.074*** [-14.15]	-0.048*** [-8.72]	-0.046*** [-8.27]
Age _t	0.000** [2.39]	-0.000 [-0.17]	0.000* [1.78]	-0.000 [-0.51]
Cash _t	0.086*** [11.71]	0.074*** [10.54]	0.067*** [7.44]	0.058*** [6.75]
CAPEX _t	-0.115*** [-12.55]	-0.085*** [-9.91]	-0.090*** [-8.49]	-0.066*** [-6.13]
Growth _t	-0.005*** [-4.08]	-0.005*** [-4.19]	-0.003** [-2.11]	-0.004** [-2.14]
Inst _t	0.015*** [4.15]	0.010*** [2.75]	0.010*** [2.59]	0.006 [1.49]
Return _t	-0.000 [-0.02]	0.001 [0.58]	0.003** [2.07]	0.003** [2.39]
Illiquidity _t	-0.013*** [-6.29]	-0.012*** [-5.78]	-0.006** [-2.57]	-0.005** [-2.33]

Return volatility _t	0.049	0.076	-0.010	0.022
	[0.85]	[1.31]	[-0.17]	[0.36]
HHI _t	-0.119***	-0.102***	-0.089***	-0.083***
	[-11.88]	[-8.61]	[-8.95]	[-7.02]
HHI_sq _t	0.094***	0.081***	0.072***	0.068***
	[10.51]	[7.93]	[8.15]	[6.58]
R&D/Assests _t	0.284***	0.272***	0.475***	0.464***
	[9.39]	[9.00]	[12.09]	[11.77]
Constant	0.059***	0.059***	0.031***	0.031***
	[11.51]	[11.32]	[5.67]	[5.41]
Observations	32,194	32,194	32,194	32,194
Adjusted R ²	0.464	0.476	0.509	0.514
Industry FE	NO	YES	NO	YES
Year FE	YES	YES	YES	YES

Panel B: Innovation Outputs

	LnPatent _{t+2}		LnCitation _{t+2}	
	(1)	(2)	(3)	(4)
FX hedge _t	0.148*** [5.76]	0.102*** [4.09]	0.162*** [5.43]	0.115*** [3.93]
Size _t	0.087*** [10.44]	0.111*** [12.80]	0.102*** [11.02]	0.123*** [12.77]
M/B _t	0.035*** [8.69]	0.038*** [9.67]	0.042*** [8.85]	0.045*** [9.73]
Foreign income _t	0.024 [1.14]	0.009 [0.42]	0.026 [1.08]	0.008 [0.33]
Leverage _t	-0.266*** [-8.83]	-0.236*** [-7.90]	-0.307*** [-8.69]	-0.271*** [-7.72]
PPE _t	0.006 [1.52]	0.027*** [5.00]	0.000 [0.10]	0.024*** [3.78]
ROA _t	0.069*** [3.35]	0.055*** [2.84]	0.112*** [4.82]	0.091*** [4.10]
Age _t	-0.007*** [-10.83]	-0.007*** [-10.78]	-0.006*** [-8.03]	-0.006*** [-7.88]
Cash _t	0.221*** [6.39]	0.239*** [7.09]	0.182*** [4.54]	0.201*** [5.17]
CAPEX _t	-0.021 [-0.48]	0.090** [2.02]	0.018 [0.38]	0.094* [1.86]
Growth _t	-0.002 [-0.43]	0.002 [0.39]	-0.001 [-0.12]	0.004 [0.70]
Inst _t	-0.050 [-1.40]	-0.072** [-2.06]	-0.080* [-1.96]	-0.100** [-2.47]
Return _t	-0.001 [-0.32]	0.002 [0.36]	-0.005 [-0.99]	-0.002 [-0.40]
Illiquidity _t	0.028*** [2.61]	0.051*** [4.70]	0.054*** [4.61]	0.077*** [6.47]
Return volatility _t	1.108*** [3.91]	0.973*** [3.56]	1.256*** [3.89]	0.961*** [3.04]
HHI _t	-0.319*** [-4.06]	-0.293*** [-3.16]	-0.241*** [-2.72]	-0.151 [-1.42]
HHI_sq _t	0.259*** [3.48]	0.244*** [2.91]	0.185*** [2.19]	0.120 [1.25]
Patent Measure _t	1.080*** [72.68]	1.026*** [67.69]	0.909*** [51.34]	0.863*** [48.02]
Constant	-0.227*** [-5.40]	-0.461*** [-10.15]	-0.357*** [-7.40]	-0.590*** [-11.27]
Observations	32,194	32,194	32,194	32,194
Adjusted R ²	0.711	0.726	0.585	0.601
Industry FE	NO	YES	NO	YES
Year FE	YES	YES	YES	YES

Table 3 Necessities of FX Hedging

This table examines how the FX hedging necessities affect the relation between *FX hedge* and innovation outputs. In Panels A to C, we employ *FX exposure*, *International competition*, and *FX volatility* respectively. *LnPatent* is the natural logarithm of (1+Patent Number), and *LnCitation* is the natural logarithm of (1+Citation). Columns (1) and (2) test the effect of hedging on *LnPatent*, while columns (3) and (4) test the effect on *LnCitation*. Columns (1) and (3) include year fixed effect, and columns (2) and (4) include year and 2-digit SIC industry fixed effects. We cluster the standard errors at the firm level. ***, ** and * represent significance levels at 1%, 5% and 10% respectively with t-statistics given in brackets.

Panel A: FX Exposure

	LnPatent _{t+2}		LnCitation _{t+2}	
	(1)	(2)	(3)	(4)
FX hedge _t	0.097*** [3.19]	0.062** [2.09]	0.120*** [3.35]	0.084** [2.42]
High FX exposure _t	0.013 [1.51]	0.011 [1.34]	0.014 [1.37]	0.009 [0.86]
FX hedge _t ×High FX exposure _t	0.115*** [2.90]	0.092** [2.38]	0.096** [2.00]	0.080* [1.70]
Size _t	0.088*** [10.48]	0.111*** [12.83]	0.103*** [11.07]	0.115*** [12.32]
M/B _t	0.035*** [8.73]	0.038*** [9.69]	0.042*** [8.88]	0.043*** [9.46]
Foreign income _t	0.026 [1.23]	0.010 [0.49]	0.028 [1.18]	0.006 [0.27]
Leverage _t	-0.267*** [-8.85]	-0.237*** [-7.94]	-0.308*** [-8.73]	-0.251*** [-7.36]
PPE _t	0.006 [1.56]	0.027*** [5.00]	0.001 [0.15]	0.023*** [3.70]
ROA _t	0.064*** [3.15]	0.052*** [2.66]	0.108*** [4.68]	0.091*** [4.13]
Age _t	-0.007*** [-10.54]	-0.007*** [-10.54]	-0.006*** [-7.82]	-0.006*** [-7.82]
Cash _t	0.215*** [6.23]	0.235*** [6.98]	0.177*** [4.43]	0.144*** [3.62]
CAPEX _t	-0.021 [-0.49]	0.090** [2.01]	0.017 [0.36]	0.080 [1.63]
Growth _t	-0.002 [-0.36]	0.002 [0.44]	-0.001 [-0.10]	0.002 [0.45]
Inst _t	-0.048 [-1.35]	-0.070** [-2.01]	-0.078* [-1.91]	-0.075* [-1.87]
Return _t	-0.003 [-0.59]	0.001 [0.13]	-0.007 [-1.21]	-0.006 [-1.21]
Illiquidity _t	0.030*** [2.83]	0.052*** [4.82]	0.057*** [4.82]	0.086*** [7.60]
Return volatility _t	1.007*** [3.61]	0.901*** [3.31]	1.152*** [3.62]	0.881*** [3.05]
HHI _t	-0.307*** [-3.92]	-0.284*** [-3.05]	-0.232*** [-2.62]	-0.159* [-1.71]
HHI_sq _t	0.249***	0.236***	0.178**	0.123

	[3.36]	[2.82]	[2.11]	[1.39]
Patent Measure _{it}	1.080***	1.026***	0.909***	0.886***
	[72.84]	[67.71]	[51.37]	[49.87]
Constant	-0.239***	-0.473***	-0.371***	-0.525***
	[-5.53]	[-10.15]	[-7.43]	[-10.37]
Observations	32,194	32,194	32,194	32,194
Adjusted R ²	0.711	0.726	0.586	0.596
Industry FE	NO	YES	NO	YES
Year FE	YES	YES	YES	YES

Panel B: International Competition

	LnPatent _{t+2}		LnCitation _{t+2}	
	(1)	(2)	(3)	(4)
FX hedge _t	0.091*** [2.94]	0.053* [1.75]	0.091** [2.48]	0.048 [1.35]
High international competition _t	-0.023** [-2.20]	-0.002 [-0.14]	-0.018 [-1.53]	-0.008 [-0.61]
FX hedge _t ×High international competition _t	0.126*** [2.92]	0.109*** [2.58]	0.158*** [3.09]	0.148*** [2.94]
Size _t	0.087*** [10.47]	0.111*** [12.82]	0.103*** [11.02]	0.123*** [12.77]
M/B _t	0.035*** [8.71]	0.038*** [9.70]	0.042*** [8.87]	0.045*** [9.75]
Foreign income _t	0.025 [1.19]	0.010 [0.48]	0.027 [1.14]	0.009 [0.39]
Leverage _t	-0.267*** [-8.87]	-0.236*** [-7.91]	-0.307*** [-8.72]	-0.271*** [-7.73]
PPE _t	0.006 [1.55]	0.028*** [5.13]	0.001 [0.17]	0.025*** [3.90]
ROA _t	0.069*** [3.39]	0.054*** [2.80]	0.111*** [4.82]	0.090*** [4.07]
Age _t	-0.007*** [-10.77]	-0.007*** [-10.74]	-0.006*** [-7.94]	-0.006*** [-7.80]
Cash _t	0.219*** [6.37]	0.238*** [7.06]	0.180*** [4.53]	0.199*** [5.13]
CAPEX _t	-0.013 [-0.30]	0.090** [2.02]	0.023 [0.47]	0.095* [1.86]
Growth _t	-0.002 [-0.39]	0.002 [0.43]	-0.000 [-0.08]	0.004 [0.75]
Inst _t	-0.051 [-1.44]	-0.073** [-2.10]	-0.082** [-2.01]	-0.102** [-2.52]
Return _t	-0.001 [-0.32]	0.002 [0.38]	-0.005 [-0.99]	-0.002 [-0.38]
Illiquidity _t	0.027** [2.57]	0.050*** [4.69]	0.054*** [4.58]	0.076*** [6.45]
Return volatility _t	1.135*** [4.02]	0.980*** [3.59]	1.277*** [3.97]	0.973*** [3.08]
HHI _t	-0.315*** [-3.99]	-0.283*** [-3.05]	-0.228** [-2.54]	-0.138 [-1.30]
HHI_sq _t	0.256*** [3.42]	0.236*** [2.83]	0.175** [2.06]	0.110 [1.15]
Lag_Patent Measure	1.079*** [72.65]	1.026*** [67.78]	0.908*** [51.29]	0.863*** [48.03]
Constant	-0.219*** [-5.18]	-0.463*** [-10.21]	-0.353*** [-7.25]	-0.590*** [-11.25]
Observations	32,194	32,194	32,194	32,194
Adjusted R ²	0.711	0.726	0.586	0.602
Industry FE	NO	YES	NO	YES
Year FE	YES	YES	YES	YES

Panel C: FX Volatility

	LnPatent _{t+2}		LnCitation _{t+2}	
	(1)	(2)	(3)	(4)
FX hedge _t	0.135*** [5.20]	0.089*** [3.52]	0.136*** [4.51]	0.089*** [3.01]
High FX volatility _t	-0.004 [-0.31]	-0.008 [-0.61]	-0.008 [-0.53]	-0.010 [-0.61]
FX hedge _t ×High FX volatility _t	0.030* [1.72]	0.030* [1.80]	0.060*** [2.82]	0.059*** [2.84]
Size _t	0.087*** [10.45]	0.111*** [12.81]	0.103*** [11.04]	0.123*** [12.78]
M/B _t	0.035*** [8.70]	0.038*** [9.68]	0.042*** [8.87]	0.045*** [9.75]
Foreign income _t	0.024 [1.15]	0.009 [0.43]	0.026 [1.09]	0.008 [0.34]
Leverage _t	-0.267*** [-8.84]	-0.236*** [-7.91]	-0.308*** [-8.71]	-0.271*** [-7.74]
PPE _t	0.006 [1.52]	0.028*** [5.01]	0.001 [0.11]	0.024*** [3.80]
ROA _t	0.069*** [3.35]	0.055*** [2.84]	0.112*** [4.82]	0.091*** [4.10]
Age _t	-0.007*** [-10.83]	-0.007*** [-10.78]	-0.006*** [-8.04]	-0.006*** [-7.88]
Cash _t	0.221*** [6.39]	0.240*** [7.09]	0.182*** [4.55]	0.201*** [5.17]
CAPEX _t	-0.021 [-0.49]	0.090** [2.02]	0.018 [0.37]	0.094* [1.85]
Growth _t	-0.002 [-0.43]	0.002 [0.39]	-0.001 [-0.12]	0.004 [0.70]
Inst _t	-0.049 [-1.40]	-0.072** [-2.05]	-0.080* [-1.95]	-0.100** [-2.46]
Return _t	-0.001 [-0.29]	0.002 [0.39]	-0.005 [-0.95]	-0.002 [-0.35]
Illiquidity _t	0.028*** [2.66]	0.051*** [4.74]	0.055*** [4.70]	0.078*** [6.54]
Return volatility _t	1.105*** [3.90]	0.970*** [3.54]	1.251*** [3.88]	0.955*** [3.02]
HHI _t	-0.319*** [-4.06]	-0.293*** [-3.16]	-0.241*** [-2.72]	-0.151 [-1.42]
HHI_sq _t	0.259*** [3.48]	0.244*** [2.91]	0.185** [2.19]	0.120 [1.25]
Patent Measure _t	1.080*** [72.68]	1.026*** [67.68]	0.909*** [51.35]	0.863*** [48.02]
Constant	-0.253*** [-6.10]	-0.456*** [-10.00]	-0.386*** [-8.04]	-0.585*** [-11.11]
Observations	32,194	32,194	32,194	32,194
Adjusted R ²	0.711	0.726	0.586	0.602
Industry FE	NO	YES	NO	YES
Year FE	YES	YES	YES	YES

Table 4 Robustness Checks

In this table, we conduct a battery of robustness checks on our main results. In Panel A, we employ the negative binomial regression to test the relation between FX hedge and innovation outputs. In Panel B, we restrict the sample to before year 2004. In Panel C, we restrict the sample to after SFAS 133, i.e., after year 2002. *LnPatent* is the natural logarithm of (1+Patent Number), and *LnCitation* is the natural logarithm of (1+Citation). Columns (1) and (2) test the effect of hedging on *Patent/LnPatent*, while columns (3) and (4) test the effect on *Citation/LnCitation*. Columns (1) and (3) include year fixed effect, and columns (2) and (4) include year and 2-digit SIC industry fixed effects. We cluster the standard errors at the firm level. ***, ** and * represent significance levels at 1%, 5% and 10% respectively with t-statistics given in brackets.

Panel A: Count Model

	Patent _{t+2}		Citation _{t+2}	
	(1)	(2)	(3)	(4)
FX hedge _t	0.460*** [5.82]	0.240*** [3.50]	0.422*** [5.00]	0.211*** [2.81]
Size _t	0.335*** [8.09]	0.445*** [11.89]	0.291*** [6.63]	0.378*** [8.83]
M/B _t	0.057*** [3.45]	0.059*** [4.43]	0.063*** [4.02]	0.070*** [5.23]
Foreign income _t	0.102 [1.62]	0.046 [0.88]	0.075 [1.11]	0.009 [0.16]
Leverage _t	-0.783*** [-3.36]	-0.602*** [-2.79]	-0.997*** [-4.04]	-0.689*** [-2.94]
PPE _t	-0.035 [-1.06]	0.049 [0.82]	-0.028 [-0.80]	0.055 [0.87]
ROA _t	0.055 [0.53]	-0.054 [-0.57]	0.064 [0.54]	-0.042 [-0.37]
Age _t	-0.004* [-1.76]	-0.004* [-1.68]	-0.003 [-1.53]	-0.004* [-1.90]
Cash _t	1.065*** [5.44]	0.811*** [4.48]	0.959*** [5.02]	0.731*** [3.95]
CAPEX _t	-0.863** [-2.35]	-0.338 [-0.98]	-0.673* [-1.81]	-0.205 [-0.54]
Growth _t	-0.053* [-1.72]	-0.026 [-0.99]	-0.031 [-0.87]	-0.005 [-0.15]
Inst _t	0.652*** [3.30]	0.425** [2.35]	0.572*** [2.66]	0.324 [1.61]
Return _t	0.067*** [2.70]	0.082*** [3.70]	0.076*** [3.13]	0.088*** [3.74]
Illiquidity _t	-1.831*** [-6.57]	-1.509*** [-5.80]	-2.248*** [-6.38]	-1.964*** [-5.86]
Return volatility _t	8.312*** [2.95]	4.216 [1.49]	9.414*** [3.04]	3.963 [1.23]
HHI _t	-0.941** [-2.09]	-0.879** [-2.15]	-0.631 [-1.31]	-0.398 [-0.89]
HHI_sq _t	0.868* [1.89]	0.743* [1.80]	0.618 [1.23]	0.379 [0.82]
Patent measure _t	0.050*** [16.78]	0.032*** [10.38]	0.047*** [18.59]	0.033*** [12.18]
Constant	-1.242***	-1.546***	-0.890**	-0.998**

	[-3.56]	[-4.43]	[-2.35]	[-2.57]
Observations	32,194	32,194	32,194	32,194
Pseudo R ²	0.564	0.564	0.564	0.564
Industry FE	NO	YES	NO	YES
Year FE	YES	YES	YES	YES

Panel B: Before Year 2004

	LnPatent _{t+2}		LnCitation _{t+2}	
	(1)	(2)	(3)	(4)
FX hedge _t	0.116*** [4.49]	0.111*** [4.31]	0.139*** [4.56]	0.134*** [4.42]
Size _t	0.107*** [13.00]	0.102*** [12.24]	0.120*** [12.92]	0.114*** [12.22]
M/B _t	0.036*** [9.00]	0.036*** [9.07]	0.043*** [9.24]	0.043*** [9.26]
Foreign income _t	0.014 [0.70]	0.016 [0.76]	0.014 [0.57]	0.016 [0.65]
Leverage _t	-0.242*** [-8.10]	-0.230*** [-7.75]	-0.275*** [-7.80]	-0.264*** [-7.51]
PPE _t	0.026*** [4.83]	0.023*** [4.31]	0.022*** [3.55]	0.020*** [3.13]
ROA _t	0.054*** [2.76]	0.064*** [3.22]	0.092*** [4.02]	0.100*** [4.35]
Age _t	-0.007*** [-10.47]	-0.007*** [-9.96]	-0.006*** [-7.31]	-0.006*** [-6.96]
Cash _t	0.225*** [6.55]	0.210*** [6.15]	0.193*** [4.80]	0.181*** [4.55]
CAPEX _t	0.076* [1.66]	0.116** [2.48]	0.086 [1.64]	0.120** [2.25]
Growth _t	0.002 [0.39]	0.003 [0.65]	0.004 [0.70]	0.005 [0.82]
Inst _t	-0.063* [-1.75]	-0.083** [-2.31]	-0.090** [-2.16]	-0.106** [-2.51]
Return _t	-0.002 [-0.40]	0.001 [0.28]	-0.005 [-0.85]	-0.003 [-0.51]
Illiquidity _t	0.048*** [5.00]	0.033*** [3.21]	0.070*** [6.45]	0.059*** [5.08]
Return volatility _t	1.352*** [5.12]	1.244*** [4.51]	1.520*** [4.89]	1.245*** [3.83]
HHI _t	-0.196** [-2.14]	-0.227** [-2.48]	-0.101 [-0.95]	-0.137 [-1.28]
HHI_sq _t	0.162* [1.94]	0.184** [2.20]	0.082 [0.85]	0.108 [1.11]
Patent measure _t	1.042*** [68.13]	1.046*** [68.26]	0.882*** [48.45]	0.885*** [48.66]
Constant	-0.434*** [-9.79]	-0.422*** [-9.45]	-0.562*** [-10.82]	-0.549*** [-10.47]
Observations	25,545	25,545	25,545	25,545
Adjusted R ²	0.742	0.742	0.622	0.623
Industry FE	NO	YES	NO	YES
Year FE	YES	YES	YES	YES

Panel C: After SFAS 133 (Year 2000)

	LnPatent _{t+2}		LnCitation _{t+2}	
	(1)	(2)	(3)	(4)
FX hedge _t	0.090*** [2.94]	0.091*** [2.98]	0.092*** [2.61]	0.094*** [2.66]
Size _t	0.141*** [12.74]	0.138*** [12.42]	0.155*** [12.33]	0.151*** [12.01]
M/B _t	0.048*** [8.71]	0.048*** [8.69]	0.053*** [8.25]	0.053*** [8.16]
Foreign income _t	0.009 [0.35]	0.011 [0.40]	0.012 [0.41]	0.014 [0.48]
Leverage _t	-0.286*** [-6.96]	-0.283*** [-6.89]	-0.307*** [-6.27]	-0.305*** [-6.23]
PPE _t	0.035*** [4.64]	0.034*** [4.61]	0.033*** [3.78]	0.033*** [3.84]
ROA _t	0.047* [1.69]	0.040 [1.43]	0.074** [2.40]	0.062** [1.98]
Age _t	-0.008*** [-10.65]	-0.008*** [-10.69]	-0.007*** [-7.97]	-0.007*** [-8.13]
Cash _t	0.308*** [6.93]	0.306*** [6.89]	0.249*** [4.85]	0.251*** [4.90]
CAPEX _t	0.145** [2.11]	0.136* [1.94]	0.154** [1.98]	0.122 [1.54]
Growth _t	0.005 [0.76]	0.006 [0.89]	0.009 [1.11]	0.009 [1.05]
Inst _t	-0.121*** [-2.74]	-0.116*** [-2.61]	-0.160*** [-3.14]	-0.149*** [-2.89]
Return _t	-0.009 [-1.64]	-0.003 [-0.54]	-0.012* [-1.66]	-0.003 [-0.42]
Illiquidity _t	0.066*** [5.38]	0.060*** [4.63]	0.085*** [6.16]	0.084*** [5.82]
Return volatility _t	0.943*** [2.84]	0.577 [1.54]	1.118*** [2.91]	0.463 [1.08]
HHI _t	-0.425*** [-3.29]	-0.425*** [-3.29]	-0.195 [-1.34]	-0.197 [-1.35]
HHI_sq _t	0.356*** [3.09]	0.356*** [3.09]	0.145 [1.13]	0.147 [1.14]
Patent measure _t	0.985*** [53.28]	0.984*** [53.14]	0.831*** [37.73]	0.830*** [37.59]
Constant	-0.571*** [-9.67]	-0.584*** [-9.86]	-0.716*** [-10.54]	-0.723*** [-10.59]
Observations	17,945	17,945	17,945	17,945
Adjusted R ²	0.679	0.680	0.559	0.559
Industry FE	NO	YES	NO	YES
Year FE	YES	YES	YES	YES

Table 5 Change Regression

In this table, we report the results from change regression. All the independent variables are computed as the differences between year t and $t-1$, while dependent variables are computed as the differences between year $t+2$ and year $t+1$. Columns (1) and (2) test the effect of hedging on $\Delta \text{LnPatent}$, while columns (3) and (4) test the effect on $\Delta \text{LnCitation}$. Columns (1) and (3) include year fixed effect, and columns (2) and (4) include year and 2-digit SIC industry fixed effects. The standard errors at clustered at firm level. ***, ** and * represent significance levels at 1%, 5% and 10% respectively with t-statistics given in brackets.

	$\Delta \text{LnPatent}_{t+2}$		$\Delta \text{LnCitation}_{t+2}$	
	(1)	(2)	(3)	(4)
$\Delta \text{FX hedge}_t$	0.050*** [3.39]	0.036** [2.51]	0.054*** [2.97]	0.042** [2.33]
ΔSize_t	0.085*** [5.33]	0.112*** [7.14]	0.092*** [4.89]	0.114*** [6.10]
$\Delta \text{M/B}_t$	-0.012*** [-4.02]	-0.008*** [-2.62]	-0.010*** [-2.72]	-0.005 [-1.56]
$\Delta \text{Foreign income}_t$	0.018** [2.00]	0.017* [1.93]	0.029*** [2.59]	0.029*** [2.60]
$\Delta \text{Leverage}_t$	0.063* [1.76]	0.058 [1.62]	0.057 [1.33]	0.061 [1.44]
ΔPPE_t	0.005 [0.56]	0.018* [1.95]	0.012 [1.02]	0.024** [2.10]
ΔROA_t	0.034* [1.74]	0.045** [2.38]	-0.002 [-0.10]	0.007 [0.32]
ΔCash_t	-0.083** [-2.47]	-0.083** [-2.49]	-0.111*** [-2.69]	-0.111*** [-2.69]
ΔCAPEX_t	-0.242*** [-5.71]	-0.243*** [-5.95]	-0.254*** [-5.42]	-0.236*** [-5.16]
ΔGrowth_t	-0.011*** [-2.93]	-0.012*** [-3.31]	-0.013*** [-2.77]	-0.013*** [-2.87]
ΔInst_t	0.345*** [6.67]	0.338*** [6.87]	0.340*** [5.69]	0.333*** [5.75]
ΔReturn_t	0.008*** [2.95]	0.007*** [2.74]	0.009*** [2.73]	0.009** [2.56]
$\Delta \text{Illiquidity}_t$	0.014* [1.87]	0.011 [1.44]	0.012 [1.31]	0.006 [0.67]
$\Delta \text{Volatility}_t$	-1.986*** [-8.83]	-1.730*** [-7.82]	-1.690*** [-6.12]	-1.455*** [-5.30]
ΔHHI_t	-0.299*** [-3.14]	-0.302*** [-3.23]	-0.063 [-0.52]	-0.104 [-0.88]
$\Delta \text{HHI_sq}_t$	0.208*** [2.74]	0.217*** [2.91]	0.023 [0.25]	0.060 [0.65]
Constant	0.193*** [22.91]	0.089*** [8.85]	0.101*** [10.96]	-0.019 [-1.43]
Observations	26,518	26,518	26,518	26,518
Adjusted R ²	0.015	0.082	0.012	0.047
Industry FE	NO	YES	NO	YES
Year FE	YES	YES	YES	YES

Table 6 Difference-in-Differences Regression

In this table, we conduct a difference-in-differences analysis based on FX hedging initiation. We construct the matched sample based on all control variables in the baseline regression. In Panel A, we report the covariate balance for the matched sample. In Panel B, we run a difference-in-differences regression using the paired firms. Columns (1) and (2) test the effect of hedging on *LnPatent*, while columns (3) and (4) test the effect on *LnCitation*. Columns (1) and (3) include year and 2 digit industry fixed effects, and columns (2) and (4) include year and firm fixed effects. We cluster the standard errors at firm level. ***, ** and * represent significance levels at 1%, 5% and 10% respectively with t-statistics given in brackets

Panel A: Covariate Balance

Variable	Treat	Control	Treat-Control	p value
Size	6.096	5.96	0.136	0.298
M/B	1.424	1.531	-0.107	0.291
Foreign income	0.127	0.106	0.021	0.448
Leverage	0.241	0.224	0.017	0.254
PPE	3.768	3.768	0.000	0.999
ROA	0.12	0.127	-0.007	0.558
Age	24.223	23.067	1.156	0.327
Cash	0.145	0.148	-0.003	0.872
CAPEX	0.07	0.065	0.005	0.413
Growth	0.228	0.271	-0.043	0.441
Inst	0.511	0.499	0.012	0.544
Return	0.144	0.179	-0.035	0.522
Illiquidity	0.309	0.289	0.020	0.589
Volatility	0.031	0.032	-0.001	0.681
HHI	0.217	0.216	0.001	0.985
HHI_sq	0.119	0.121	-0.002	0.935

Panel B Difference-in-Differences Regression

	LnPatent _{t+2}	LnPatent _{t+2}	LnCitation _{t+2}	LnCitation _{t+2}
	(1)	(2)	(3)	(4)
Initiation _t	-0.046 [-1.45]		-0.009 [-0.24]	
Post _t	-0.057*** [-3.09]	-0.076*** [-3.17]	-0.021 [-0.79]	-0.042 [-1.24]
Initiation _t ×Post _t	0.119*** [4.50]	0.135*** [4.17]	0.077* [1.96]	0.081* [1.67]
Size _t	0.031* [1.91]	0.025 [0.44]	0.026 [1.63]	0.014 [0.12]
M/B _t	0.020 [1.34]	0.017 [0.87]	0.015 [0.82]	-0.004 [-0.12]
Foreign income _t	0.031 [0.79]	-0.041 [-0.78]	0.007 [0.15]	-0.109 [-1.42]
Leverage _t	-0.109 [-1.32]	-0.403** [-2.04]	-0.103 [-0.83]	-0.207 [-0.62]
PPE _t	-0.005 [-0.29]	-0.098 [-1.34]	0.013 [0.62]	-0.152 [-1.32]
ROA _t	0.055 [0.59]	0.051 [0.43]	-0.022 [-0.22]	0.052 [0.27]
Age _t	-0.002** [-2.28]	-0.051*** [-5.61]	-0.001 [-1.17]	0.007 [1.15]
Cash _t	0.070 [0.61]	-0.323 [-1.23]	0.180 [1.09]	-0.067 [-0.11]
CAPEX _t	-0.098 [-0.70]	-0.117 [-0.65]	0.033 [0.21]	-0.004 [-0.02]
Growth _t	-0.011 [-0.63]	-0.011 [-0.32]	-0.038 [-1.48]	-0.024 [-0.46]
Inst _t	-0.007 [-0.07]	-0.060 [-0.36]	0.039 [0.38]	0.217 [0.73]
Return _t	-0.009 [-0.46]	-0.012 [-0.44]	-0.009 [-0.38]	-0.041 [-0.90]
Illiquidity _t	-0.059 [-1.43]	0.033 [0.63]	-0.072 [-1.59]	-0.026 [-0.31]
Return volatility _t	3.750*** [3.02]	2.089 [1.34]	2.972** [2.16]	1.726 [0.74]
HHI _t	-0.011 [-0.05]	-0.034 [-0.11]	0.225 [0.84]	-0.202 [-0.48]
HHI_sq _t	0.038 [0.19]	0.084 [0.34]	-0.169 [-0.73]	0.277 [0.65]
Patent measure _t	1.128*** [17.25]	0.833*** [9.04]	0.895*** [12.02]	0.548*** [3.91]
Constant	-0.136 [-1.03]	1.617*** [3.74]	-0.247* [-1.69]	0.389 [0.54]
Observations	1,192	1,192	1,192	1,192
Adjusted R ²	0.681	0.903	0.515	0.757
Industry FE	YES	No	YES	No
Firm FE	No	YES	No	YES
Year FE	YES	YES	YES	YES

Table 7 Instrumental Variable Regression

This table presents the results of two-stage residual inclusion regression by Hausman (1978), using tax convexity as an IV. The first stage is a Logit regression with dependent variable being the FX hedge and instrumental variable as tax convexity. The second stage is an OLS regression controlling for variables as in main regression and residual from first stage Logit regression. In Panel A, we follow the definition of tax convexity in literature (Smith and Stulz (1985), Campello et al. (2011), Manconi et al. (2017)). In Panel B, we exclude *TIVOL* (volatility of taxable income) from tax convexity calculation. In Panel C, we use the state tax convexity as IV. Columns (1) and (2) report the first stage results. Columns (3) and (4) report the results of second stage regression. Year and 2-digit SIC industry fixed effects are included. We cluster the standard errors at firm level. ***, ** and * represent significance levels at 1%, 5% and 10% respectively using robust standard errors with t-statistics given in brackets.

Panel A: Normal Definition of Convexity

	FX hedge _t	FX hedge _t	LnPatent _{t+2}	LnCitation _{t+2}
	(1)	(2)	(3)	(4)
Convexity _t	0.055*** [3.00]	0.055*** [3.04]		
FX hedge _t			0.087*** [3.36]	0.078*** [2.59]
Size _t	0.354*** [9.31]	0.360*** [9.46]	0.066*** [6.73]	0.041*** [3.76]
M/B _t	0.009 [0.35]	0.007 [0.27]	0.036*** [7.28]	0.039*** [6.67]
Foreign income _t	0.832*** [9.73]	0.849*** [9.96]	-0.125*** [-4.71]	-0.233*** [-7.31]
Leverage _t	-0.922*** [-4.38]	-0.929*** [-4.42]	-0.139*** [-4.18]	-0.089** [-2.26]
PPE _t	-0.036 [-1.04]	-0.037 [-1.08]	0.027*** [4.46]	0.031*** [4.32]
ROA _t	0.806*** [3.11]	0.815*** [3.10]	0.082*** [2.97]	0.107*** [3.30]
Age _t	0.001 [0.16]	0.001 [0.29]	-0.007*** [-9.75]	-0.007*** [-8.27]
Cash _t	0.012 [0.06]	-0.005 [-0.02]	0.209*** [5.49]	0.201*** [4.54]
CAPEX _t	-3.221*** [-4.92]	-3.248*** [-4.96]	0.266*** [4.28]	0.423*** [5.50]
Growth _t	-0.188*** [-2.99]	-0.195*** [-3.03]	0.005 [0.91]	0.010 [1.46]
Inst _t	0.652*** [3.24]	0.633*** [3.15]	-0.122*** [-3.13]	-0.213*** [-4.63]
Return _t	-0.052 [-1.57]	-0.050 [-1.51]	0.007 [1.35]	0.011* [1.80]
Illiquidity _t	-0.139 [-1.27]	-0.130 [-1.18]	0.045*** [4.14]	0.061*** [5.15]
Return volatility _t	1.145 [0.41]	0.867 [0.31]	0.361 [1.16]	-0.153 [-0.42]
HHI _t	0.261 [0.55]	0.310 [0.65]	-0.389*** [-3.85]	-0.306*** [-2.63]
HHI_sq _t	-0.061	-0.103	0.312***	0.232**

	[-0.13]	[-0.22]	[3.44]	[2.22]
Patent measure _{it}	0.409***	0.383***	0.955***	0.744***
	[8.81]	[8.95]	[48.80]	[32.88]
First stage residuals _{it}			-0.917***	-1.764***
			[-5.89]	[-9.19]
Constant	-4.852***	-4.864***	0.698***	1.579***
	[-16.19]	[-16.25]	[3.83]	[7.06]
Observations	24,236	24,236	24,236	24,236
Pseudo/Adjusted R ²	0.202	0.202	0.772	0.655
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Panel B: Excluding Taxable Income Volatility in Convexity Calculation

	FX hedge	FX hedge	LnPatent	LnCitation
	(1)	(2)	(3)	(4)
Convexity	0.055***	0.056***		
	[2.94]	[2.98]		
FX hedge			0.087***	0.078***
			[3.36]	[2.60]
Controls	YES	YES	0.087***	0.078***
Observations	24,236	24,236	24,236	24,236
Pseudo/Adjusted R ²	0.202	0.202	0.772	0.655
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Panel C: State tax convexity

	FX hedge	FX hedge	LnPatent	LnCitation
	(1)	(2)	(3)	(4)
Convexity	0.206**	0.198**		
	[2.29]	[2.20]		
FX hedge			0.094***	0.094***
			[3.61]	[3.08]
Controls	YES	YES	YES	YES
Observations	24,236	24,236	24,236	24,236
Pseudo/Adjusted R ²	0.202	0.202	0.772	0.652
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Table 8 Reverse Causality

e analyze the effect of prior innovation output in year t on the probability of change of FX hedging policy (from year t to year $t+1$) using a Logit regression. Columns (1) and (2) report the probability of firm beginning hedging. The dependent variable is *Begin Hedging* dummy that equals to 1 if firm does not hedge in year t but starts hedging in year $t+1$, and 0 otherwise. Columns (3) and (4) reports the probability of firm quitting hedging. The dependent variable is *Quit Hedging* dummy that equals to 1 if firm hedges in year t but stops hedging in year $t+1$, and 0 otherwise. Control variables are measured in year t . We control for both year dummies and industry dummies (2-digit SIC code) in all specifications. We cluster at firm level. ***, ** and * represent significance levels at 1%, 5% and 10% respectively with t-statistics given in brackets.

	Begin Hedging _{t+1}		Quit Hedging _{t+1}	
	(1)	(2)	(3)	(4)
LnPatent _t	0.035 [0.52]		0.013 [0.24]	
LnCitation _t		0.060 [1.06]		-0.000 [-0.00]
Size _t	0.085* [1.86]	0.079* [1.74]	0.050 [1.21]	0.052 [1.28]
M/B _t	-0.074** [-2.01]	-0.077** [-2.08]	-0.077*** [-2.82]	-0.077*** [-2.81]
Foreign income _t	0.074 [0.53]	0.073 [0.53]	0.409*** [3.96]	0.411*** [3.98]
Leverage _t	0.289 [1.13]	0.304 [1.19]	-0.300 [-1.16]	-0.304 [-1.18]
PPE _t	0.029 [0.80]	0.030 [0.81]	-0.062 [-1.24]	-0.061 [-1.23]
ROA _t	0.258 [1.12]	0.251 [1.09]	0.427** [1.96]	0.428** [1.96]
Age _t	-0.000 [-0.09]	-0.000 [-0.08]	-0.002 [-0.59]	-0.002 [-0.65]
Cash _t	0.093 [0.32]	0.076 [0.26]	-0.510** [-2.07]	-0.508** [-2.06]
CAPEX _t	-1.320* [-1.70]	-1.315* [-1.69]	0.176 [0.29]	0.178 [0.30]
Growth _t	-0.095 [-1.01]	-0.095 [-1.01]	0.052 [0.90]	0.052 [0.90]
Inst _t	0.278 [1.11]	0.277 [1.10]	0.481** [2.42]	0.478** [2.41]
Return _t	0.242*** [3.50]	0.242*** [3.51]	0.055 [0.90]	0.056 [0.90]
Illiquidity _t	-0.303* [-1.75]	-0.306* [-1.77]	-0.878*** [-4.67]	-0.876*** [-4.67]
Return volatility _t	-4.767 [-1.24]	-4.930 [-1.28]	3.462 [1.03]	3.487 [1.04]
HHI _t	0.178 [0.29]	0.196 [0.32]	-0.504 [-0.90]	-0.505 [-0.90]
HHI_sq _t	0.012 [0.02]	-0.004 [-0.01]	0.584 [1.10]	0.585 [1.10]
Patent measure _t	0.040 [0.42]	0.023 [0.29]	0.017 [0.23]	0.031 [0.50]

Constant	-5.039*** [-12.18]	-5.006*** [-12.07]	-12.636*** [-11.51]	-12.649*** [-11.39]
Observations	22,780	22,780	22,780	22,780
Pseudo R ²	0.035	0.035	0.035	0.035
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Table 9 Information Asymmetry

This table examines how information asymmetry affects the relation between FX hedge and innovation outputs. In Panels A to C, we employ *Analyst forecast dispersion*, *Breadth of ownership*, and *PIN* respectively. *LnPatent* is the natural logarithm of (1+Patent Number), and *LnCitation* is the natural logarithm of (1+Citation). Columns (1) and (2) test the effect of hedging on *LnPatent*, while columns (3) and (4) test the effect on *LnCitation*. Columns (1) and (3) include year fixed effect, and columns (2) and (4) include year and 2-digit SIC industry fixed effects. We cluster the standard errors at firm level. ***, ** and * represent significance levels at 1%, 5% and 10% respectively with t-statistics given in brackets.

Panel A: Analyst Forecast Dispersion

	LnPatent _{t+2}		LnCitation _{t+2}	
	(1)	(2)	(3)	(4)
FX hedge _t	0.102*** [2.84]	0.036 [1.05]	0.107** [2.53]	0.039 [0.96]
High dispersion _t	0.036** [2.34]	0.018 [1.23]	0.052*** [2.94]	0.030* [1.76]
FX hedge _t ×High dispersion _t	0.108** [2.33]	0.097** [2.19]	0.130** [2.38]	0.121** [2.33]
Size _t	0.114*** [8.95]	0.149*** [11.46]	0.136*** [9.80]	0.166*** [11.65]
M/B _t	0.035*** [5.69]	0.042*** [7.12]	0.042*** [5.96]	0.050*** [7.39]
Foreign income _t	0.030 [1.05]	0.004 [0.14]	0.022 [0.68]	-0.007 [-0.21]
Leverage _t	-0.345*** [-6.74]	-0.273*** [-5.37]	-0.381*** [-6.37]	-0.297*** [-4.94]
PPE _t	0.014* [1.88]	0.045*** [4.36]	0.005 [0.62]	0.040*** [3.32]
ROA _t	0.111*** [3.23]	0.071** [2.20]	0.184*** [4.83]	0.131*** [3.59]
Age _t	-0.009*** [-9.21]	-0.008*** [-8.53]	-0.008*** [-7.15]	-0.007*** [-6.56]
Cash _t	0.345*** [6.16]	0.336*** [6.11]	0.321*** [4.97]	0.310*** [4.89]
CAPEX _t	-0.110* [-1.67]	0.062 [0.88]	-0.040 [-0.54]	0.090 [1.12]
Growth _t	-0.010 [-1.14]	-0.004 [-0.51]	-0.009 [-0.83]	-0.001 [-0.15]
Inst _t	-0.077 [-1.62]	-0.103** [-2.21]	-0.097* [-1.77]	-0.123** [-2.27]
Return _t	0.010 [1.36]	0.015** [2.06]	0.015 [1.62]	0.019** [2.13]
Illiquidity _t	-0.020 [-0.53]	0.048 [1.31]	0.035 [0.83]	0.104** [2.47]
Return volatility _t	3.040*** [4.12]	1.648** [2.35]	3.135*** [3.76]	1.308 [1.60]
HHI _t	-0.452*** [-3.56]	-0.477*** [-3.23]	-0.341** [-2.37]	-0.273 [-1.60]
HHI_sq _t	0.375***	0.404***	0.267*	0.220

	[3.07]	[3.01]	[1.93]	[1.43]
Patent Measure _{it}	1.099***	1.013***	0.938***	0.864***
	[67.25]	[57.74]	[49.16]	[42.56]
Constant	-0.441***	-0.752***	-0.642***	-0.948***
	[-5.45]	[-9.40]	[-7.04]	[-10.40]
Observations	18,157	18,157	18,157	18,157
Adjusted R ²	0.711	0.734	0.595	0.620
Industry FE	NO	YES	NO	YES
Year FE	YES	YES	YES	YES

Panel B: Breadth of Ownership

	LnPatent _{t+2}		LnCitation _{t+2}	
	(1)	(2)	(3)	(4)
FX hedge _t	0.167*** [5.55]	0.124*** [4.27]	0.183*** [5.21]	0.139*** [4.06]
High breadth _t	-0.014 [-1.50]	-0.016* [-1.65]	0.000 [0.02]	-0.002 [-0.15]
FX hedge _t ×High breadth _t	-0.102** [-2.42]	-0.123*** [-2.95]	-0.115** [-2.22]	-0.134*** [-2.61]
Size _t	0.085*** [10.06]	0.109*** [12.42]	0.101*** [10.78]	0.122*** [12.54]
M/B _t	0.035*** [8.44]	0.037*** [9.40]	0.042*** [8.69]	0.045*** [9.56]
Foreign income _t	0.024 [1.15]	0.009 [0.43]	0.026 [1.09]	0.008 [0.33]
Leverage _t	-0.264*** [-8.72]	-0.233*** [-7.79]	-0.307*** [-8.67]	-0.270*** [-7.69]
PPE _t	0.006 [1.46]	0.027*** [4.96]	0.000 [0.07]	0.024*** [3.76]
ROA _t	0.068*** [3.31]	0.054*** [2.79]	0.112*** [4.83]	0.091*** [4.10]
Age _t	-0.007*** [-10.84]	-0.007*** [-10.80]	-0.006*** [-8.06]	-0.006*** [-7.92]
Cash _t	0.221*** [6.39]	0.240*** [7.11]	0.182*** [4.55]	0.202*** [5.20]
CAPEX _t	-0.020 [-0.48]	0.091** [2.04]	0.018 [0.38]	0.095* [1.88]
Growth _t	-0.002 [-0.46]	0.002 [0.36]	-0.001 [-0.13]	0.004 [0.69]
Inst _t	-0.063* [-1.72]	-0.087** [-2.43]	-0.086** [-2.05]	-0.108*** [-2.60]
Return _t	-0.001 [-0.12]	0.003 [0.57]	-0.005 [-0.90]	-0.002 [-0.29]
Illiquidity _t	0.030*** [2.89]	0.053*** [5.03]	0.054*** [4.79]	0.077*** [6.68]
Return volatility _t	1.033*** [3.64]	0.886*** [3.24]	1.217*** [3.75]	0.911*** [2.87]
HHI _t	-0.320*** [-4.08]	-0.295*** [-3.18]	-0.240*** [-2.71]	-0.151 [-1.42]
HHI_sq _t	0.260*** [3.49]	0.245*** [2.93]	0.184** [2.18]	0.120 [1.25]
Patent measure _t	1.079*** [72.37]	1.024*** [67.42]	0.907*** [51.10]	0.862*** [47.81]
Constant	-0.201*** [-4.45]	-0.433*** [-9.15]	-0.346*** [-6.68]	-0.576*** [-10.58]
Observations	30,194	32,194	32,194	32,194
Adjusted R ²	0.711	0.726	0.586	0.602
Industry FE	NO	YES	NO	YES
Year FE	YES	YES	YES	YES

Panel C: PIN

	LnPatent _{t+2}		LnCitation _{t+2}	
	(1)	(2)	(3)	(4)
FX hedge _t	0.074** [2.57]	0.005 [0.16]	0.045 [1.34]	-0.027 [-0.77]
High PIN _t	0.054*** [4.58]	0.053*** [4.65]	0.069*** [4.87]	0.069*** [5.01]
FX hedge _t ×High PIN _t	0.116*** [2.72]	0.144*** [3.45]	0.176*** [3.48]	0.205*** [4.12]
Size _t	0.088*** [9.52]	0.114*** [12.02]	0.102*** [9.84]	0.125*** [11.70]
M/B _t	0.033*** [7.63]	0.036*** [8.69]	0.039*** [7.77]	0.043*** [8.71]
Foreign income _t	0.025 [1.13]	0.009 [0.42]	0.026 [1.02]	0.006 [0.24]
Leverage _t	-0.286*** [-8.30]	-0.249*** [-7.28]	-0.334*** [-8.26]	-0.290*** [-7.23]
PPE _t	0.007 [1.51]	0.032*** [5.16]	0.001 [0.15]	0.029*** [3.96]
ROA _t	0.069*** [3.01]	0.054** [2.52]	0.120*** [4.62]	0.097*** [3.93]
Age _t	-0.008*** [-10.74]	-0.008*** [-10.61]	-0.007*** [-8.07]	-0.006*** [-7.88]
Cash _t	0.238*** [6.29]	0.258*** [7.01]	0.199*** [4.55]	0.222*** [5.22]
CAPEX _t	-0.021 [-0.45]	0.111** [2.28]	0.019 [0.35]	0.113** [2.05]
Growth _t	-0.003 [-0.61]	0.001 [0.17]	-0.001 [-0.18]	0.004 [0.62]
Inst _t	-0.075* [-1.95]	-0.102*** [-2.69]	-0.114** [-2.56]	-0.139*** [-3.16]
Return _t	-0.006 [-1.23]	-0.001 [-0.32]	-0.009 [-1.56]	-0.005 [-0.80]
Illiquidity _t	0.035*** [3.08]	0.062*** [5.21]	0.067*** [5.18]	0.093*** [7.03]
Return volatility _t	1.265*** [3.75]	1.020*** [3.14]	1.196*** [3.11]	0.775** [2.05]
HHI _t	-0.330*** [-3.85]	-0.302*** [-2.99]	-0.242** [-2.50]	-0.149 [-1.29]
HHI_sq _t	0.268*** [3.30]	0.250*** [2.75]	0.186** [2.02]	0.117 [1.13]
Patent measure _t	1.066*** [70.51]	1.002*** [63.83]	0.893*** [49.33]	0.840*** [45.06]
Constant	-0.227*** [-4.79]	-0.489*** [-9.63]	-0.350*** [-6.40]	-0.609*** [-10.39]
Observations	29,158	29,158	29,158	29,158
Adjusted R ²	0.707	0.724	0.581	0.599
Industry FE	NO	YES	NO	YES
Year FE	YES	YES	YES	YES

Table 10 FX Hedging and Investment Horizon

In this table, we test whether FX hedging affects firm's investment horizon. Panel A tests the effect of *FX hedge* on *Long term investment*. The *Long term investment* is computed as R&D expense scaled by sum of capital expenditure and R&D expense. Columns (1) and (2) employ the *Long term investment* at year $t+1$, and Columns (3) and (4) employ the *Long term investment* at year $t+2$. Columns (1) and (3) include year fixed effect, and columns (2) and (4) include year and 2-digit SIC industry fixed effects. In Panel B, we test how *FX hedge* affect the relation between cutting R&D expense (*CUT RD*) and small earnings decrease dummy (*SD dummy*). We include year and 2-digit SIC industry fixed effects. In Panels C and D, we employ *Market competition* and *CEO entrenchment* respectively, to examine how market pressure affects the relation between FX hedge and innovation outputs. *LnPatent* is the natural logarithm of (1+Patent Number), and *LnCitation* is the natural logarithm of (1+Citation). Columns (1) and (2) test the effect of hedging on *LnPatent*, while columns (3) and (4) test the effect on *LnCitation*. Columns (1) and (3) include year fixed effect, and columns (2) and (4) include year and 2-digit SIC industry fixed effects. We cluster the standard errors at the firm level. ***, ** and * represent significance levels at 1%, 5% and 10% respectively with t-statistics given in brackets.

Panel A: FX Hedging and Long Term Investment

	Long Term Investment _{t+1}		Long Term Investment _{t+2}	
	(1)	(2)	(3)	(4)
FX hedge _t	0.010*** [6.67]	0.006*** [3.64]	0.009*** [5.60]	0.004*** [2.73]
Size _t	-0.003*** [-5.62]	-0.003*** [-4.66]	-0.000 [-0.48]	0.001 [0.89]
M/B _t	-0.000 [-0.31]	-0.001 [-1.13]	0.002*** [4.36]	0.002*** [3.80]
Foreign income _t	0.004** [2.28]	0.002 [0.91]	0.005*** [2.79]	0.002 [1.21]
Leverage _t	-0.012*** [-3.74]	-0.010*** [-2.86]	-0.017*** [-4.67]	-0.016*** [-4.01]
PPE _t	0.001** [2.29]	0.006*** [8.02]	-0.002*** [-3.83]	0.000 [0.23]
ROA _t	-0.013*** [-3.98]	-0.016*** [-4.76]	-0.000 [-0.11]	-0.004 [-1.03]
Age _t	0.000*** [3.58]	0.000*** [2.91]	0.000*** [2.69]	0.000 [1.08]
Cash _t	0.031*** [7.06]	0.034*** [7.39]	0.040*** [8.23]	0.045*** [8.88]
CAPEX _t	0.073*** [8.90]	0.082*** [9.59]	0.044*** [5.39]	0.058*** [6.53]
Growth _t	-0.002 [-1.33]	-0.002 [-1.50]	0.001 [0.59]	0.001 [0.47]
Inst _t	0.001 [0.44]	-0.002 [-0.53]	0.001 [0.31]	-0.001 [-0.37]
Return _t	-0.017*** [-14.81]	-0.016*** [-13.98]	0.000 [0.19]	0.000 [0.29]
Illiquidity _t	-0.014*** [-7.90]	-0.013*** [-7.38]	-0.004** [-2.12]	-0.004* [-1.92]
Return volatility _t	0.257*** [5.02]	0.243*** [4.57]	0.089 [1.57]	0.106* [1.79]
HHI _t	-0.050*** [-6.42]	-0.051*** [-5.44]	-0.064*** [-7.51]	-0.065*** [-6.56]

HHI_sq _t	0.042*** [5.66]	0.043*** [5.12]	0.055*** [6.81]	0.057*** [6.25]
Long term investment _t	0.946*** [312.81]	0.915*** [227.90]	0.941*** [297.38]	0.911*** [214.45]
Constant	0.029*** [5.97]	0.015*** [2.85]	0.021*** [3.91]	0.015*** [2.66]
Observations	29,552	29,552	27,070	27,070
R-squared	0.914	0.915	0.916	0.917
Industry FE	NO	YES	NO	YES
Year FE	YES	YES	YES	YES

Panel B: Real Earnings Management

	CUT R&D _{t+1}	
	(1)	(2)
FX hedge _t	-0.099** [-2.14]	-0.096** [-2.08]
SD dummy _t	0.269*** [9.58]	0.267*** [9.43]
FX hedge _t ×SD dummy _t	-0.190*** [-3.06]	-0.179*** [-2.86]
Distance _t	-0.004 [-0.28]	-0.005 [-0.36]
Size _t	-0.009 [-1.43]	-0.007 [-1.02]
M/B _t	0.011 [0.29]	0.021 [0.56]
Foreign income _t	-0.056 [-0.68]	-0.058 [-0.69]
Leverage _t	0.008 [0.46]	0.016 [0.85]
PPE _t	-0.125*** [-2.60]	-0.138*** [-2.85]
ROA _t	0.001 [0.50]	0.001 [0.68]
Age _t	0.071 [0.99]	0.068 [0.92]
Cash _t	-0.091 [-0.50]	-0.121 [-0.65]
CAPEX _t	0.007 [0.46]	0.012 [0.81]
Growth _t	0.023 [0.28]	-0.001 [-0.01]
Inst _t	-0.045** [-2.48]	-0.047** [-2.54]
Return _t	0.053 [1.39]	0.065* [1.69]
Illiquidity _t	2.391** [2.35]	2.071** [2.01]
Return volatility _t	-0.106 [-0.53]	-0.408* [-1.82]
HHI _t	0.183 [0.91]	0.424** [1.98]
HHI_sq _t	-0.004 [-0.28]	-0.005 [-0.36]
Constant	-0.319*** [-2.99]	-0.710*** [-5.81]
Observations	11,087	11,087
Pseudo R ²	0.050	0.050
Industry FE	NO	YES
Year FE	YES	YES

Panel C: Market Competition

	LnPatent _{t+2}		LnCitation _{t+2}	
	(1)	(2)	(3)	(4)
FX hedge _t	0.091*** [3.31]	0.044 [1.64]	0.110*** [3.41]	0.060* [1.92]
High market competition _t	0.031* [1.85]	0.038** [2.01]	0.015 [0.73]	0.012 [0.56]
FX hedge _t ×High market competition _t	0.194*** [3.19]	0.198*** [3.41]	0.178** [2.54]	0.185*** [2.73]
Size _t	0.087*** [10.45]	0.111*** [12.85]	0.102*** [10.96]	0.123*** [12.75]
M/B _t	0.035*** [8.65]	0.038*** [9.69]	0.042*** [8.81]	0.045*** [9.72]
Foreign income _t	0.026 [1.21]	0.011 [0.55]	0.027 [1.15]	0.010 [0.41]
Leverage _t	-0.261*** [-8.72]	-0.232*** [-7.83]	-0.303*** [-8.59]	-0.268*** [-7.66]
PPE _t	0.006 [1.43]	0.026*** [4.76]	0.000 [0.05]	0.023*** [3.66]
ROA _t	0.062*** [3.04]	0.049** [2.56]	0.106*** [4.60]	0.086*** [3.88]
Age _t	-0.007*** [-10.49]	-0.007*** [-10.48]	-0.006*** [-7.73]	-0.006*** [-7.61]
Cash _t	0.205*** [6.00]	0.225*** [6.75]	0.171*** [4.31]	0.194*** [4.98]
CAPEX _t	-0.025 [-0.58]	0.093** [2.09]	0.016 [0.33]	0.096* [1.90]
Growth _t	-0.002 [-0.35]	0.002 [0.44]	-0.000 [-0.06]	0.004 [0.75]
Inst _t	-0.049 [-1.40]	-0.071** [-2.03]	-0.079* [-1.94]	-0.099** [-2.44]
Return _t	-0.001 [-0.29]	0.001 [0.30]	-0.005 [-0.99]	-0.002 [-0.44]
Illiquidity _t	0.028*** [2.64]	0.050*** [4.75]	0.053*** [4.59]	0.075*** [6.43]
Return volatility _t	1.047*** [3.75]	0.932*** [3.45]	1.222*** [3.84]	0.952*** [3.04]
HHI _t	-0.128 [-1.40]	-0.103 [-1.04]	-0.114 [-1.10]	-0.038 [-0.34]
HHI_sq _t	0.100 [1.21]	0.086 [0.98]	0.080 [0.85]	0.027 [0.27]
Patent measure _t	1.078*** [72.44]	1.024*** [67.49]	0.907*** [51.15]	0.862*** [47.85]
Constant	-0.282*** [-6.27]	-0.488*** [-10.34]	-0.405*** [-7.84]	-0.602*** [-11.07]
Observations	32,194	32,194	32,194	32,194
Adjusted R ²	0.712	0.727	0.586	0.602
Industry FE	NO	YES	NO	YES
Year FE	YES	YES	YES	YES

Panel D: CEO Entrenchment

	LnPatent _{t+2}		LnCitation _{t+2}	
	(1)	(2)	(3)	(4)
FX hedge _t	0.200*** [4.12]	0.107*** [2.64]	0.190*** [3.35]	0.085* [1.83]
High CEO entrenchment _t	0.060** [2.28]	0.039* [1.77]	0.067** [2.21]	0.042 [1.46]
FX hedge _t ×High CEO entrenchment _t	-0.129** [-2.06]	-0.086* [-1.73]	-0.146** [-2.03]	-0.094* [-1.71]
Size _t	0.115*** [7.02]	0.154*** [7.97]	0.135*** [7.64]	0.172*** [8.36]
M/B _t	0.046*** [3.70]	0.063*** [7.64]	0.052*** [3.62]	0.075*** [6.39]
Foreign income _t	0.008 [0.26]	-0.020 [-0.60]	0.006 [0.17]	-0.028 [-0.67]
Leverage _t	-0.292*** [-3.99]	-0.257*** [-3.44]	-0.285*** [-3.42]	-0.224** [-2.47]
PPE _t	-0.009 [-0.83]	0.029 [1.26]	-0.020* [-1.72]	0.028 [1.10]
ROA _t	0.298*** [3.11]	0.194*** [2.62]	0.376*** [3.33]	0.256*** [3.09]
Age _t	-0.008*** [-7.51]	-0.007*** [-6.44]	-0.007*** [-6.34]	-0.007*** [-5.10]
Cash _t	0.492*** [5.22]	0.346*** [3.95]	0.467*** [4.46]	0.297** [2.30]
CAPEX _t	-0.532*** [-3.83]	-0.205 [-1.02]	-0.436*** [-2.66]	-0.228 [-1.04]
Growth _t	-0.008 [-0.32]	0.002 [0.13]	-0.012 [-0.43]	0.002 [0.07]
Inst _t	-0.135* [-1.81]	-0.144** [-2.38]	-0.153* [-1.77]	-0.187*** [-2.75]
Return _t	0.008 [0.67]	0.014 [1.03]	0.002 [0.14]	0.003 [0.22]
Illiquidity _t	-0.196*** [-2.71]	-0.133* [-1.87]	-0.111 [-1.39]	-0.052 [-0.73]
Return volatility _t	4.447*** [3.64]	2.895** [2.17]	3.523** [2.48]	1.684 [0.99]
HHI _t	-0.642*** [-3.99]	-0.607*** [-2.62]	-0.543*** [-2.98]	-0.387 [-1.62]
HHI_sq _t	0.579*** [3.85]	0.525*** [2.68]	0.485*** [2.83]	0.343 [1.64]
Patent measure _t	1.050*** [56.98]	0.966*** [54.94]	0.919*** [44.83]	0.841*** [38.10]
Constant	-0.406*** [-3.43]	-0.683*** [-4.92]	-0.566*** [-4.20]	-0.904*** [-5.32]
Observations	9,443	9,443	9,443	9,443
Adjusted R ²	0.762	0.784	0.645	0.671
Industry FE	NO	YES	NO	YES
Year FE	YES	YES	YES	YES

Table 11 Accounting Conservatism

This table examines how accounting conservatism affects the relation between FX hedge and innovation outputs. *LnPatent* is the natural logarithm of (1+Patent Number), and *LnCitation* is the natural logarithm of (1+Citation). Columns (1) and (2) test the effect of hedging on *LnPatent*, while columns (3) and (4) test the effect on *LnCitation*. Columns (1) and (3) include year fixed effect, and columns (2) and (4) include year and 2-digit SIC industry fixed effects. We cluster the standard errors at the firm level. ***, ** and * represent significance levels at 1%, 5% and 10% respectively with t-statistics given in brackets.

	LnPatent _{t+2}		LnCitation _{t+2}	
	(1)	(2)	(3)	(4)
FX hedge _t	0.205*** [4.27]	0.206*** [4.27]	0.272*** [4.73]	0.274*** [4.73]
High conservatism _t	0.005 [0.28]	-0.016 [-0.85]	0.017 [0.74]	-0.007 [-0.31]
FX hedge _t ×High conservatism _t	-0.134*** [-2.82]	-0.138*** [-2.89]	-0.207*** [-3.63]	-0.211*** [-3.68]
Size _t	0.111*** [12.57]	0.103*** [11.58]	0.123*** [12.31]	0.114*** [11.40]
M/B _t	0.037*** [8.43]	0.036*** [8.15]	0.046*** [8.45]	0.044*** [8.10]
Foreign income _t	0.001 [0.04]	0.002 [0.08]	-0.002 [-0.07]	-0.000 [-0.01]
Leverage _t	-0.240*** [-6.58]	-0.222*** [-6.11]	-0.262*** [-6.07]	-0.246*** [-5.69]
PPE _t	0.031*** [5.36]	0.029*** [5.02]	0.026*** [3.94]	0.025*** [3.71]
ROA _t	0.075*** [3.12]	0.082*** [3.36]	0.112*** [4.07]	0.115*** [4.09]
Age _t	-0.007*** [-10.81]	-0.007*** [-10.46]	-0.006*** [-7.80]	-0.006*** [-7.63]
Cash _t	0.236*** [6.64]	0.225*** [6.34]	0.193*** [4.66]	0.186*** [4.52]
CAPEX _t	0.049 [1.01]	0.075 [1.53]	0.080 [1.39]	0.094 [1.60]
Growth _t	0.000 [0.04]	0.002 [0.34]	0.002 [0.26]	0.002 [0.37]
Inst _t	-0.053 [-1.47]	-0.062* [-1.69]	-0.088** [-2.09]	-0.091** [-2.13]
Return _t	-0.002 [-0.50]	-0.001 [-0.25]	-0.007 [-1.25]	-0.004 [-0.69]
Illiquidity _t	0.056*** [5.58]	0.040*** [3.75]	0.079*** [6.95]	0.068*** [5.64]
Return volatility _t	1.278*** [4.88]	1.151*** [3.99]	1.357*** [4.40]	0.997*** [2.95]
HHI _t	-0.292*** [-3.07]	-0.315*** [-3.31]	-0.131 [-1.21]	-0.158 [-1.44]
HHI_sq _t	0.239*** [2.78]	0.256*** [2.96]	0.101 [1.03]	0.119 [1.21]
Patent measure _t	1.022*** [65.17]	1.023*** [65.12]	0.862*** [46.56]	0.863*** [46.55]

Constant	-0.461***	-0.412***	-0.599***	-0.543***
	[-9.19]	[-7.99]	[-10.03]	[-8.84]
Observations	29,330	29,330	29,330	29,330
Adjusted R ²	0.741	0.741	0.618	0.619
Industry FE	NO	YES	NO	YES
Year FE	YES	YES	YES	YES

Table 12 Innovation Efficiency

This table test the relation between *FX hedge* and innovation efficiency. In Panel A, we include *R&D/Assets* as an additional control variable. *LnPatent* is the natural logarithm of (1+Patent Number), and *LnCitation* is the natural logarithm of (1+Citation). Columns (1) and (2) test the effect of hedging on *LnPatent*, while columns (3) and (4) test the effect on *LnCitation*. Columns (1) and (3) include year fixed effect, and columns (2) and (4) include year and 2-digit SIC industry fixed effects. In Panel B, we employ a battery of innovation efficiency measures. *Generality* is measured as one minus the Herfindahl concentration index of technological classes for citation received by the patent. *Originality* is measured as one minus the Herfindahl concentration index of technological classes for citation made by the patent. *Citation per patent* is the average adjusted citation received by a patent. *Economic value* is the market-value weighted patents. *Research quotients* are firm-specific output elasticity of R&D. We include year and 2-digit SIC industry fixed effects in all regression. Columns (1) – (5) report the results with respect to *Generality*, *Originality*, *Citation per patent*, *Economic value*, and *Research quotient* respectively. We cluster the standard errors at the firm level. ***, ** and * represent significance levels at 1%, 5% and 10% respectively with t-statistics given in brackets.

Panel A: Including R&D Expenditures

	LnPatent _{t+2}		LnCitation _{t+2}	
	(1)	(2)	(3)	(4)
FX hedge _t	0.144*** [5.69]	0.099*** [4.02]	0.158*** [5.32]	0.111*** [3.85]
R&D/Assets _t	0.932*** [13.49]	0.935*** [14.65]	1.112*** [13.35]	1.142*** [14.68]
Size _t	0.101*** [11.96]	0.122*** [14.02]	0.118*** [12.59]	0.136*** [14.06]
M/B _t	0.023*** [6.07]	0.027*** [7.24]	0.028*** [6.16]	0.032*** [7.19]
Foreign income _t	0.022 [1.08]	0.008 [0.39]	0.023 [0.97]	0.006 [0.26]
Leverage _t	-0.270*** [-8.97]	-0.234*** [-7.91]	-0.311*** [-8.77]	-0.268*** [-7.65]
PPE _t	0.001 [0.36]	0.024*** [4.45]	-0.005 [-1.11]	0.020*** [3.19]
ROA _t	0.107*** [5.45]	0.087*** [4.71]	0.157*** [7.05]	0.130*** [6.14]
Age _t	-0.007*** [-10.56]	-0.007*** [-10.43]	-0.006*** [-7.62]	-0.005*** [-7.38]
Cash _t	0.114*** [3.45]	0.144*** [4.46]	0.055 [1.44]	0.086** [2.31]
CAPEX _t	0.088** [2.12]	0.160*** [3.68]	0.148*** [3.17]	0.180*** [3.63]
Growth _t	-0.003 [-0.63]	0.001 [0.31]	-0.002 [-0.33]	0.003 [0.63]
Inst _t	-0.065* [-1.87]	-0.083** [-2.43]	-0.097** [-2.42]	-0.113*** [-2.84]
Return _t	-0.008* [-1.74]	-0.005 [-1.10]	-0.013** [-2.41]	-0.010* [-1.87]
Illiquidity _t	0.036*** [3.44]	0.058*** [5.46]	0.064*** [5.44]	0.086*** [7.24]
Return volatility _t	1.273*** [4.57]	1.044*** [3.88]	1.459*** [4.57]	1.055*** [3.37]
HHI _t	-0.185***	-0.159*	-0.085	0.010

	[-2.42]	[-1.75]	[-0.98]	[0.10]
HHI_sq _t	0.152**	0.134	0.060	-0.011
	[2.08]	[1.64]	[0.72]	[-0.12]
Patent measure _t	1.048***	1.001***	0.872***	0.834***
	[69.70]	[65.54]	[48.05]	[45.57]
Constant	-0.339***	-0.538***	-0.489***	-0.684***
	[-8.04]	[-11.69]	[-10.03]	[-12.87]
Observations	32,194	32,194	32,194	32,194
Adjusted R ²	0.720	0.735	0.599	0.615
Industry FE	NO	YES	NO	YES
Year FE	YES	YES	YES	YES

Panel B: Effectiveness Measures

	Generality _{t+2}	Originality _{t+2}	Citation per Patent _{t+2}	Economic Value _{t+2}	Research Quotient _{t+2}
	(1)	(2)	(3)	(4)	(5)
FX hedge _t	0.015*** [3.19]	0.006** [2.06]	0.015** [2.01]	0.109*** [4.79]	0.006*** [4.83]
Size _t	0.016*** [11.52]	0.011*** [12.30]	0.019*** [8.20]	0.178*** [19.93]	0.000 [0.42]
M/B _t	0.007*** [7.52]	0.005*** [7.36]	0.011*** [7.58]	0.055*** [13.57]	0.001*** [3.00]
Foreign income _t	0.005 [1.11]	0.000 [0.05]	0.001 [0.24]	0.071*** [3.77]	0.004*** [3.39]
Leverage _t	-0.039*** [-5.84]	-0.029*** [-6.57]	-0.057*** [-5.57]	-0.263*** [-9.47]	-0.011*** [-3.78]
PPE _t	0.005*** [3.84]	0.003*** [3.29]	0.009*** [4.37]	0.020*** [3.64]	0.001* [1.76]
ROA _t	0.011** [2.14]	0.009** [2.33]	0.015* [1.89]	0.028 [1.54]	0.007** [2.30]
Age _t	0.001*** [4.44]	0.000*** [3.80]	-0.001*** [-5.01]	0.004*** [5.65]	-0.000 [-0.72]
Cash _t	0.035*** [4.69]	0.020*** [3.84]	0.086*** [6.79]	0.260*** [9.66]	0.002 [0.40]
CAPEX _t	0.014 [1.08]	0.011 [1.22]	-0.000 [-0.02]	0.113** [2.28]	-0.018*** [-3.43]
Growth _t	-0.001 [-0.49]	0.000 [0.09]	0.004** [2.22]	0.006 [1.08]	0.002 [1.58]
Inst _t	-0.000 [-0.02]	-0.006 [-1.41]	-0.003 [-0.26]	-0.187*** [-6.35]	0.001 [0.59]
Return _t	0.005** [2.33]	0.004** [2.49]	0.000 [0.06]	-0.019*** [-2.87]	-0.000 [-0.05]
Illiquidity _t	-0.007** [-2.47]	0.003* [1.74]	-0.002 [-0.53]	0.117*** [10.85]	-0.003** [-2.12]
Return volatility _t	-0.023 [-0.30]	-0.037 [-0.74]	0.129 [1.24]	1.082*** [4.28]	0.037 [0.95]
HHI _t	-0.021 [-1.10]	-0.008 [-0.63]	0.028 [0.88]	0.019 [0.23]	-0.003 [-0.47]
HHI_sq _t	0.028 [1.55]	0.012 [1.02]	-0.020 [-0.70]	0.025 [0.33]	0.003 [0.62]
Efficiency measure _t	0.596*** [74.38]	0.555*** [66.99]	0.535*** [42.72]	0.760*** [101.37]	0.825*** [58.72]
Constant	-0.090*** [-7.70]	-0.050*** [-6.01]	-0.093*** [-6.07]	-0.545*** [-10.37]	0.006* [1.74]
Observations	32,194	32,194	32,194	32,194	32,194
Adjusted R ²	0.536	0.522	0.410	0.744	0.638
Industry FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Table 13 Cost of Capital

In this table, we examine the alternative explanation: cost of capital channel. In Panel A, we test the effect of *FX hedge* on cost of capital. In columns (1) and (2), we use the implied cost of capital (*ICC*) at year $t+1$, while in columns (3) and (4), we use *ICC* at year $t+2$. Columns (1) and (3) include year fixed effect, and columns (2) and (4) include year and 2-digit SIC industry fixed effects. In Panel B, we add *ICC* as an additional control variable to the regression of innovation outputs on *FX hedge*. Columns (1) and (2) test the effect of hedging on *LnPatent*, while columns (3) and (4) test the effect on *LnCitation*. Columns (1) and (3) include year fixed effect, and columns (2) and (4) include year and 2-digit SIC industry fixed effects. We cluster the standard errors at the firm level. ***, ** and * represent significance levels at 1%, 5% and 10% respectively with t-statistics given in brackets.

Panel A: FX Hedging and Implied Cost of Capital

	ICC _{t+1}		ICC _{t+2}	
	(1)	(2)	(3)	(4)
FX hedge _t	-0.004*** [-4.85]	-0.003*** [-3.40]	-0.003*** [-2.67]	-0.002 [-1.43]
Beta _t	-0.007 [-1.58]	-0.008* [-1.67]	-0.006 [-1.01]	-0.007 [-1.19]
Idiosyncratic Risk _t	0.002 [0.18]	0.003 [0.38]	0.019* [1.71]	0.018* [1.71]
Size _t	-0.001* [-1.78]	-0.001*** [-3.15]	0.000 [0.30]	-0.000 [-0.71]
M/B _t	-0.004*** [-15.22]	-0.004*** [-14.37]	-0.004*** [-11.83]	-0.003*** [-10.59]
Foreign income _t	0.002* [1.70]	0.003*** [2.87]	-0.002 [-1.40]	-0.001 [-0.41]
Leverage _t	0.008*** [2.78]	0.006** [1.98]	0.029*** [8.24]	0.028*** [7.83]
PPE _t	0.002*** [4.73]	0.001*** [2.73]	0.001** [2.08]	0.000 [0.53]
ROA _t	0.060*** [11.82]	0.062*** [11.95]	0.018*** [3.75]	0.019*** [3.85]
Age _t	0.000*** [2.91]	0.000*** [2.79]	0.000*** [2.75]	0.000*** [2.79]
Cash _t	0.013*** [4.46]	0.014*** [4.81]	0.009** [2.51]	0.011*** [3.06]
CAPEX _t	-0.018*** [-3.58]	-0.018*** [-3.12]	-0.015** [-2.47]	-0.020*** [-2.94]
Growth _t	0.003*** [3.88]	0.003*** [3.52]	0.004*** [3.38]	0.004*** [3.18]
Inst _t	0.000 [0.17]	0.002 [1.09]	0.004* [1.79]	0.004* [1.83]
Return _t	-0.002*** [-4.10]	-0.003*** [-4.53]	0.001 [1.34]	0.001 [0.90]
Illiquidity _t	0.015*** [7.75]	0.014*** [7.47]	0.016*** [7.47]	0.015*** [7.13]
Return volatility _t	-0.438*** [-6.72]	-0.419*** [-6.27]	-0.110 [-1.40]	-0.105 [-1.30]
HHI _t	0.027*** [5.28]	0.018*** [3.10]	0.016*** [2.74]	0.003 [0.48]
HHI_sq _t	-0.021***	-0.015***	-0.008	0.001

	[-4.33]	[-2.75]	[-1.41]	[0.19]
ICC _t	0.422***	0.410***	0.326***	0.316***
	[25.81]	[25.32]	[20.65]	[19.88]
Constant	0.025***	0.028***	0.022***	0.024***
	[6.58]	[7.30]	[4.79]	[5.25]
Observations	16,228	16,228	16,228	16,228
Adjusted R ²	0.374	0.379	0.249	0.257
Industry FE	NO	YES	NO	YES
Year FE	YES	YES	YES	YES

Panel B: Including Implied Cost of Capital

	LnPatent _{t+2}		LnCitation _{t+2}	
	(1)	(2)	(3)	(4)
FX hedge _t	0.136*** [4.65]	0.090*** [3.15]	0.135*** [4.06]	0.091*** [2.78]
ICC _t	-0.137** [-2.06]	-0.180*** [-2.71]	-0.142** [-2.01]	-0.178** [-2.49]
Size _t	0.090*** [8.12]	0.119*** [10.49]	0.103*** [8.62]	0.131*** [10.74]
M/B _t	0.046*** [6.44]	0.048*** [6.98]	0.052*** [6.32]	0.056*** [6.94]
Foreign income _t	0.058* [1.96]	0.040 [1.44]	0.059* [1.79]	0.038 [1.22]
Leverage _t	-0.234*** [-4.95]	-0.248*** [-5.21]	-0.251*** [-4.82]	-0.263*** [-5.01]
PPE _t	0.009 [1.58]	0.029*** [3.54]	0.003 [0.51]	0.026*** [2.82]
ROA _t	0.088 [1.56]	0.087 [1.59]	0.113* [1.73]	0.108* [1.71]
Age _t	-0.007*** [-8.64]	-0.007*** [-8.68]	-0.007*** [-7.31]	-0.006*** [-7.32]
Cash _t	0.324*** [5.79]	0.279*** [5.05]	0.309*** [4.80]	0.256*** [4.02]
CAPEX _t	-0.101 [-1.62]	0.115* [1.66]	-0.034 [-0.49]	0.152* [1.94]
Growth _t	-0.002 [-0.19]	-0.002 [-0.14]	-0.005 [-0.38]	-0.004 [-0.28]
Inst _t	-0.055 [-1.25]	-0.064 [-1.48]	-0.084* [-1.70]	-0.098** [-2.02]
Return _t	-0.005 [-0.70]	0.001 [0.09]	0.000 [0.02]	0.004 [0.52]
Illiquidity _t	0.053*** [3.04]	0.089*** [4.96]	0.086*** [4.58]	0.124*** [6.36]
Return volatility _t	2.083*** [3.91]	1.964*** [3.68]	1.746*** [2.93]	1.515** [2.49]
HHI _t	-0.333*** [-3.28]	-0.333*** [-2.84]	-0.266** [-2.36]	-0.237* [-1.79]
HHI_sq _t	0.296*** [3.08]	0.297*** [2.81]	0.217** [2.02]	0.197* [1.65]
Patent measure _t	1.101*** [63.66]	1.039*** [57.37]	0.970*** [50.61]	0.915*** [45.55]
Constant	-0.334*** [-5.62]	-0.578*** [-9.03]	-0.441*** [-6.61]	-0.699*** [-9.76]
Observations	18,301	18,301	18,301	18,301
Adjusted R ²	0.762	0.776	0.661	0.676
Industry FE	NO	YES	NO	YES
Year FE	YES	YES	YES	YES

Internet Appendix: Nonzero Innovation and Nonmissing R&D Subsamples

This table tests whether our findings are robust to the subsamples of nonzero innovation and nonmissing R&D expenditures. In Panel A, we use the nonzero innovation subsample, while in in Panel B, we use the nonmissing R&D subsample. Columns (1) and (2) test the effect of hedging on *LnPatent*, while columns (3) and (4) test the effect on *LnCitation*. Columns (1) and (3) include year fixed effect, and columns (2) and (4) include year and 2-digit SIC industry fixed effects.

Panel A: Nonzero Innovation Subsample

	R&D/Assets _{t+2}		LnPatent _{t+2}		LnCitation _{t+2}	
	(1)	(2)	(3)	(4)	(5)	(6)
FX hedge _t	0.007** [2.51]	0.006** [2.14]	0.204*** [4.37]	0.170*** [3.86]	0.213*** [3.57]	0.170*** [2.97]
Size _t	-0.010*** [-5.58]	-0.009*** [-4.37]	0.314*** [17.39]	0.360*** [20.53]	0.325*** [14.61]	0.360*** [16.26]
M/B _t	0.012*** [5.94]	0.011*** [5.66]	0.056*** [8.22]	0.066*** [10.13]	0.072*** [7.68]	0.083*** [8.99]
Foreign income _t	0.002 [0.86]	0.001 [0.41]	-0.023 [-0.58]	-0.038 [-1.04]	-0.046 [-0.88]	-0.068 [-1.34]
Leverage _t	0.020 [1.40]	0.008 [0.59]	-0.566*** [-6.31]	-0.491*** [-5.38]	-0.760*** [-6.56]	-0.659*** [-5.68]
PPE _t	0.010*** [4.16]	0.005** [1.99]	-0.054** [-2.54]	0.033 [1.51]	-0.074*** [-2.74]	0.037 [1.28]
ROA _t	-0.074*** [-5.55]	-0.066*** [-4.87]	0.153*** [3.13]	0.054 [1.19]	0.285*** [4.20]	0.153** [2.36]
Age _t	0.000 [1.52]	0.000 [0.56]	-0.013*** [-7.34]	-0.009*** [-5.65]	-0.013*** [-6.33]	-0.010*** [-5.17]
Cash _t	0.093*** [4.47]	0.082*** [4.09]	0.182** [2.42]	0.298*** [4.10]	0.196* [1.91]	0.362*** [3.67]
CAPEX _t	-0.168*** [-3.94]	-0.128*** [-2.89]	0.512*** [3.36]	0.301** [2.04]	0.580*** [2.86]	0.299 [1.46]
Growth _t	0.001 [0.28]	0.001 [0.18]	-0.015 [-1.30]	-0.005 [-0.42]	-0.006 [-0.40]	0.010 [0.64]
Inst _t	0.002 [0.21]	0.002 [0.20]	-0.162* [-1.84]	-0.225*** [-2.72]	-0.171 [-1.44]	-0.250** [-2.23]
Return _t	0.004 [1.43]	0.005 [1.59]	0.008 [0.66]	0.010 [0.79]	0.004 [0.22]	0.008 [0.43]
Illiquidity _t	-0.004 [-0.52]	-0.004 [-0.46]	0.074* [1.96]	0.134*** [3.55]	0.068 [1.32]	0.126** [2.47]
Return volatility _t	0.110 [0.54]	0.269 [1.36]	6.118*** [5.50]	5.167*** [4.78]	5.728*** [3.79]	4.308*** [2.86]
HHI _t	-0.116*** [-4.61]	-0.118*** [-3.85]	-0.564** [-2.31]	-0.319 [-1.26]	-0.368 [-1.20]	0.065 [0.20]
HHI_sq _t	0.089*** [3.92]	0.092*** [3.44]	0.387 [1.62]	0.223 [0.93]	0.215 [0.71]	-0.087 [-0.29]
Innovation measure _t	0.402*** [9.91]	0.393*** [9.80]	0.614*** [25.56]	0.520*** [20.40]	0.579*** [21.13]	0.516*** [18.09]
Constant	0.051*** [3.30]	0.068*** [4.03]	-0.390*** [-3.33]	-0.982*** [-8.43]	-0.637*** [-4.17]	-1.327*** [-8.64]
Observations	8,735	8,735	8,735	8,735	8,735	8,735

Adjusted R ²	0.475	0.477	0.532	0.571	0.389	0.427
Industry FE	NO	YES	NO	YES	NO	YES
Year FE	YES	YES	YES	YES	YES	YES

Panel B: Nonmissing R&D Subsample

	R&D/Assets _{t+2}		LnPatent _{t+2}		LnCitation _{t+2}	
	(1)	(2)	(3)	(4)	(5)	(6)
FX hedge _t	0.007*** [2.98]	0.006** [2.48]	0.186*** [4.70]	0.118*** [3.11]	0.212*** [4.59]	0.136*** [3.07]
Size _t	-0.005*** [-3.71]	-0.005*** [-3.15]	0.173*** [10.92]	0.211*** [13.16]	0.208*** [11.93]	0.242*** [13.74]
M/B _t	0.011*** [7.54]	0.010*** [7.24]	0.042*** [7.37]	0.048*** [8.90]	0.051*** [7.69]	0.057*** [9.12]
Foreign income _t	0.003 [1.39]	0.001 [0.52]	0.050 [1.46]	0.012 [0.37]	0.045 [1.15]	-0.001 [-0.02]
Leverage _t	0.001 [0.05]	-0.005 [-0.47]	-0.403*** [-6.71]	-0.313*** [-5.26]	-0.493*** [-6.94]	-0.385*** [-5.51]
PPE _t	0.008*** [4.29]	0.004* [1.91]	0.064*** [5.12]	0.066*** [5.11]	0.055*** [3.91]	0.064*** [4.22]
ROA _t	-0.071*** [-7.78]	-0.067*** [-7.38]	0.083** [2.39]	0.053* [1.66]	0.124*** [3.16]	0.085** [2.30]
Age _t	0.000 [0.99]	-0.000 [-0.68]	-0.011*** [-8.45]	-0.011*** [-9.03]	-0.010*** [-6.90]	-0.010*** [-7.30]
Cash _t	0.068*** [4.63]	0.057*** [4.08]	0.288*** [5.13]	0.328*** [5.97]	0.262*** [3.96]	0.314*** [4.91]
CAPEX _t	-0.137*** [-5.39]	-0.104*** [-3.81]	0.071 [0.70]	0.276*** [2.77]	0.088 [0.77]	0.261** [2.23]
Growth _t	-0.001 [-0.50]	-0.002 [-0.66]	0.001 [0.08]	0.006 [0.73]	0.009 [0.86]	0.015 [1.50]
Inst _t	0.016** [2.09]	0.016** [2.02]	-0.146** [-2.13]	-0.164** [-2.54]	-0.206*** [-2.60]	-0.216*** [-2.88]
Return _t	0.005* [1.95]	0.005* [1.92]	-0.000 [-0.02]	0.001 [0.17]	-0.003 [-0.28]	-0.001 [-0.09]
Illiquidity _t	-0.002 [-0.48]	-0.002 [-0.38]	0.062*** [2.96]	0.105*** [5.07]	0.100*** [4.34]	0.148*** [6.47]
Return volatility _t	0.059 [0.44]	0.119 [0.90]	2.312*** [3.91]	1.817*** [3.21]	2.510*** [3.68]	1.657** [2.48]
HHI _t	-0.113*** [-6.10]	-0.106*** [-4.79]	-0.744*** [-4.55]	-0.634*** [-3.45]	-0.622*** [-3.41]	-0.361* [-1.76]
HHI_sq _t	0.094*** [5.61]	0.090*** [4.59]	0.589*** [3.70]	0.498*** [2.89]	0.490*** [2.78]	0.272 [1.43]
Innovation measure _t	0.454*** [10.43]	0.446*** [10.20]	1.006*** [52.65]	0.946*** [49.11]	0.883*** [41.01]	0.834*** [38.92]
Constant	0.020* [1.91]	0.036*** [2.97]	-0.641*** [-7.54]	-0.878*** [-10.22]	-0.847*** [-8.91]	-1.067*** [-11.01]
Observations	14,683	14,683	14,683	14,683	14,683	14,683
Adjusted R ²	0.535	0.537	0.712	0.734	0.621	0.646
Industry FE	NO	YES	NO	YES	NO	YES
Year FE	YES	YES	YES	YES	YES	YES

Chapter 3

Do Law Firms Matter for Securities Class Action Lawsuit Outcomes?

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Abstract

Using securities class action lawsuits from 1996 to 2013, we document a measure of law firm expertise that predicts the outcome of future lawsuits conducted by law firms. We use prior Dismissed Ratio as law firm expertise. We find that law firms with a lower prior Dismissed Ratio are more likely to be skilled law firms with less agency problem. Cases conducted by skilled law firms with less agency problem are more likely to be settled, have more negative cumulative abnormal return during the filing date, win larger settlement amounts, result in a larger probability of CEO turnover and are associated with larger short interest one week prior to the filing event. Skilled law firms contribute to better outcomes by exerting more effort in the litigation process, as evident by the longer Case Length from filing date to status date. In addition, the market share of law firms increase after performing as skilled law firms and skilled law firms are less likely to disappear from the market. Overall, predictive power and persistence of law firm expertise suggest law firm fixed effect in securities class action lawsuits. Robustness tests suggest existence of law firm expertise beyond case selection.

Keywords: Securities class action lawsuits, Agency problem, Law firm expertise, Corporate Governance

JEL Classification: D21, G30, K22, K41

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I. Introduction

Plaintiff law firms are at centre stage of securities class action lawsuits²⁸. Traditionally, law firms are viewed as an agent of the client and advise as independent professionals. However, in the scenario of class actions, dispersed and disorganized shareholders, as plaintiffs, do not have the incentives nor ability to effectively monitor the law firms. In “large-scale, small-claim” litigation, agency costs of law firms arise when the individual interest of the class is small and the overall liability is large (Macey and Miller, 1991). There has been long-time debate on whether securities class action lawsuits is of merit due to the expertise and agency problem of law firms. The enforcement system and incentive structure implies that risk-averse law firms prefer to settle (Coffee, 1986), because the attorney fee comes from the recovery for the class members (Alexander, 1991; Coffee, 1986; Macey and Miller, 1991). Therefore, it leads to excessive settlement rates or extremely low settlement amounts (Starkman, 1997; Niehaus and Roth, 1999; Perino, 2012). Consequently, law firms derive private interests that diverge from shareholders, bear the litigation risk, and “exercise plenary control over nearly all important decisions in the lawsuit” (Macey and Miller, 1991).

Given the controversial and complex features of securities class actions as inferred above, it is interesting to quantify the existence of law firm expertise and agency problem. If heterogeneous law firm expertise lead to different outcomes, then it implies that law firms play an important role in shaping the results of securities class actions. If law firms indeed provide expertise in the litigation process, cases conducted by law firms with higher quality and less agency problem would

²⁸ Securities class action litigation under Securities and Exchange Commission Rule 10b-5 is filed on firms where there is allegation of omission of material facts or misrepresentation of information that inflates the market price of the firm’s stocks.

achieve more favorable outcomes. In contrast, if law firms exhibit pure rent seeking behavior and litigate only for the purpose of earning attorney fees, law firm expertise could not predict litigation outcomes. The existence of law firm expertise remains an unexplored empirical question. In different settings, performance of investment banks (Ban and Edmans, 2011), auditors (Cai et al., 2016) and legal advisors²⁹ (Beatty and Welch, 1996; Krishnan and Masulis 2013) have been widely studied in the M&A and IPO literature. In contrast to performance persistence documented in investment banks, auditors, and legal advisors, existence of skilled mutual fund managers is not found (Carhart (1997)). In the paper, we propose a quantitative measure for law firm expertise and agency problem in securities class actions. Particularly, we use Dismissed Ratio (DR) as the proxy for both expertise and agency problem, which is calculated in a rolling window of 5 years³⁰ prior to filing date of the case. As law firms have the opportunistic behavior of excessive settlement due to the contingency attorney fee, settling the case might not indicate that the case is of merit. In contrast, dismissing the case provides a clear evidence that the case is of less merit. Since law firms will not be reimbursed following unsuccessful action, they must conduct cost benefit analysis in advance to determine whether to undertake the action (Coffee, 2006). Law firms will therefore advance the expense of the action and estimate the expected fee award. Most importantly, the law firms are the principal enforcer of securities law liabilities, and are indifferent to the source of the

²⁹ Beatty and Welch (1996) adopts prior market shares to identify top law firms in the context of IPO and studies the reputation effect of advisers. Using market share measure, the effect of legal advisor expertise has been studied in the context of mergers and acquisitions in Krishnan and Masulis (2013). It is found that bidder law firms with top market share are associated with higher offer completion rates, whereas top target law firms are associated with higher offer withdrawal rates.

³⁰ Our results remain robust using rolling window of 3 years or 4 years.

settlement. According to Weiss and Beckerman (1995), class counsel usually prefer a quick settlement and conduct the litigation in an aggressive manner.

Hence, at the law firm level, dismissing more cases proportional to all cases taken previously is a signal of relative lower expertise and larger agency problem. We further document DR to be a significant predictor for litigation outcomes: cases conducted by skilled law firms are more likely to be settled, have more negative cumulative abnormal returns during the filing dates, win larger settlement amounts, and are associated with larger short interest in the filing months.

In addition to outcome predictability, we further examine the corporate governance outcomes of cases conducted by skilled law firms. This is because lawsuits by shareholders are filed after the break down of other mechanisms. Indeed, we found that cases conducted by skilled law firms will result in larger probability of CEO turnover. By linking law firm expertise and agency problem measure to CEO turnover, we contribute to the literature on shareholders rights and litigation risk³¹. Law firms could contribute to better corporate governance outcomes through litigating cases that are of merit. We therefore supplement the study on the monitoring role of institutions³² in the lawsuits.

³¹ Lowry and Shu (2002) study litigation risk related to IPO underpricing; Skinner (1994, 1997) study financial reporting and accounting disclosure; Crane (2011) studies leverage effects; Seetharaman, Gul, and Lynn (2002) study audit fees; Arena and Julio (2015) study corporate savings and investment policy.

³² Cheng et al. (2010) study the function of institutional monitoring and conclude that institutional lead plaintiffs will lead to less likelihood of dismissal and larger monetary settlements. In addition, subsequent governance improvements in the long term demonstrates the effectiveness of institution monitoring. In Wei and Zhang (2016), a firm-level measure of litigation risk is created for firms sharing the same institutional shareholders. They find that this shareholder linkage predicts short interest and cash holdings, reflecting weak governance and poor monitoring by institutional shareholders.

Besides DR, we identify two other measures of law firms that are related to efforts and market share respectively. For law firms that possess better expertise and less agency problem, they are more likely to devote themselves in the cases. We therefore use Case Length (CL)³³ as a proxy for law firm efforts. Indeed, we find that skilled law firms pay more efforts and conduct due diligence during the litigation process, and is associated with longer CL. In addition, the Market Share (MS)³⁴ of a law firm increases after performing as a skilled law firm and skilled law firms are less likely to disappear from the market. This suggests that clients do recognize the expertise of law firms and skilled law firms will have increasing market share after better performance. Therefore, we document the existence of law firm fixed effects in securities class action lawsuits and provides implications for the traceable evidence for law firm expertise.

We address the case selection versus law firm expertise issue by focusing on the cases where case selection is minimized. If prior results are driven by systematic selection of cases with certain characteristics by law firms, then it is more likely that law firms select cases in the same industry. Therefore, we create a Dismissed Ratio excluding cases in the same industry for the focal case, and it remains a significant predictor for litigation outcomes. Hence, our results are not entirely driven by case selection.

Identifying expertise and agency problems of plaintiff law firms has been difficult. Firstly, plaintiff law firms seek a viable strategy to file frivolous lawsuits to conduct discovery and to find claims that were not alleged in the complaint. Moreover, this opportunistic behavior of law firms

³³ Case Length (CL) is the number of days between filing dates and status dates, scaled by 365 days.

³⁴ Market Share (MS) is defined as number of cases conducted by a law firm divided by number of all cases in year t .

is often confounded by the unobservable reason of large stock price declines following optimistic statements for outside investors: whether it is due to fraud, risk, market movement, or simple bad luck (Pritchard and Ferris, 2001). Prior to 1995, law firms opportunistically attempted to profit from stock price falls and would approach and persuade the plaintiff shareholders to file for class action lawsuits³⁵. Nevertheless, not all significant price declines at the disclosure will lead to class actions. The opportunistic behavior of plaintiff law firms has led to the enactment of 1995 Private Securities Litigation Reform Act (PSLRA)³⁶, which is intended to curtail frivolous securities lawsuits and prevent professional advisors from abusive class action litigation. The nature of securities fraud changes over time. In recent times, lawsuits have been filed when there are serious declines in the fortune of the firm.

In spite of the important role of law firms in all the stages of securities class action lawsuits, there is scant research that has identified which dimensions of law firms really matter for the litigation outcome. A closely related paper written by Badawi and Webber (2015) gauges the quality of law firms in deal litigation by using the settlements published by RiskMetrics and annual rankings of Securities Class Action Services (SCAS). Their main focus is the case selection ability of law firms and their sample only includes law firms that appear on the SCAS top 10 list at least once during 2003 to 2008. Another study by Krishnan, Solomon and Thomas (2016) identifies the

³⁵ Alexander (1991) and Jones and Weingram (1996) contend large and sudden stock price declines during information releases as a measure of ex ante litigation risk. Kellogg (1984) have documented the price declines that have triggered the securities class litigation are larger than 10% of firm market capitalizations. Beck and Bhagat (1997) adopt two criteria to jointly access unusual negative share-price performance. These are a combination of cumulative quarterly raw returns less than -0.1 and cumulative abnormal returns less than -0.2.

³⁶ Particularly, there are three mechanisms in the PSLRA, all of which are targeted at the law firms' incentives and behaviors. The three mechanisms are summarized in Choi and Thompson (2006) as "raising the bar as to what constitutes securities fraud, empowering lead plaintiffs to rein in their lawyers in class actions, and requiring judges to sanction securities lawyers for frivolous litigation".

top 5 law firms in merger litigation only and gauges the effectiveness of law firms based on the number of lead or co-lead counsel and the ability to obtain attorney fees. They find that top law firms are less likely to dismiss cases and they obtain higher settlement amounts. In addition, they also find that top law firms submit more filings and more docket entries, which is consistent with our results that skilled law firms spend more efforts during the litigation process.

Different from prior literature, our paper gauges both law firm expertise and agency problems quantitatively in a unifying manner. Furthermore, we do not rely on existing rankings to identify top law firms. Instead, we gauge law firm expertise and agency problems by utilizing past lawsuit information, as dismissing the case is a definite signal of lower law firm expertise and larger agency problem. Our aim is to examine whether law firm characteristics is a determinant of litigation outcomes, from the perspectives of both law firm expertise and agency problems. Particularly, we shed light on whether law firm expertise is an omitted variable in the current models of securities class action outcomes.

We also add to the debate on the merit of securities class action lawsuits. According to Griffin, Grundfest and Perino (2004), proponents contend the rife of securities fraud among public companies and support litigation as supplement to the anti-fraud enforcement program of SEC. Opponents hold the view that the litigation process creates incentives for law firms to benefit from the merit of plaintiffs' claims³⁷. There are also criticisms of filing frivolous or low-probability

³⁷ For example, Macey and Miller (1991) has criticized the regulatory system and advocated a reform to reduce agency costs when law firms control the litigation. Macey and Miller (1991) further point out the fundamental error of regulatory shortfalls as failure to recognize the difference between "entrepreneurial litigation nature of class action" and "traditional litigation". Romano (1991) questions the efficacy of shareholder litigation as a governance mechanism since the cost of bringing a lawsuit exceeds the "pro rata benefit of shareholder-plaintiff". Principal-agent problem arises from the misalignment between law firms' incentives and shareholders' interest. Romano (1991) argues that law firms, instead of shareholders are the principal beneficiaries of cash payouts in lawsuits. Grundfest (1994) argues that lawsuits will be of no merit if law firms expect the defendants to settle and attorney fee is larger than law firms' litigation cost. Judges, practitioners, and academics have been increasingly criticized that plaintiff law firms take

lawsuits for the purpose of coercing settlements (Coffee, 2006). Furthermore, Beck and Bhagat (1997) identifies another criticism as the stack of allegations. The actual proof of the allegation is unknown since the case is not adjudicated but simply settled. By identifying a measure of law firm quality, we would be able to imply the case outcomes and merit from the law firms involved in the case.

Last but not least, our law firm expertise measure sheds light on the effectiveness of PSLRA. Since the enactment of PSLRA in 1995, a strand of literature has studied the market reaction³⁸ to the PSLRA and assesses the effectiveness of the regulation. Choi and Thompson (2006) examined the effectiveness of the focus of PSLRA in regulating lawyers' behavior in the first decade after the enactment. They find that institutional lead plaintiffs tend to repeat relationships with certain top law firms after the PSLRA. Despite the increasing cost in filing lawsuits after PSLRA, plaintiff law firms could still approach individual shareholders as "group of persons" with the largest financial stake, according to Berger, Coffey, and Silk (2001). Nevertheless, in our findings, law firms have a higher probability of existing after performing as low quality law firms, as measured by high DR ratio. This suggests the effectiveness of PSLRA that clients could imply the quality of law firms and low quality law firms would therefore have decreasing market share.

advantage of the litigation system by settling too cheaply instead of raising stronger claims (Thomas and Thompson, 2012). Macey and Miller (1991) further point out the fundamental error of regulatory shortfalls as failure to recognize the difference between "entrepreneurial litigation nature of class action" and "traditional litigation".

³⁸ Johnson, Kasznik and Nelson (2000) studied the reaction of stock price to PSLRA using high-technology firms, showing that PSLRA is less beneficial for firms for which lawsuits are meritorious but wealth-increasing for firms with greater risk of class actions. Spiess and Tkac (1997) confirmed the dominance of the positive effects of the act over the inability to bring meritorious suits using four industries: biotechnology, computers, electronics, and retailing.

The paper is structured as follows. Section II develops hypothesis. Section III describes data and variables. Section IV presents results. Section V provides robustness test. Section VI concludes.

II. Hypothesis Development

We developed three testable hypothesis related to plaintiff law firms' expertise and agency problems in the securities class action lawsuits. The first hypothesis is the law firm skill hypothesis. This hypothesis argues that law firm skill matters in the likelihood of a case being dismissed. The second hypothesis is the predictive outcome hypothesis. This argues that skilled law firms will achieve more favorable litigation outcomes. The third hypothesis is the law firm effort hypothesis. This argues whether skilled law firms will exert more effort and provide better outcomes. The fourth hypothesis is the market share hypothesis. This tests the predictive power of market share and whether clients chase past performance. These hypotheses are stated as follows:

H1: Law firms with lower prior Dismissed Ratios are skilled law firm with less agency problems.

H2: Law firms with lower prior Dismissed Ratios are more likely to conduct cases with meritorious outcomes. Skilled law firms will have higher probability of settling the case in the future, and more negative market reaction at the filing event date, achieve higher settlement amount and are associated with greater short interest of the sued company prior to the filing date.

H3: Law firms with lower prior Dismissed Ratios will put more effort into the litigation process and it takes longer time for the results of the case to be revealed.

H4: Law firms with lower prior Dismissed Ratios will have increasing market share in the future. Law firms with higher prior Dismissed Ratios will more likely disappear from the market.

III. Data and Variables

i. Data

Security class action information is obtained from the Stanford Law School Securitas Class Action Clearinghouse <http://securities.stanford.edu/index.html>. Sample period of the lawsuits ranges from 1996 to 2013. The lawsuits with ongoing status as of May 1st, 2016 are excluded from the sample. Since it takes 5 years to compute the Dismissed Ratio for year 2001, lawsuits from 1996 to 2000 are used to compute initial independent variables and are therefore excluded from dependent variables. Due to the availability of control variables, 1420 lawsuits filed between 2001 and 2013 are included for the analysis. Stock returns and accounting data are from CRSP and COMPUSTAT. Institutional holdings data are from Thomason CDA/Spectrum 13F database. Settlement amounts are from RiskMetrics.

ii. Main Variables

a. Class Period Start Date, Class Period End Date, Filing Date, Status Date

The fact that several distinct and sequential events characterize the litigation process aggravates the complexity of the litigation. Upon a serious price decline, plaintiff's counsel analyses the events for corrective disclosure and facts that might lead to the filing. The truth is revealed to the market at the class period end date. Therefore, the Beginning of the Class Period (BCP) marks the beginning of the fraud on the market. The Class Period End Date (CPED) is the date of a corrective disclosure. The class period starts from the date where the defendant committed the alleged misconduct and ends on the date of the revelation of the event. The CP is the period between BCP and CPED. Niehaus and Roth (1999) indicates that corporate insiders are usually the net sellers during the Class Period (CP), though average selling behavior is not abnormal. After the end of CPED, filing of the complaint happens on the Filing Date (FD). Since filing action is

regarded as a foregone conclusion by the market, market reaction on the FD manifests the residual uncertainty since the CPED (Griffin, Grundfest and Perino, 2004).

The events studied in this paper are consistent with Griffin, Grundfest and Perino (2004), which analyze stock price responses to news at class period start dates, class period end dates and filing dates. They find that the market interprets these three events in a sequential and conditional way. They further find no price momentum beyond announcement dates, suggesting the efficiency of markets. Using a different time period of cases, it takes close to two years on average from filing to settlement for class actions in Klausner and Hegland (2010). Gande and Lewis (2009) reveals the partial anticipation of lawsuits by shareholders through other firms in the same industry and the capitalization of losses prior to lawsuit filing dates. Therefore, using filing dates alone will understate the magnitude of shareholder losses.

A typical timeline for a securities class action lawsuit is as follows:

- 1) Class Period Length = Class Period End Date – Class Period Start Date
- 2) Filing Period Length = Filing Date – Class Period End Date
- 3) Case Length = Status Date – Filing Date

b. Dismissed Ratio (DR)

The Dismissed Ratio (DR) is calculated in a rolling window of 5 years prior to filing date of the case, which is intended to minimize look-ahead bias. DR for law firm j at time t is defined as the number of dismissed cases divided by the total number of cases conducted by law firm j from year $t-5$ to year $t-1$. Aggregated at the case level, DR for lawsuit i is defined as the average of DR of all

law firms j engaging in case i . Following Bao and Edmans (2011) and Krishnan, Solomon and Thomas (2016), each law firm is given full credit for each lawsuit it is engaged. Therefore, each measure at the case level is the equal weighted average of all law firms engaging in the case.

We used the past 5 years to calculate DR since the mean number of years for the results of the cases to be known is between 4 and 5 years. Considering the economic meaning of DR, we drop the observations when law firms conduct less than 5 cases within the prior five years. In unreported results, using the prior 3 or 4 years suggests qualitatively similar conclusions. Consistent with prior literature, Cheng et al. (2010) considers the lower likelihood of dismissal as a meritorious outcome. Krishnan, Solomon and Thomas (2016) argue that top law firms file cases that are less likely to be dismissed.

c. Case Length (CL)

Case Length (CL) is the number of days between filing dates and status dates, scaled by 365 days. CL is a measure of law firm efforts and an implicit indicator of agency problems. The possibility of using time length for the test is made possible due to the clear identification of different stages in securities class action data. Since only investors who bought or sold a company's securities within a specific period of time (class period) file for the litigation, the timeline for the class action is trackable and is available in the filing files. After controlling for case characteristics, time length of different stage of the case partially reveals the effort of law firms, and less efforts further suggests larger agency problems. If the law firm is skilled or does not file for frivolous cases for quick settlement, then the settling period will more likely to be longer.

A longer CL is consistent with findings in Krishnan, Solomon and Thomas (2016) that top law firms might "file for more documents and bring injunction motions to enjoin a transaction". A

longer class period is likely to be related to larger investor damages and also to prove the scienter of the defendant, as documented in Cheng et al. (2010). In Cheng et al. (2010), they provided evidence that institutional lead plaintiffs will influence the settlement time on behalf of investors. However, they do not conclude whether a longer or shorter period is beneficial. In this paper, a detailed look into CL will help refine the answer. Weiss and White (2004) also reveals the negative side of law firms as “file early, then free ride”, since law firms are there to settle cases instead of litigating. Consistent with our third hypothesis, Bajaj, Mazumdar and Sarin (2002) compare the average speed of settlements before and after the reform. The average speed of settlements are 4 and 5 years in pre and after reform period respectively. Their results partially support our hypothesis that law firms with less agency problems tend to have longer Case Length and file for less frivolous lawsuits, which is in line with the trend of less frivolous lawsuits after the PSLRA.

Moreover, Case Length is related to the area of behavioral law and economics. In Daniel Kahneman’s book “Thinking, fast and slow”, two systems of thinking are proposed: the intuitive and quick “system 1” and the deliberate and slow “system 2”. Olazabal (2012) shows that the speed of thinking is related to scienter and psychological illusion not only exists in individual but also in organizations. A slower organizational thinking will help to reduce recklessness and prevent securities fraud. In a similar manner, a slower thinking process for law firms will curb the frivolous lawsuits and reduce agency costs of the law firms. The comparable notion of “system 2” thinking applied to law firms would translate into a longer Case Length.

d. Market Share (MS)

In Beatty and Welch (1996) and Krishnan and Masulis (2013), market share of law firms is used as proxy for law firm expertise. In this paper, Market Share (MS) of law firm j in year t is defined as the number of cases conducted by law firm j in year t , divided by the total number of cases in

year t . If the law firm has lower DR in the past, then the market share of the law firm will increase in the future. Consistent with prior literature, Choi and Thompson (2006) use pre-PSLRA market share as a proxy for expertise and examine whether law firms with higher pre-PSLRA market share will increase in the post-PSLRA period. In addition, we also test whether the DR or the MS have any predictive power for the survival of law firms.

e. Prior Average CAR

Bao and Edmans (2011) show that the existence of investment bank fixed effects implies the persistence of bank average CARs in M&A events. Similarly, in this paper we use alternative law firm fixed effects measured by law firm Prior Average CAR as robustness. For each case i , we average the prior 5 years of Cumulative Abnormal Returns of the cases conducted by law firms engaged in the case i . If the dependent variable is CAR $(-1,1)$, then prior average CAR is the prior 5 years of average CAR $(-1,1)$. If the dependent variable is CAR $(-10,1)$ or CAR $(-30,1)$, then the prior average CAR is measured based on $(-10,1)$ or $(-30,1)$ correspondingly.

iii. Control Variables

Firm-level controls include size, Market to Book ratio, book leverage, profitability, cash holdings, Amihud illiquidity measure (Amihud, 2002), industry classification and stock return volatility. Since size is likely to be correlated with the limits for insurance policies and the undisclosed policy limits are highly correlated with settlement amounts, firm size is likely to be a determinant of lawsuit outcomes. Market to Book ratio controls for the growth opportunity of firms, since rapid growth firms will tend to misstate financial statements to present a stable growth picture (Loebbecke et al., 1989; Beasley, 1996). According to Coffee (2006), there are three factors that might principally determine the probability of a firm being sued: stock price volatility, industry

classification and firm size. Kim and Skinner (2012) have identified measure of firm characteristics including size, growth and stock volatility as predictive measure of litigation risk, in addition to previous documented industry membership. Kim and Skinner (2012) further argue that corporate governance quality proxy and managerial opportunism do not provide additional predictive power for litigation risk, these variables are therefore not included as control variables in this paper.

Following Cheng et al. (2010), two dummy variables are used to control for the allegation type. IPO dummy is equal to 1 if the case is related to IPO violations. GAAP dummy is equal to 1 if the lawsuit involves violations of Generally Accepted Accounting Principles (GAAP). A pension dummy is added to consider for pension fund participation, due to the importance of institution types in the lawsuit. According to Murphy and Van Nuys (1994) and Woidtke (2002), public pension fund managers are more likely to lead securities class litigation due to political or reputational reasons. It is also shown that public pension funds are more effective in shareholder activism (Gillan and Starks, 2000). Industry dummy is equal to 1 if the industry is biotechnology, computer, and retail (Francis, Philbrick, and Schipper (1994a, 1994b). Biotech: SIC codes 2833-2838 8731-8734; Computer: SIC codes 3570-3577, 7370-7374; Electronics: SIC codes 3600-3674; Retail: SIC codes 5200-5961.

These set of variables control for the firms' prior performance and are measured one year before the lawsuit. This is to avoid the effect of stock price falls that triggers the lawsuit. Year fixed effects are included to control for time-varying macroeconomic trends. Standard errors are clustered at the law firm level in the regressions. Summary statistics of main variables and control variables are in Table I.

[Insert Table I Here]

From Table I, the average CAR around the announcement date (-1,1) is -3.93%. Strikingly, average CAR for the period 10 days before the announcement is -10.1% and for the period 30 days prior to the announcement is as large as -15.3%. The average settlement amount is \$98.19 million with a maximum of \$7,241 million and minimum of just over \$400,000. The mean whole period length is 5.6 years, with a mean class period length of 1.23 years. The mean case length is around 4 years.

IV. Results

We tabulate the ranking of law firms by the number of cases conducted in our sample period, and report law firms that conducted more than 100 cases in Table II. We give full credit to each law firm if multiple law firms are involved in one case. As shown in Table II, Milberg Weiss Bershad Hynes & Lerach LLP conducted over 1,000 cases and represented approximately 10% of the total number of cases. The Dismissed Ratio for this firm is 0.23. This means that 23% of the total number of cases conducted by this firm in the past 5 years were dismissed. Among the firms tabulated in Table II, Robbins, Geller Rudman and Dowd LLP has the highest Dismissed Ratio, implying that 55% of their cases in the past 5 years were dismissed.

[Insert Table II Here]

i. Predicting Litigation Outcome

We test the second implication of our hypothesis that cases conducted by skilled law firms are more likely to be settled. A probit model is used to examine the relation between law firm expertise proxy (Dismissed Ratio) and the probability of settling. This model is shown below:

$$\text{Litigation Status Dummy}_{i,t} = \alpha + \lambda \times \text{Dismissed Ratio}_{i,t-1} + \gamma \times X_{i,t-1} + \varepsilon_{i,t} \quad (1)$$

where Litigation Status Dummy is 1 if the case is settled and 0 if the case is dismissed. In Column (1), we study the effect of Dismissed Ratio on Litigation Status Dummy. In Column (2), we add characteristics of the firm involved in the securities class action lawsuits. The vector of control are as previously defined in the control variables session. We additionally control for year fixed effect in column (3) and (4). In Column (4), we further include the type of the case and industry dummies. Following Cheng et al. (2010), two dummy variables are used to control for the allegation type. IPO dummy is equal to 1 if the case is related to IPO violations. GAAP dummy is equal to 1 if the lawsuit involves violations of Generally Accepted Accounting Principles (GAAP). A pension dummy is added to consider for pension fund participation, due to the importance of institution types in the lawsuit. As shown in Table III, we find a significantly negative relation between the DR and the litigation dummy across four different specifications of Model 1. This provides preliminary evidence that skilled law firms (lower prior Dismissed Ratio) are more likely to settle cases in the future. The status of settlement is associated with more favorable litigation outcomes. On average, firm characteristics such as size, illiquidity and institutional ownership are significantly related to case outcomes.

[Insert Table III Here]

ii. Cumulative Abnormal Return

We next focus on the cumulative abnormal return (CAR (-1,1), CAR(-10,1), CAR (-30,1)) around the filing date. Stock prices are expected to decline during the filing of the lawsuit, since securities class action lawsuits usually involve disclosure of bad news. According to Gande and Lewis (2009), there are two components related to the expected losses. The first aspect is the response to the information that triggers the lawsuit and the second aspect is the deadweight loss born by the

impaired shareholders. The cumulative abnormal return around the filing date is calculated using market model with -300 to -46 days before the filing date as the estimation period.

The dependent variable of column (1) CAR (-1,1) is the 3-day CAR around the filing date, from one day before the filing date to one day after the filing date. In Column (2), the dependent variable CAR(-10,1) is 12-day CAR around the filing date, from ten days before the filing date to one day after the filing date. In Column (3), dependent variable CAR (-30,1) is 32-day CAR around the filing date, from thirty days before the filing date to one day after the filing date. Across all three specifications, the Dismissed Ratio is positive and significant. This means that lower quality law firms are correlated with higher (less negative) CARs, and similarly higher quality firms conduct cases with lower CARs. More negative market reaction further supports the hypothesis that skilled law firms with less agency problems will file for less frivolous lawsuits, which is related to release of negative information and therefore more negative market reaction.

In addition, we find larger market reactions during the longer event horizon CAR (-30, 1) and CAR (-10, 1), which is consistent with the corporate disclosure policies of firms at risk of litigation. Upon the filing of a lawsuit by the skilled law firm, there is additional negative market reaction relative to the filing effect (Badawi and Webber (2015)). Skinner (1994) has documented the preemptive disclosure behavior of firms to reduce the risk of being sued. Romano (1991) interpreted the negative stock price effect before filing as the expectation that lawsuits will adversely affect firm future cash flows. In a stock price reaction event study by Pritchard and Ferris (2001), there is a large and significant negative reaction to revelation of potential fraud, a smaller but significant reaction to filing and no significant reaction to the dismissal of a lawsuit.

[Insert Table IV Here]

iii. Settlement Amount

In the securities class action lawsuits, law firms obtain their attorney fee contingent on the total settlement amount. Eisenberg and Miller (2004) report an average attorney fee of 21.9 percent of the total recovery for lawsuits from 1993 to 2002, and conclude the amount of client recovery as the key determinant of the attorney fee, providing a better explanatory power than the lodestar calculation (product of hours and hourly rate) by the court. An earlier study by Martin, Juneja, Foster, and Dunbar (1999) estimate the fee to be between 30 and 33 percent of the settlement amount. Kritzer (2002) undermines the myths of contingency fees and makes an argument that “contingency fee lawyers and their clients are routinely in conflict”. Hence, the contingency attorney fee leads to a statement that securities class actions are frivolous and only benefit the law firms, casting doubt on whether the fees awarded by courts follow the reasonableness checking against the lodestar calculation. Therefore, settlement amount is a key indicator of whether the lawsuits are of merit. In Table V Column (1), we calculate settlement amounts scaled by the market capitalization of firms one year prior to the beginning of the class period action. In Column (2), we exclude all cases with zero settlement amount. In Column (1), it is shown that law firms with a lower Dismissed Ratio will settle the case with large settlement amount. Our result remains robust when we exclude cases with a zero settlement amount in Column (2). Higher settlement amounts could be translated into better law firm skills and less agency problems, since the class will get a larger recovery. In addition, attorney fees are contingent on the amount of settlement recovery in U.S., and therefore skilled law firms will perform due diligence to achieve higher settlement amounts.

[Insert Table V Here]

iv. Utilization Rate

Since information about future stock price movements are contained in the short selling activity (Miller, 1977; Diamond and Verrecchia, 1987; Diether, Lee, and Werner, 2009), utilization rate in the month of filing date is another relevant test for law firm expertise. We measure utilization rate as the ratio of number of shares borrowed to the number of shares willing to be lent by institutional investors. Following Blau and Tew (2001), Gande and Lewis (2009), and Wei and Zhang (2016), we test whether markets anticipate the litigation risk. Blau and Tew (2001) investigated the hypothesis that lawyers might leak information about filing dates to short sellers on purpose. High return predictability of short selling and increases in short selling activities are documented during the pre-filing period. Gande and Lewis (2009) document negative market reaction to peer firms generated by lawsuits. It is likely that short sellers infer the information from the law firm expertise to exploit litigation risk.

In Table VI, a lower Dismissed Ratio predicts a higher short interest in the one week prior to the filing event. The coefficient is not significant in the week of the filing nor one week after the filing. The utilization rate results are consistent with results in Table IV that a lower Dismissed Ratio predict more negative market reaction in the cases conducted by the law firms.

[Insert Table VI Here]

v. Case Length

Case Length (CL) is the number of days between filing dates and status dates, scaled by 365 days. CL is a measure of law firm efforts and an implicit indicator of agency problems. According to Krishnan, Solomon and Thomas (2016), top law firms might “file for more documents and bring injunction motions to enjoin a transaction”. Completion time is also studied in other contexts such

as mergers and acquisitions (M&A), where investment banks might have a different interest compared with their principal, either bidder or target. However, the agency problem of investment banks could not be measured, since a deal is only known at announcement and the effort of investment banks is before the announcement. Hence, there is no available data on either the time length of effort or amount of effort by the investment bank. Investment banks with less agency problem could either complete the deal quickly or slowly, as the time length is only measurable upon announcement before which a lot of effort of investment bank have been invested. Therefore, although completion time of M&As is used to study legal advisor expertise in Krishnan and Masulis (2013), they did not interpret completion time as a measure of agency problem. In Deng, Kang and Low (2013), completion time is regarded as the ex-post obstacle to complete the deal from stakeholders. Deng, Kang and Low (2013) show that acquirers conducting more corporate social responsibilities take less time to complete the M&A deal.

In Table VII, we study whether Dismissed Ratio is a predictor of Case Length conducted by the law firms in the future. We control for year fixed effect in Column (2) and (3), and additional firm characteristics in Column (3). In all specifications, skilled law firms will put more effort in the litigation process, as evident by longer case length. In Panel B, we further separately study the Case Length effect in the subsample of settled case and dismissed case respectively. The law firm expertise measure remains significant after controlling for the outcome of the case. This effect is significant in the settled subsample but not in the dismissed subsample, suggesting that the result is not driven by the shorter length of dismissed case compared with the settled case. For the cases that ultimately settle, law firms also put more effort into the litigation process. Therefore, we might interpret agency problems of law firms from the time length.

[Insert Table VII Here]

vi. Market Share

In Beatty and Welch (1996) and Krishnan and Masulis (2013), market share of law firms is used as proxy for law firm expertise. In this paper, Market Share (MS) of law firm j in year t is defined as the number of cases conducted by law firm j in year t , divided by the total number of cases in year t . If the law firm has lower DR in the past, then the market share of the law firm will increase in the future. Whether law firm skill has an impact on the market share of law firms provides answer to whether clients chase performance.

In Table VIII Panel A, we find that a lower Dismissed Ratio predicts an increase in the market share in the future, suggesting that law firm skill matters and is recognized by the market. In Panel B, we study whether larger Dismissed Ratio, proxy for lower quality of law firms, could predict disappearance of the law firm in the future. We define a Disappear Dummy for law firm j in year $t+K$, which equals to 1 if law firm has zero market share in the year $t+k$ and nonzero market share in the year t ; equals to 0 otherwise. K equals to 3, 4, or 5 years. A larger Dismissed Ratio will increase the likelihood of law firms disappearing from the market after 3, 4, or 5 years.

[Insert Table VIII Here]

vii. CEO turnover

Shareholders exercise their rights through dividends, voting, selling stocks and suing in the event of material misstatement or omission of fact. Lawsuits by shareholders are filed after the breakdown of other mechanisms. According to Shleifer and Vishny (1997), class actions play an important role as a corporate governance mechanism. After the settlement of lawsuits, top management can face adverse consequences as a result of lawsuits. CEO turnover represents a real consequence of the lawsuits on the corporate governance of the defendant firm. If lawsuits result

in CEO turnover after the class period, then it could shed light on the debate on whether lawsuits have merit, and whether lawsuits are pure settlement seeking behavior of law firms. Niehaus and Roth (1999) document larger probability of CEO turnover rates in the defendant firms that settle, compared with a match sample with large stock price falls. They also find that CEO turnover is related to insider sales during the class period and the settlement amount of the lawsuit. Livingston (1996) also documents abnormally high management turnover for firms that are filed lawsuits by the SEC. Strahan (1998) finds that firms more subject to agency problems are more likely to be filed for class actions and CEO turnover increases significantly after the filings for these firms.

In Table IX, we relate our measure of law firm expertise, the Dismissed Ratio, to both CEO turnover and forced turnover in the year of filing event. If lawsuits are of merit and the law firms indeed play a role in achieving meritorious outcomes in lawsuits, then we would expect law firms with smaller dismissed ratio, who are more likely to file for meritorious cases in the past, predict larger likelihood of CEO turnover. In Table IX, we use the Dismissed Ratio to predict the probability of CEO turnover in column (1) and forced CEO turnover in column (2). Consistent with our hypothesis, law firms with smaller Dismissed Ratios are related to larger CEO turnover and forced turnover, after controlling for case characteristics. In addition to supporting the merit of securities class actions, CEO turnover also provides deterrent effects and could foster the release of information. Despite the majority of settlements coming from insurance and indemnification agreements (Martin, Juneja, Foster, and Dunbar, 1999, and Arlen and Carney, 1992), potential CEO turnover suggests that top managers could be disciplined by the corporate governance mechanism by shareholders and in the market for corporate control. Thus, our results not only reinforce prior results on the meritorious nature of securities class action litigation, but also pioneer work in relating law firm expertise to real consequences of lawsuits.

[Insert Table IX Here]

V. Robustness

Though our proxy for law firm expertise, the Dismissed Ratio could predict the lawsuit outcomes well, whether it represents law firm's selection into cases or law firm's ability to shape the outcomes remains unclear. Therefore, we conduct several robustness tests to partially address the selection versus ability issue. First, we split the sample by the case count of each law firm and define a law firm to be large law firm if the number of cases conducted by the law firm is above the 25 percentile of law firms in our sample. We define a law firm to be small law firm if the number of cases conducted by the law firm is below the 75 percentile of law firms in our sample. When calculating the Dismissed Ratio, only large law firms or small law firms are used separately for each case. The cut off points are selected to remove the effect of extremely large or small law firms and to ensure we have sufficient observations for the Dismissed Ratio and regression analysis. We report the main tests of case outcomes and cumulative abnormal returns for large and small law firms separately in Table X. Panel A1 and A2 document large law firms and Panel B1 and B2 document results of small law firms.

Our main results show cases conducted by law firms with lower Dismissed Ratio have a larger probability of settlement, are associated with a more negative market reaction, which holds for large and small firms separately. To the extent that small firms are less likely to select the cases, the qualitatively similar results in the small firm sample suggest the role of law firm ability is a factor in the outcomes.

[Insert Table X Here]

As a further attempt to separate selection from ability, we exclude cases of the same industry sector when calculating the Dismissed Ratio of the focal case. If prior results are driven by systematic selection of cases with certain characteristics by law firms, then it is more likely that law firms select cases in the same industry. When calculating the Dismissed Ratio for case i , we exclude cases in the same industry as case i during the calculation. The industry sector is defined for each case on the Stanford Law School Securitas Class Action Clearinghouse website and includes: Basic Materials, Capital Goods, Conglomerates, Consumer Cyclical, Consumer Non-Cyclical, Energy, Financial, Healthcare, Services, Technology, Transportation, and Utilities. We perform our main regressions using the Dismissed Ratio calculated by excluding the same industry. If law firms are more likely to select cases within the same industry, then the predictability of the Dismissed Ratio calculated using cases in other industries suggest the presence of law firm expertise beyond case selection.

We present the results in Table XI panel A for case outcomes and panel B for cumulative abnormal returns (CAR). The results remain qualitatively the same with our regression results in Table III and IV when all cases are included. In addition, the effect of the Dismissed Ratio on the CARs is slightly stronger when same industry cases are excluded in the calculation of the Dismissed Ratio. Though we cannot fully rule out selection from ability and case selection as not entirely independent from prior records of law firms, the robustness tests on size and industry suggests the presence of law firm ability beyond selection in shaping the litigation outcomes.

[Insert Table XI Here]

As an alternative measure of law firm expertise, we use another measure based on past CAR of cases conducted by all law firms engaging in the focal case. The past 5 year average of CAR is

measured in a similar way to the Dismissed Ratio, except that we use the CAR instead of the percentage of dismissed cases by the law firms.

In Table XII, we use the past CAR measures to predict the CAR of the focal case with three windows. For each case i , we average the prior 5 years of Cumulative Abnormal Returns of the cases conducted by law firms engaged in the case i . For the regression with the dependent variable of CAR $(-1,1)$, the Prior Average CAR is measured using the prior CAR $(-1,1)$. Similarly, for the regressions with the dependent variables of CAR $(-10,1)$ and CAR $(-30,1)$, the Prior Average CAR is measured using the prior CAR $(-10,1)$ and CAR $(-30,1)$, respectively. Other studies that use persistence of CAR to study performance persistence include Bao and Edmans (2011) who study investment bank fixed effects. We find a highly persistent law firm performance from the measure of past average CAR, further confirming law firm fixed effects in the securities class action lawsuits.

[Insert Table XII Here]

VI. Conclusions

Performance persistence and expertise of financial intermediaries or professional advisors are often obscure and difficult to measure. Securities class action lawsuits provide a unique and ideal playground to test the agency problem of law firms. This paper provides novel evidence in interpreting the agency problem and law firm expertise from the Dismissed Ratio. The Dismissed Ratio could predict various dimensions of lawsuit outcomes such as status, CAR and settlement amounts. Particularly, Case Length is a traceable indicator of law firm effort and agency problems, since abundant literature on law firms documented agency problems, such as settling quickly for

small settlements. A longer Case Length suggests that law firms conduct due diligence in investigating the truth and fight for justice.

The contributions of the research are as follows. First, this paper contributes to the law firm fixed effects literature by identifying law firm characteristics that have predictive power for future lawsuit results. Second, this paper contributes to the strand of literature on litigation risk. This paper hinges on components of risk arising from the agency problem of law firms, since they are the group that approach shareholders for initiation of litigation after calculating their expected attorney fees. Last but not least, this paper adds to the debate on whether securities class action is of merit from the perspective of law firm expertise. The paper provides policy implication for the regulation of securities class actions and the attorney fees. Competent law firms might be rewarded higher due to the different source of settlements, instead of the aggregate amounts. The testable measure of law firm competency would be an indicator of law firm agency problems, and partially a determinant of the attorney fee in the settlements. This paper also partially sheds light on the effectiveness of PSLRA after two decades by a direct examination of plaintiff law firms' behaviors.

In addition to agency problem and expertise of plaintiff's law firms, director & officer (D&O) insurance adds another layers of agency problem by insiders which remains an interesting future topic. It remain an interesting topic to explore the interaction effect of agency problem of both plaintiff's law firms and directors with D&O insurance.

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Table I Summary Statistics

This table reports summary statistics of the sample of cases. It documents the number of observations, mean, standard deviation, minimum and maximum values for the variables.

VARIABLES	(1) Number of Observations	(2) Mean	(3) Standard Deviation	(4) Minimum	(5) Maximum
CAR (-1,1)	1,209	-0.0393	0.152	-1.062	1.001
CAR (-10,1)	1,211	-0.101	0.275	-1.308	1.961
CAR (-30,1)	1,211	-0.153	0.393	-1.601	1.916
Status Dummy	1,420	0.648	0.478	0	1
Settlement (US\$millions)	387	98.19	451.4	0.406	7,241
Dismissed Ratio	1,189	0.456	0.140	0	1
Utilization Rate	642	26.51	29.02	0	97.87
Whole Period Length (yrs)	1,417	5.616	2.964	0.255	16.26
Class Period Length (yrs)	1,417	1.233	1.081	0	7.501
Filing Period Length (yrs)	1,417	0.386	0.512	0	4.863
Case Length (yrs)	1,420	4.001	2.577	0.175	11.84
Profit (US\$millions)	1,212	-0.0112	0.267	-3.422	0.427
Cash Holding (US\$millions)	1,212	0.302	0.273	0	0.997
Yearly Return (%)	1,212	-0.0703	0.821	-0.890	2.988
Illiquidity	1,211	0.116	0.201	0.004	2.955
Volatility	1,201	0.0416	0.0243	0.006	0.148
Institution Ownership	1,202	0.495	0.292	0.000	1
GAAPdummy	1,212	0.408	0.492	0	1
IPOdummy	1,212	0.272	0.445	0	1
PensionDummy	1,212	0.259	0.438	0	1
Market Share (%)	384	0.0173	0.0261	0.000384	0.153

Table II Top 20 Law Firm Cases

This table reports summary statistics of law firm case frequencies, percentage of total cases, and average Dismissed Ratio from 1996 to 2013. The top 20 law firms ranked by number of cases are listed.

Law Firm	Number of Cases	Percent (%) of Total Cases	Dismissed Ratio
Milberg Weiss Bershad Hynes & Lerach LLP	1,023	9.92	0.23
Schiffrin & Barroway LLP	612	5.93	0.21
Stull, Stull & Brody	509	4.93	0.19
Wolf Haldenstein Adler Freeman & Herz LLP	506	4.9	0.16
Bernstein Liebhard & Lifshitz, LLP	420	4.07	0.17
Lerach Coughlin Stoia Geller Rudman & Robbins LLP	394	3.82	0.35
Milberg Weiss Bershad & Schulman LLP	357	3.46	0.21
Sirota & Sirota LLP	314	3.04	0.01
Bernstein Litowitz Berger & Grossmann LLP	192	1.86	0.15
Labaton Sucharow & Rudoff LLP	191	1.85	0.29
Berger & Montague PC	171	1.66	0.27
Coughlin Stoia Geller Rudman & Robbins LLP	169	1.64	0.51
Robbins Geller Rudman & Dowd LLP	159	1.54	0.55
Weiss & Yourman	154	1.49	0.36
Cohen Milstein Hausfeld & Toll PLLC	151	1.46	0.29
Glancy Binkow & Goldberg LLP	130	1.26	0.45
Berman DeValerio Pease Tabacco Burt & Pucillo	109	1.06	0.21
Kaplan Fox & Kilsheimer, LLP	107	1.04	0.21
Barrack, Rodos & Bacine	105	1.02	0.33

Table III Predicting Future Litigation Result

This table shows whether our proxy for law firm expertise could predict the probability of settling the case conducted by the law firm. Specifically, we estimate the following probit model:

$$\text{Litigation Status Dummy}_{i,t} = \alpha + \lambda \times \text{Dismissed Ratio}_{i,t-1} + \gamma \times X_{i,t-1} + \varepsilon_{i,t} \quad (1)$$

Where the dependent variable is a dummy variable that equals to 1 if the case being sued in year t is ultimately settled and 0 being dismissed. The main variables of interest are Dismissed Ratio_{i,t-1}, defined as the equal-weighted Dismissed Ratio (number of dismissed case/number of total case) for each law firm j engaging in the lawsuit i from year t-5 to year t-1. In Column (1), we study the effect of Dismissed Ratio on Litigation Status Dummy. In Column (2), we add characteristics of the firm involved in the securities class action lawsuits. The vector of control are defined in the control variables session. We additionally control for year fixed effect in column (3) and (4). In Column (4), we further include the type of the case and industry dummies. Robust standard errors with z-statistics are given in parentheses. ***, ** and * represent significance levels at 1%, 5%, and 10%, respectively.

	(1.1)	(1.2)	(1.3)	(1.4)
		Litigation Status Dummy		
Dismissed Ratio	-0.646*** (-6.29)	-0.520*** (-5.12)	-0.366*** (-3.42)	-0.369*** (-3.52)
Size		-0.025*** (-2.71)	-0.029*** (-3.07)	-0.030*** (-3.35)
Market to Book		-0.003 (-0.71)	-0.009* (-1.81)	-0.007 (-1.34)
Leverage		0.076 (1.06)	0.077 (1.11)	0.100 (1.45)
Profitability		0.009 (0.13)	-0.058 (-0.77)	-0.076 (-1.02)
Cash Holding		-0.068 (-0.98)	-0.067 (-0.96)	-0.101 (-1.41)
Return		-0.048** (-2.56)	-0.033 (-1.54)	-0.024 (-1.13)
Illiquidity		-0.358*** (-3.16)	-0.253** (-2.34)	-0.191* (-1.92)
Volatility		4.061*** (3.86)	1.092 (0.83)	-0.479 (-0.36)
Institutional Ownership		-0.172*** (-2.96)	-0.106* (-1.81)	-0.102* (-1.74)
Industry Dummy				-0.015 (-0.48)
GAAP Dummy				0.056** (1.99)
IPO Dummy				0.259*** (5.05)
Pension Dummy				0.016 (0.48)
Year FE	No	No	Yes	Yes
Observations	1,189	1,169	1,169	1,169

Table IV Cumulative Abnormal Return (CAR) of Litigation

In this table, we present the relation between law firm expertise proxies and CAR of different event windows. The cumulative abnormal return around the filing date is calculated using market model with -300 to -46 days before the filing date as the estimation period.

The dependent variable of column (1) is the 3-day CAR around the filing date, from one day before the filing date to one day after the filing date. In Column (2), the dependent variable is 12-day CAR around the filing date, from ten days before the filing date to one day after the filing date. In Column (3), dependent variable is 32-day CAR around the filing date, from thirty days before the filing date to one day after the filing date.

Main independent variables are the Dismissed Ratio. We control for firm characteristics, year fixed effect, industry dummies, and the type of the case in all columns.

$$CAR(-1,1)_{i,t} = \alpha + \beta \times \text{Dismissed Ratio}_{i,t-1} + \gamma \times X_{i,t-1} + \varepsilon_{i,t} \quad (2.1)$$

$$CAR(-10,1)_{i,t} = \alpha + \beta \times \text{Dismissed Ratio}_{i,t-1} + \gamma \times X_{i,t-1} + \varepsilon_{i,t} \quad (2.2)$$

$$CAR(-30,1)_{i,t} = \alpha + \beta \times \text{Dismissed Ratio}_{i,t-1} + \gamma \times X_{i,t-1} + \varepsilon_{i,t} \quad (2.3)$$

Robust standard errors with t-statistics are given in parentheses. ***, ** and * represent significance levels at 1%, 5%, and 10%, respectively.

	(2.1) CAR (-1,1)	(2.2) CAR (-10,1)	(2.3) CAR (-30,1)
Dismissed Ratio	0.090** (2.20)	0.116* (1.76)	0.230*** (2.68)
Size	0.002 (0.78)	0.008 (1.60)	0.020*** (2.95)
Market to Book	-0.002* (-1.68)	-0.005 (-1.62)	-0.007 (-1.47)
Leverage	-0.008 (-0.40)	-0.038 (-0.90)	-0.067 (-1.06)
Profitability	-0.007 (-0.29)	0.014 (0.30)	0.051 (0.75)
Cash Holding	0.011 (0.47)	-0.071* (-1.66)	-0.038 (-0.67)
Return	-0.013 (-1.42)	-0.035** (-2.15)	-0.071*** (-3.55)
Illiquidity	-0.052 (-1.37)	0.022 (0.18)	0.076 (0.53)
Volatility	0.338 (0.85)	1.034 (1.35)	2.408** (2.03)
Institutional Ownership	0.004 (0.21)	0.010 (0.28)	0.050 (1.12)
Industry Dummy	0.005 (0.54)	0.008 (0.48)	0.029 (1.23)
GAAP Dummy	-0.011 (-1.18)	-0.026 (-1.44)	-0.024 (-0.92)
IPO Dummy	0.006 (0.42)	0.093*** (3.38)	0.130*** (2.77)
Pension Dummy	0.007 (0.74)	0.007 (0.39)	0.025 (1.01)
Constant	-0.105*** (-2.66)	-0.241*** (-3.21)	-0.533*** (-5.29)
Year FE	Yes	Yes	Yes
Observations	1,166	1,168	1,168
R-squared	0.033	0.071	0.101
r2_a	0.011	0.050	0.080

Table V Settlement Amount

In this table, we document the relation between the settlement amount and the Dismissed Ratio. The dependent variable in both columns are settlement amount, scaled by the total market capitalization of the firm one year prior to the beginning of the securities class litigation. The first column contains all available settlement dollar data. The second column excludes zero settlement dollar data.

$$Settlement_Scaled_{i,t} = \alpha + \beta \times Dismissed\ Ratio_{i,t-1} + \gamma \times X_{i,t-1} + \varepsilon_{i,t} \quad (3)$$

We control for firm characteristics, year fixed effect, industry dummies, and the type of the case in all columns.

Robust standard errors with t-statistics are given in parentheses. ***, ** and * represent significance levels at 1%, 5%, and 10%, respectively.

	(3.1) Scaled Settlement Dollars	(3.2) Scaled Settlement Dollars Exclude 0 Settlement
Dismissed Ratio	-68.640** (-2.54)	-91.890** (-2.40)
Size	-2.874** (-2.06)	-4.032* (-1.86)
Market to Book	-1.843 (-1.13)	-2.529 (-1.19)
Leverage	9.535 (0.78)	22.56 (0.94)
Profitability	44.900* (1.85)	66.650** (2.16)
Cash Holding	14.700 (0.82)	19.940 (0.89)
Return	1.472 (0.31)	2.216 (0.36)
Illiquidity	29.350 (0.75)	25.450 (0.56)
Volatility	996.900*** (2.68)	1,126.000** (2.56)
Institutional Ownership	-27.910* (-1.72)	-43.610* (-1.91)
Industry Dummy	-9.977 (-1.35)	-10.930 (-1.11)
GAAP Dummy	2.647 (0.49)	0.640 (0.07)
IPO Dummy	18.220 (0.74)	17.410 (0.60)
Pension Dummy	-1.711 (-0.29)	-4.618 (-0.52)
Constant	62.860** (2.51)	94.510** (2.35)
Year FE	Yes	Yes
Observations	598	373
R-squared	0.154	0.182
r2_a	0.115	0.123

Table VI Utilization Rate around Filing Date

In this table, utilization rate of the sued firm is studied. In Column (1), dependent variable is the utilization rate one week prior to the filing date in year t. In Column (2), dependent variable is the utilization rate of the week of filing date in year t. In Column (3), dependent variable is the utilization rate one week after the filing date in year t.

$$Utilization\ Rate_{i,t} = \alpha + \beta \times Dismissed\ Ratio_{i,t-1} + \gamma \times X_{i,t-1} + \varepsilon_{i,t} \quad (4.1)$$

We control for firm characteristics, year fixed effect, industry dummies, and the type of the case in all columns.

Robust standard errors with t-statistics are provided in parentheses. ***, ** and * represent significance levels at 1%, 5%, and 10%, respectively.

	(4.1) Utilization Rate Prior 1 Week	(4.1) Utilization Rate Current Week	(4.1) Utilization Rate Post 1 week
Dismissed Ratio	-15.760** (-1.99)	-5.304 (-0.71)	-3.647 (-0.45)
Book Size	-3.053*** (-5.18)	-3.750*** (-6.22)	-3.529*** (-5.49)
Market to Book	1.348 (1.54)	1.617** (2.09)	1.273 (1.62)
Leverage	8.172* (1.66)	9.143* (1.90)	4.310 (0.83)
Profitability	-10.490 (-1.38)	-18.020*** (-2.82)	-14.320** (-1.99)
Cash Holding	-8.304 (-1.05)	-14.390** (-2.17)	-12.060* (-1.66)
Return	2.894 (1.29)	1.891 (1.04)	0.479 (0.25)
Illiquidity	-29.580*** (-2.59)	-42.760*** (-3.35)	-49.790*** (-4.98)
Volatility	361.300*** (2.67)	190.100 (1.39)	321.900** (2.20)
Institutional Ownership	-6.248 (-1.29)	-12.630*** (-2.71)	-12.860** (-2.50)
Status Dummy	2.636 (1.17)	0.809 (0.37)	0.668 (0.30)
Industry Dummy	-6.622** (-2.52)	-5.958** (-2.32)	-5.559** (-2.08)
GAAP Dummy	3.660 (1.47)	4.120* (1.70)	6.148** (2.36)
IPO Dummy	0.029 (0.01)	-4.008 (-1.03)	4.967 (1.00)
Pension Dummy	-5.906** (-2.32)	-4.543* (-1.84)	-3.922 (-1.55)
Constant	51.910*** (5.48)	64.580*** (6.98)	58.210*** (6.10)
Year FE	Yes	Yes	Yes
Observations	539	615	554
R-squared	0.289	0.266	0.276
r2_a	0.253	0.234	0.240

Table VII Length of the Lawsuit

This table tests whether law firm skill measure is a predictor of case length of the lawsuit. Case length is number of days from filing date to status date, scaled by 365 days.

The regression is as follows:

$$\text{Case Length}_{i,t} = \alpha + \beta \times \text{Dismissed Ratio}_{i,t-1} + \gamma \times X_{i,t-1} + \varepsilon_{i,t} \quad (5)$$

In Panel A, a Status Dummy is added to control the status of the case, either settled or dismissed. In Column (1), we include Dismissed Ratio and Status Dummy only. In Column (2), we add year fixed effect. In Column (3), we control for firm characteristics, year fixed effect, industry dummies, and the type of the case. In Panel B, settled and dismissed cases are studied separately. We control for firm characteristics, year fixed effect, industry dummies, and the type of the case in all columns. Robust standard errors with t-statistics are provided in parentheses. ***, ** and * represent significance levels at 1%, 5%, and 10%, respectively.

Panel A Case Length with Status Dummy

	(5.1) Case Length	(5.2) Case Length	(5.3) Case Length
Dismissed Ratio	-2.993*** (-6.10)	-2.634*** (-5.79)	-1.606*** (-4.21)
Status Dummy	2.598*** (18.15)	1.523*** (12.16)	1.213*** (11.37)
Size			0.300*** (8.89)
Market to Book			0.048*** (3.67)
Leverage			0.015 (0.07)
Profitability			0.285 (1.39)
Cash Holding			-0.101 (-0.56)
Return			-0.131** (-2.29)
Illiquidity			-0.312 (-1.10)
Volatility			37.110*** (11.28)
Institutional Ownership			-0.481** (-2.52)
Industry Dummy			0.037 (0.44)
GAAP Dummy			-0.054 (-0.58)
IPO Dummy			1.263*** (6.77)
Pension Dummy			-0.131 (-1.16)
Constant	3.777*** (14.05)	4.349*** (16.81)	0.439 (1.08)
Year FE	No	Yes	Yes
Observations	1,189	1,189	1,169
R-squared	0.265	0.616	0.746
r2_a	0.263	0.612	0.740

Panel B Subsample Analysis for Case Length

	(5.3) Case Length Settled Subsample	(5.3) Case Length Dismissed Subsample
Dismissed Ratio	-1.886*** (-3.74)	-0.754 (-1.43)
Size	0.300*** (7.26)	0.295*** (4.81)
Market to Book	0.0452*** (3.34)	0.0635 (1.25)
Leverage	0.198 (0.73)	-0.535 (-1.53)
Profitability	0.166 (0.60)	-0.039 (-0.14)
Cash Holding	0.183 (0.94)	-0.846** (-2.50)
Return	-0.164** (-2.04)	-0.004 (-0.06)
Illiquidity	-0.609 (-1.39)	-0.024 (-0.07)
Volatility	33.610*** (8.42)	35.890*** (5.83)
Institutional Ownership	-0.480** (-2.08)	-0.483 (-1.57)
Industry Dummy	0.081 (0.78)	0.009 (0.07)
GAAP Dummy	-0.028 (-0.24)	-0.114 (-0.76)
IPO Dummy	1.367*** (5.90)	-0.042 (-0.15)
Pension Dummy	-0.101 (-0.71)	-0.080 (-0.48)
Constant	1.972*** (3.88)	-0.034 (-0.05)
Year FE	Yes	Yes
Observations	801	368
R-squared	0.753	0.308
r2_a	0.745	0.255

Table VIII Predicting Market Share

In this table, we examine whether law firm expertise has predictive power for market share of law firms in Panel A and the probability of law firms' disappearing from the market in Panel B. The main independent variable is the Dismissed Ratio at law firm level, controlling for the market share of law firm j in the past year. *Dismissed Ratio* $_{j,t-1}$, defined as the equal-weighted Dismissed Ratio (number of dismissed case/number of total case) for law firm j from year $t-5$ to year $t-1$.

In Panel A, dependent variable is the market share of law firm j in year t . We run the regression as follows:

$$\text{Market Share}_{j,t} = \alpha + \beta \times \text{Dismissed Ratio}_{j,t-1} + \gamma \times \text{Market Share}_{j,t-1} + \varepsilon_{j,t} \quad (6.1)$$

In Panel B, we define *Disappear Dummy* $_{j,t+k}$, which equals to 1 if law firm has zero market share in the year $t+k$ and nonzero market share in the year t ; equals to 0 otherwise. K equals to 3, 4, or 5 years.

We run probit regression as follows:

$$\text{Disappear Dummy}_{j,t+k} = \alpha + \beta \times \text{Dismissed Ratio}_{j,t-1} + \gamma \times \text{Market Share}_{j,t-1} + \varepsilon_{j,t} \quad (6.2)$$

We control for lagged market share in both panels, and year fixed effect in panel B. Errors are clustered at the law firm level in all specifications. Robust standard errors with t-statistics are given in parentheses. ***, ** and * represent significance levels at 1%, 5%, and 10%, respectively.

Panel A Dismissed Ratio and Market Share

	(6.1) Market Share
Market Share Lagged	0.459*** (8.55)
Dismissed Ratio	-0.008* (-1.92)
Constant	0.012*** (4.92)
Observations	255
R-squared	0.541
r2_a	0.516

Panel B Dismissed Ratio and Probability of Disappearance

	(6.2) Disappear Dummy After 3 years	(6.2) Disappear Dummy After 4 years	(6.2) Disappear Dummy After 5 years
Dismissed Ratio	0.410** (2.26)	0.725*** (3.40)	0.729*** (3.11)
Market Share Lagged	-3.167 (-1.62)	-1.758 (-0.93)	-2.460 (-1.21)
Year FE	Yes	Yes	Yes
Cluster	Firm	Firm	Firm
Observations	319	303	271

Table IX Effect on CEO Turnover

We relate CEO turnover and forced turnover to the year of the case's filing date, and examine the effect of the prior Dismissed Ratio on the probability of turnover or forced turnover. We study the probability of turnover in Column (1) and forced turnover in Column (2). We control for firm characteristics, year fixed effect, industry dummies, and the type of the case in all columns. Robust standard errors with t-statistics are given in parentheses. ***, ** and * represent significance levels at 1%, 5%, and 10%, respectively.

	(1) Turnover	(2) Forced Turnover
Dismissed Ratio	-0.068** (-2.05)	-0.047* (-1.75)
Size	0.009*** (2.93)	0.007*** (2.99)
Market to Book	-0.001 (-0.70)	-0.001 (-0.66)
Leverage	0.027 (1.39)	0.030** (1.96)
Profitability	-0.030 (-0.97)	-0.020 (-0.82)
Cash Holding	-0.036 (-1.18)	-0.011 (-0.60)
Return	0.001 (0.18)	0.004 (0.71)
Illiquidity	-0.106 (-1.01)	-0.0525 (-0.66)
Volatility	0.181 (0.49)	0.307 (1.01)
Institutional Ownership	0.035 (1.60)	0.046** (2.47)
Industry Dummy	0.007 (0.63)	-0.001 (-0.02)
GAAP Dummy	0.018* (1.81)	0.015* (1.82)
IPO Dummy	-0.005 (-0.32)	-0.005 (-0.37)
Pension Dummy	0.020 (1.60)	0.024** (2.23)
Observations	1,169	1,169

Table X Subsample Analysis: Law Firm Size

We conduct subsample analysis for main regressions in Table III and Table IV. We split the sample by the case count of each law firm and define a law firm to be large law firm, if the number of cases conducted by the law firm is above the 25 percentile of law firms in our sample. We define a law firm to be small law firm, if the number of cases conducted by the law firm is below the 75 percentile of law firms in our sample. When calculating the Dismissed Ratio, only large law firms or small law firms are used separately for each case. In Panel A1 and Panel A2, we calculate the Dismissed Ratio for large law firms and regress the status dummy and the CAR on the Dismissed Ratio for large law firms. In Panel B1 and Panel B2, we calculate the Dismissed Ratio for small law firms and regress the status dummy and CAR on the Dismissed Ratio for small law firms. Robust standard errors with t-statistics are given in parentheses. ***, ** and * represent significance levels at 1%, 5%, and 10%, respectively.

Panel A1 Large Law Firm and Case Outcome

	(1) Status Dummy	(2) Status Dummy	(3) Status Dummy	(4) Status Dummy
Dismissed Ratio	-0.637*** (-5.77)	-0.511*** (-4.68)	-0.400*** (-3.50)	-0.411*** (-3.70)
Size		-0.022** (-2.25)	-0.023** (-2.36)	-0.025*** (-2.61)
Market to Book		-0.004 (-1.00)	-0.009* (-1.81)	-0.007 (-1.45)
Leverage		0.108 (1.43)	0.103 (1.34)	0.117 (1.58)
Profitability		0.038 (0.47)	-0.026 (-0.33)	-0.051 (-0.65)
Cash Holding		-0.023 (-0.32)	-0.033 (-0.45)	-0.083 (-1.12)
Return		-0.041** (-2.10)	-0.024 (-1.06)	-0.012 (-0.56)
Illiquidity		-0.316*** (-2.77)	-0.224* (-1.95)	-0.153 (-1.47)
Volatility		4.195*** (3.65)	1.954 (1.35)	0.069 (0.05)
Institutional Ownership		-0.194*** (-3.13)	-0.130** (-2.08)	-0.120* (-1.94)
Industry Dummy				-0.017 (-0.53)
GAAP Dummy				0.049 (1.60)
IPO Dummy				0.289*** (5.44)
Pension Dummy				0.009 (0.26)
Year FE	No	No	Yes	Yes
Observations	1,040	1,023	1,023	1,023

Panel A2 Large Law Firm and Cumulative Abnormal Return

	(1) CAR (-1,1)	(2) CAR (-10,1)	(3) CAR (-30,1)
Dismissed Ratio	0.097** (2.23)	0.132* (1.83)	0.230** (2.44)
Size	0.002 (0.71)	0.006 (1.23)	0.019*** (2.61)
Market to Book	-0.002 (-1.17)	-0.002 (-0.86)	-0.006 (-1.16)
Leverage	-0.006 (-0.26)	-0.018 (-0.40)	-0.056 (-0.77)
Profitability	-0.008 (-0.31)	0.001 (0.01)	0.035 (0.47)
Cash Holding	0.010 (0.40)	-0.073 (-1.61)	-0.050 (-0.81)
Return	-0.016* (-1.70)	-0.044** (-2.51)	-0.083*** (-3.87)
Illiquidity	-0.046 (-1.12)	0.063 (0.46)	0.130 (0.87)
Volatility	0.289 (0.74)	0.706 (0.85)	1.905 (1.46)
Institutional Ownership	0.007 (0.32)	0.017 (0.42)	0.055 (1.11)
Industry Dummy	0.003 (0.28)	0.001 (0.09)	0.023 (0.87)
GAAP Dummy	-0.008 (-0.82)	-0.031 (-1.60)	-0.034 (-1.20)
IPO Dummy	0.005 (0.32)	0.098*** (3.30)	0.163*** (3.21)
Pension Dummy	0.006 (0.54)	0.010 (0.49)	0.029 (1.07)
Constant	-0.111*** (-2.61)	-0.239*** (-2.95)	-0.522*** (-4.74)
Year FE	Yes	Yes	Yes
Observations	1,021	1,023	1,020
R-squared	0.036	0.072	0.105
r2_a	0.010	0.048	0.081

Panel B1 Small Law Firm and Case Outcome

	(1) Status Dummy	(2) Status Dummy	(3) Status Dummy	(4) Status Dummy
Dismissed Ratio	-0.697*** (-7.11)	-0.550*** (-5.33)	-0.455*** (-4.07)	-0.441*** (-4.02)
Size		-0.021** (-1.99)	-0.020* (-1.89)	-0.022** (-2.08)
Market to Book		-0.005 (-0.86)	-0.009 (-1.45)	-0.008 (-1.17)
Leverage		0.082 (0.98)	0.068 (0.80)	0.088 (1.07)
Profitability		0.001 (0.00)	-0.052 (-0.59)	-0.079 (-0.89)
Cash Holding		-0.115 (-1.41)	-0.128 (-1.54)	-0.169** (-1.97)
Return		-0.023 (-1.03)	-0.006 (-0.26)	0.002 (0.09)
Illiquidity		-0.277** (-2.27)	-0.208* (-1.65)	-0.162 (-1.37)
Volatility		4.375*** (3.63)	3.125** (2.03)	1.598 (1.06)
Institutional Ownership		-0.159** (-2.32)	-0.112 (-1.60)	-0.098 (-1.41)
Industry Dummy				-0.052 (-1.43)
GAAP Dummy				0.060* (1.72)
IPO Dummy				0.316*** (5.19)
Pension Dummy				0.007 (0.19)
Year FE	No	No	Yes	Yes
Observations	870	855	855	855

Panel B2 Small Law Firm and Cumulative Abnormal Return

	(1) CAR (-1,1)	(2) CAR (-10,1)	(3) CAR (-30,1)
Dismissed Ratio	0.087** (2.17)	0.143** (2.13)	0.177** (2.01)
Size	0.002 (0.63)	0.007 (1.32)	0.019** (2.55)
Market to Book	-0.001 (-0.50)	0.001 (0.04)	0.002 (0.44)
Leverage	0.008 (0.31)	-0.038 (-0.73)	-0.066 (-1.04)
Profitability	-0.017 (-0.55)	-0.001 (-0.02)	0.048 (0.61)
Cash Holding	0.008 (0.27)	-0.087* (-1.66)	-0.065 (-0.98)
Return	-0.017 (-1.55)	-0.044** (-2.33)	-0.095*** (-4.13)
Illiquidity	-0.049 (-1.05)	0.091 (0.58)	0.146 (0.87)
Volatility	0.075 (0.16)	0.640 (0.66)	1.491 (1.24)
Institutional Ownership	0.012 (0.47)	0.041 (0.94)	0.069 (1.30)
Industry Dummy	0.001 (0.13)	-0.008 (-0.38)	0.016 (0.60)
GAAP Dummy	-0.015 (-1.27)	-0.040* (-1.84)	-0.026 (-0.91)
IPO Dummy	0.010 (0.54)	0.088*** (2.73)	0.120** (2.18)
Pension Dummy	0.003 (0.27)	-0.005 (-0.26)	-0.001 (-0.03)
Constant	-0.100** (-2.17)	-0.246*** (-2.78)	-0.475*** (-4.54)
Year FE	Yes	Yes	Yes
Observations	851	852	855
R-squared	0.034	0.064	0.096
r2_a	0.003	0.034	0.067

Table XI Law Firm Selection versus Expertise

We perform robustness test regarding law firm selection issues. If prior results are driven by systematic selection of cases with certain characteristics by law firms, then it is more likely that law firms select cases in the same industry. Therefore, we create a Dismissed Ratio excluding cases in the same industry for the focal case. When calculating the Dismissed Ratio for case *i*, we exclude cases in the same industry as case *i* during the calculation. Panel A reports main analysis as in Table III and Panel B reports analysis as in Table IV, except that the Dismissed Ratio is calculated after excluding same industry cases. Robust standard errors with t-statistics are given in parentheses. ***, ** and * represent significance levels at 1%, 5%, and 10%, respectively.

Panel A Case Outcome

	(1) Status Dummy	(2) Status Dummy	(3) Status Dummy	(4) Status Dummy
Dismissed Ratio	-0.650*** (-6.00)	-0.503*** (-4.74)	-0.373*** (-3.32)	-0.393*** (-3.59)
Size		-0.022** (-2.23)	-0.025** (-2.51)	-0.027*** (-2.76)
Market to Book		-0.003 (-0.59)	-0.008 (-1.52)	-0.006 (-1.05)
Leverage		0.096 (1.29)	0.097 (1.27)	0.113 (1.52)
Profitability		0.011 (0.13)	-0.059 (-0.72)	-0.081 (-1.01)
Cash Holding		-0.057 (-0.78)	-0.055 (-0.75)	-0.100 (-1.35)
Return		-0.042** (-2.08)	-0.026 (-1.16)	-0.016 (-0.75)
Illiquidity		-0.306*** (-2.71)	-0.213* (-1.87)	-0.146 (-1.40)
Volatility		4.106*** (3.56)	1.467 (1.01)	-0.364 (-0.25)
Institutional Ownership		-0.227*** (-3.59)	-0.165*** (-2.59)	-0.155** (-2.45)
Industry Dummy				-0.025 (-0.75)
GAAP Dummy				0.053* (1.68)
IPO Dummy				0.292*** (5.48)
Pension Dummy				0.011 (0.32)
Year FE	No	No	Yes	Yes
Observations	1,029	1,011	1,011	1,011

Panel B Cumulative Abnormal Return

	(1) CAR (-1,1)	(2) CAR (-10,1)	(3) CAR (-30,1)
Dismissed Ratio	0.104** (2.38)	0.170** (2.37)	0.250*** (2.67)
Size	0.003 (1.13)	0.009* (1.72)	0.020*** (2.71)
Market to Book	-0.002 (-1.18)	-0.001 (-0.59)	-0.006 (-1.24)
Leverage	-0.009 (-0.38)	-0.038 (-0.81)	-0.058 (-0.78)
Profitability	-0.006 (-0.22)	-0.004 (-0.09)	0.057 (0.77)
Cash Holding	0.013 (0.55)	-0.081* (-1.81)	-0.040 (-0.65)
Return	-0.012 (-1.31)	-0.038** (-2.17)	-0.084*** (-3.88)
Illiquidity	-0.025 (-0.63)	0.089 (0.65)	0.125 (0.83)
Volatility	0.299 (0.78)	0.857 (1.04)	1.906 (1.63)
Institutional Ownership	0.012 (0.54)	0.013 (0.34)	0.024 (0.47)
Industry Dummy	0.002 (0.19)	-0.001 (-0.05)	0.023 (0.92)
GAAP Dummy	-0.009 (-0.87)	-0.031 (-1.58)	-0.035 (-1.25)
IPO Dummy	0.005 (0.32)	0.104*** (3.52)	0.155*** (3.02)
Pension Dummy	0.007 (0.62)	0.010 (0.53)	0.020 (0.78)
Constant	-0.129*** (-3.03)	-0.283*** (-3.41)	-0.521*** (-4.92)
Year FE	Yes	Yes	Yes
Observations	1,009	1,011	1,008
R-squared	0.034	0.079	0.112
r2_a	0.008	0.055	0.088

Table XII Alternative Measure of Law Firm Expertise: Persistence of CAR

In this table, we provide another measure of law firm expertise as a robustness test and in a similar manner as the investment bank fixed effect in Bao and Edmans (2011). For each case *i*, we average the prior 5 years of Cumulative Abnormal Returns of the cases conducted by law firms engaged in the case *i*. If the dependent variable is CAR (-1,1), then prior average CAR is the prior 5 years of average CAR (-1,1). If the dependent variable is CAR (-10,1) or CAR (-30,1), then the prior average CAR is measured based on (-10,1) or (-30,1) correspondingly. We study persistence of CAR (-1,1) in Column (1), CAR (-10,1) in Column (2), and CAR (-30,1) in Column (3). We control for firm characteristics, year fixed effect, industry dummies, and the type of the case in all columns. Robust standard errors with t-statistics are given in parentheses. ***, ** and * represent significance levels at 1%, 5%, and 10%, respectively.

	(1) CAR(-1,1)	(2) CAR(-10,1)	(3) CAR(-30,1)
Prior Average CAR	1.224*** (9.31)	1.203*** (15.64)	1.118*** (13.61)
Size	0.001 (0.44)	0.003 (0.79)	0.012** (2.01)
Market to Book	-0.002 (-1.54)	-0.003 (-1.09)	-0.007 (-1.57)
Leverage	0.006 (0.33)	0.019 (0.57)	-0.037 (-0.61)
Profitability	0.008 (0.46)	0.022 (0.63)	0.140** (2.19)
Cash Holding	-0.001 (-0.09)	-0.063* (-1.73)	-0.002 (-0.04)
Return	-0.007 (-1.02)	-0.028** (-2.08)	-0.059*** (-3.38)
Illiquidity	-0.054 (-1.64)	-0.006 (-0.05)	0.047 (0.33)
Volatility	0.308 (0.88)	0.663 (0.99)	2.179* (1.95)
Institutional Ownership	-0.006 (-0.34)	-0.016 (-0.50)	0.012 (0.30)
Industry Dummy	0.010 (1.22)	0.022 (1.44)	0.021 (0.95)
GAAP Dummy	-0.001 (-0.05)	-0.006 (-0.38)	-0.006 (-0.28)
IPO Dummy	-0.011 (-0.87)	0.055** (2.19)	0.073 (1.63)
Pension Dummy	-0.009 (-0.96)	-0.005 (-0.33)	-0.001 (-0.07)
Constant	0.005 (0.19)	-0.020 (-0.36)	-0.175* (-1.96)
Year FE	Yes	Yes	Yes
Observations	1,188	1,190	1,190
R-squared	0.242	0.236	0.217
r2_a	0.225	0.219	0.200