ESSAYS IN CORPORATE FINANCE

by

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A DISSERTATION

Submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy
in the Department of Economics, Finance, and Legal Studies
in the Graduate School of
The University of Alabama

TUSCALOOSA, ALABAMA

2021

ABSTRACT

Despite the importance of understanding the interaction between financial markets and the real economy, the indirect effects of secondary markets on corporate outcomes, however, are not well understood. This dissertation comprises three essays that aim to shed some light on this issue by exploring the unintended consequences for firms in response to trading activities in equity and derivative markets.

Uninformative stock price fluctuations induced by volatile mutual fund flows may inflict a hidden financial cost on firms. The first essay proposes a measure of stock-level passive equity mutual fund flow-induced volatility pressure and find it to positively affect bond yield spread at issuance through higher perceived risks revealed by increased equity volatility. Although flow-induced volatility is costly to the borrowing firm, it has no significant association with future firm fundamental risk, in contrast to equity volatility. This study empirically reveals a dark side of passive investing.

The second essay examines the effects of options trading activities on corporate liquidity management. Based on a large sample of U.S. non-financial firms, it documents a positive relationship between equity options trading intensity and corporate cash holdings. Along with the instrumental variable approach, the CBOE's Penny Pilot Program as an exogenous shock and the extensive margin analysis using option listings corroborate a causality interpretation of the baseline results. The relationship is mainly driven by firms where financial distress risk is high and debt-financed investments are constrained by liquidity issues. Overall, these results suggest a precautionary saving motive due to active options markets that provide risk-shifting incentives to firms.

During 2005-2007, SEC conducted a pilot program that relaxed short-selling restrictions. Using a difference-in-differences methodology and a hand-collected dataset of derivatives usage from a sample of U.S. oil and gas producing firms, the third essay finds a relative increase in hedging intensity among pilot firms compared to non-pilot firms during the pilot program period. This effect is stronger when firms face higher financial distress risk and when managers' incentives are more closely tied to firm value. These results indicate that managers are incentivized to smooth operating income due to concerns about a rise in the cost of financial distress under short-selling pressures.

DEDICATION

This dissertation is dedicated to the LORD and my parents.

ACKNOWLEDGMENTS

I would like to thank my dissertation committee for their help and support as I completed this dissertation. I am truly indebted to Douglas O. Cook and H. Alan Tidwell, who are my invaluable mentors, co-authors, as well as friends. I also gratefully acknowledge the financial support from the Culverhouse College of Business and Graduate School at the University of Alabama. My ultimate thanks go to my beloved parents, Xianjun Wen and Huirong Luo. Without their unlimited love and support, my new journey towards freedom and faith starting from six years ago would not have been possible.

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CHAPTER 1

INTRODUCTION

One of the key research agendas in financial economics is to understand the interaction between financial markets and the real economy (Cochrane, 2005). As a crucial foundation of the real economy, firms are at the center of debate with regard to the real effects of financial markets. Therefore, it is important to investigate corporate level responses to financial market activities. Although primary financial markets directly channel resources from investors to companies, the *indirect* effects of financial markets on firms remain under-explored despite notably active secondary financial markets (Bond et al., 2012). This dissertation explores how equity and derivative trading activities influence corporate outcomes. Each of the three essays in this dissertation centers on the effects of various secondary financial market activities on corporate financing, cash policies and risk management, respectively.

An unintended consequence of the rise and popularity of passively managed mutual funds is increased equity volatility induced by uninformative trading activities resulting from passive fund flows, which are largely driven by liquidity demands. Since equity volatility serves as a timely indicator of firm risk, the first essay (Chapter 2) addresses the question of whether excessive volatility induced by passive mutual fund flows affects the cost of debt financing. Despite the exponential growth of markets for equity options in the United States over the last several decades, it is unclear how corporate financial policies respond to the potential side effects of active trading in these options. The second essay (Chapter 3) addresses this issue, focusing on corporate cash savings decisions. The last essay (Chapter 4) analyzes the market for short sales. We use a quasi-natural experiment to identify a causal impact of short-selling constraints on corporate hedging activities.

In Chapter 2, we construct a measure of concurrent passive mutual fund flow volatility pressure at the stock level. Then, we utilize an instrumental variable approach and show that excessive equity volatility induced by the pressure of fund flow variations is positively associated with the cost of debt at issuance, although there is no clear evidence that the flow-induced volatility contains any relevant information about future fundamental risk. The effect exists for both the systematic and idiosyncratic parts of equity volatility, with the former being relatively stronger. Although the economic magnitude at margin seems to be small in terms of percentage points, the monetized cost inflicted by fund flow-induced volatility is substantial due to the sheer size of the corporate bond market in the United States.

In theory, the directional effect of an active option market on corporate cash holdings is ambiguous. However, the evidence presented in Chapter 3 indicates that increased option trading activities tend to lead to higher cash reserves in the underlying firm. This result holds after conducting a host of placebo and robustness tests. After implementing multiple identification strategies that leverage instrumental variables, utilize the COBE's Penny Pilot Program and employ initial option listings to mitigate endogeneity concerns, all the evidence favors a causal interpretation. Complementary analysis points to a possible channel where risk-shifting incentives provided by options play a central role.

Using a sample of hand-collected data on derivative usage among U.S. oil and gas companies and the SEC's Regulation SHO pilot program, Chapter 4 documents that an exogenous relaxation of short-selling constraints results in an increase of corporate hedging intensity. Cross-sectional evidence suggests that the effect is concentrated in firms where the cost of financial distress is relatively higher and the managerial incentives are more tightly associated with firm value. Some placebo tests indicate that a reduction of short-selling pressures is crucial to explaining the incentives underlying how corporate risk management responds to the shock.

This dissertation makes several distinct contributions to the corporate finance literature. Although previous studies document the "first moment" price effects of fund flows on corporate policies (Edmans et al., 2012; Lou and Wang, 2018), the analysis in Chapter 2 emphasizes the "second moment" price effects that relate to a perceived risk channel. The results in Chapter 2 reveal a downside of passively managed mutual funds, which may cause excessive volatility and thus inefficiency in debt financing. Corporate liquidity management is one of the most important financial policies and a vast literature is devoted to understanding the determinants of cash holdings (Bates et al., 2009). Chapter 3 is among the first to relate equity option markets to corporate savings behavior. Lastly, since little is known about how secondary financial market frictions matter for corporate hedging activities, Chapter 4 serves as a first step toward filling this void. The empirical findings of Chapter 4 suggests a close relationship between short-selling and corporate risk management. This encourages the advancement of future theoretical research to build models that incorporate secondary financial market frictions into corporate hedging decisions.

CHAPTER 2

THE FINANCIAL COST OF FUND FLOW-INDUCED VOLATILITY

2.1 Introduction

Although stock prices can quickly aggregate relevant information about a firm, finance literature has noted that stock prices may not necessarily reflect fundamentals. This can be due to the presence of uninformative ("noise") trades that reflect either liquidity motives (Grossman and Stiglitz, 1980; Diamond and Verrecchia, 1981; Biais and Hillion, 1994) or actions of irrational agents (Black, 1986; De Long et al., 1990). As a result, uninformative trades not related to firm-specific fundamentals may overly increase the volatility of stock prices. Does this potential "excessive" volatility affect resource allocations in the real economy ? Excessive volatility due to financial market inefficiency may have an unintended impact on economic decisions, leading to allocative inefficiency in real terms.

We study this issue using corporate debt financing as a laboratory. Examining the driving forces behind the cost of a bond is important given the weighty presence of bonds in corporate capital structure in recent years.[1] In a recent paper, Rauh and Sufi (2010) document that for a random sample of U.S. nonfinancial corporations bond debt accounts for about 20% of total assets. As such, the importance of bonds in firm capital raising decisions demands a deeper understanding of the factors that affect the issuance cost of bonds. We focus on bond issues rather than loan financing as we are most interested in

[1]The 2018 SIFMA reports show that, during 2015-2017 U.S. corporate bond issuance totaled $4672.6 billion, which dwarfs the merely $677 billion worth of equity issuance during the same time period.

a perceived risk channel, and prior studies have shown that bond investors incorporate risk into yield in a greater way than do bank lending officers (Bharath et al., 2008; Hasan et al., 2014).

Motivated primarily by Greenwood and Thesmar (2011) and Edmans et al. (2012), we propose as an instrument of uninformative trading volatility pressure the absolute value of passive fund flow-induced trading at the stock level. We choose this empirical instrument for two reasons. First, passive equity mutual funds are a driving force behind liquidity-motivated or uninformed stock market trading activities (Chordia et al., 2011), but their trading is not likely to be correlated with firm-specific fundamentals[2]. For robustness and to more effectively identify uninformative trading pressures, we also employ as an instrument fund flows adjusted for fund performance. Second, to further mitigate endogeneity concerns, we use the *hypothetical* trading pressure implied by flow volatility at fund level that proportionally affects all portfolio firms[3].

We posit that volatile passive mutual fund flows may increase perceived risks by raising equity volatility, which creditors consider as a useful signal about future firm risk. However, creditors have difficulty identifying the informative part in the signal, implying that the at-issue bond yield spread might be higher for firms with higher flow-induced volatility. We test this empirically by showing first that fund flow-induced volatility pressures can explain a part of equity volatility. Next, we follow Edmans et al. (2012) and treat our measures of flow-induced volatility pressure as instrumental variables (IV) for our proxy of equity volatility. Using two-stage least squares (2SLS) regressions on a sample of 5,324 public bond issues by 1,145 US firms during the period 1993-2013, we are able to identify a positive effect of the excessive equity volatility driven by volatile passive mutual fund flows on bond spreads at issuance.

[2]It is very unlikely that investors would use large, highly diversified and passively managed funds to trade based on firm-specific private information.

[3]As suggested by Edmans et al. (2012), actual trading activities for individual stocks are more likely to correlate with firm-specific fundamentals. Moreover, we do not observe high frequency trading activities of mutual funds. Nevertheless, we use a crude proxy to validate our contention in later sections.

Next, we find that the fund flow-induced volatility has no significant explanatory power for either future sales growth volatility, a measure of firm riskiness in real terms, or bond default. On the other hand, equity volatility does have a statistically significant effect. Additionally, we use sales growth volatility as a proxy for fundamental riskiness, and the IV approach confirms that the positive effect of flow-induced volatility on bond spreads is unlikely a reflection of fundamental risks. In contrast to previous studies that focus on non-fundamental stock price levels driven by mutual fund flows (Coval and Stafford, 2007; Edmans et al., 2012), our measure of flow-induced volatility pressure is uncorrelated with Tobin's Q and also has no effect on the bond spread through an effect on Tobin's Q. The outcome indicates a distinct "second moment" effect of mutual fund flow volatility.

To illustrate the role of trading pressure, as a crude proxy for actual trading volatility we construct for each stock the average passive equity mutual fund holding volatility within a given year. As expected, we document a positive relation between equity volatility and holding volatility, and the latter positively correlates with the flow-induced volatility pressure. Using the flow-induced volatility pressure as an instrument for holding volatility, we find some evidence that volatile fund flows at the stock level increase newly issued bond spreads through more volatile trading activities.

We employ a battery of sensitivity tests to test the robustness of our baseline findings, ranging from alternative measures to a set of extra controls. However, regardless of the various empirical specifications, we obtain similar results and with statistical significance. Our study contributes to several strands of literature. Prior research has shown a positive relationship between equity volatility and the cost of debt even after controlling for a variety of proxies for creditworthiness Santos (2011); Santos and Winton (2013); Campbell and Taksler (2003). However, Gaul and Uysal (2013) note that: "equity volatility is likely an error prone measure of firm volatility" (p. 3326). They then proceed to discuss the potential biases induced by using equity volatility to explain the "global loan pricing puzzle" proposed by Carey and Nini (2007).

We are among the first to examine thoroughly the question as to whether noise in stock price variations induced by passive mutual fund flow volatility plays a non-trivial role in the cost of debt financing. We provide some novel evidence suggestive of non-fundamental risks driving bond pricing. In that regard, our findings contribute to a stream of behavioral finance literature that attributes mispricing to imperfect information processing (Hong and Stein, 1999; Campbell and Vuolteenaho, 2004), suggesting a potential real effect of faulty information on economic activities (Morck et al., 1990).

Our study also extends the burgeoning literature that examines the impact of non-fundamental stock prices on corporate activities. This literature generally builds on the notion that mutual fund fire sales are likely to be exogenous from the perspective of the affected stocks (Coval and Stafford, 2007). Edmans et al. (2012) find that non-fundamental stock prices driven by mutual funds' fire sales can affect takeover probabilities. Khan et al. (2012) follow Coval and Stafford (2007) and document a positive impact of overvalued equity on seasoned equity offerings. More recently, both Lou and Wang (2018) and Dessaint et al. (ming) use mutual funds flows to decompose stock prices into fundamental and non-fundamental parts and find that corporate investment decisions are sensitive to non-fundamental stock prices.

We differ from the aforementioned papers in at least two important respects. First, while the prior research emphasizes the first moment effect of mutual funds flows on stock prices (market to book ratio), we focus on the second moment effect by using mutual funds flow volatilities to identify uninformative price variations due to trading volatility pressure. Therefore, the perceived risk channel documented in this paper is distinct from the one in, for example, Lou and Wang (2018) where Tobin's Q is used to infer information about corporate investment. In contrast, we look to the informative role of equity volatility in risk assessment, a crucial determinant of corporate debt financing. However, our robustness tests show that controlling for the first moment impact of fund flows will not change our main results.

Second, unlike the previous related literature that analyzed the price impact of mutual fund flows on stock returns (Coval and Stafford, 2007), M&A (Edmans et al., 2012), SEOs (Khan et al., 2012) and corporate investment (Lou and Wang, 2018; Dessaint et al., ming), we address a different research question; namely, does fund flow-induced volatility affect corporate debt financing? Our findings are in line with the notion that, to the extent that equity volatility is widely used as a timely indicator for firm risk, the noisy part of this risk indicator inflicts non-negligible costs on borrowing firms.

Moreover, our article is related to studies on financial contagion (e.g., King and Wadhwani, 1990; Kyle and Xiong, 2001; Kodres and Pritsker, 2002; Pasquariello, 2007). This literature provides several explanations for the observed correlation across different markets in excess of what can be inferred from fundamentals. Although the extant research has attributed financial contagion to cross-market learning activities, most papers in this vein are theoretical and focused on secondary markets (King and Wadhwani, 1990; Cipriani and Guarino, 2008; Cespa and Foucault, 2014). The lack of strong empirical support is partly because it is difficult to separate fundamentals from non-fundamentals in the data[4]. We complement this literature by showing that volatility shocks induced by non-informative mutual fund flows in the secondary equity market can propagate into the *primary* market for new debt issues through a perceived risk channel.

Finally yet importantly, our study sheds light on the ongoing debate regarding the "dark side" of passive investing. Recently several studies caution against the potential negative impact of passive investing, such as excess price movements (Claessens and Yafeh, 2013; Ben-David et al., 2018) and lower price efficiency (Qin and Singal, 2015). In fact, even the "godfather" of passive investing, John Bogle, warned in a recent interview that

[4]Huang et al. (2015) investigate the influence of stock market sentiment on corporate bond markets. Related to our study, their findings suggest that non-fundamentals in equity markets could affect the pricing of bonds in fixed income markets. However, the proxy for stock market sentiment they use is at the aggregate level and therefore may capture other confounding factors.

"if everybody indexed, the only word you could use is chaos, catastrophe"[5]. We contribute to this debate by showing that excessive equity volatility induced by volatile passive fund flows has an unintended effect on the cost of debt. Thus, our findings provide additional caveats to the rapid growth of passively managed funds in the last decades.

The remainder of this paper proceeds as follows: Section 2.2 introduces the research design and data. Section 2.3 contains the main empirical results. Section 2.4 provides some placebo and robustness tests. Section 2.5 concludes.

2.2 Empirical Research Design and Data

2.2.1 Flow-induced volatility pressure

Inspired by Greenwood and Thesmar (2011) and Edmans et al. (2012), we utilize mutual fund flow-induced trading pressure to capture the uninformative part of equity volatility. In order to address endogeneity concerns, we only focus on passively managed equity mutual funds. We begin by extracting monthly mutual fund net asset value and return from the CRSP Mutual Fund Database. Since mutual fund holdings data are only available at the fund portfolio level, we aggregate the share classes to the portfolio level by using the link tables developed by Russ Wermers (Wermers, 2000), and then calculate the monthly net fund flow for each mutual fund f following the literature standard:

$$Flow_{fm} = \frac{\sum_{s \in f} TNA_{sfm} - \sum_{s \in f} TNA_{sfm-1}(1 + Return_{sm})}{\sum_{s \in f} TNA_{sfm-1}} \tag{2.1}$$

where TNA_{sfm} is the total net assets value of share class s that belongs to fund f in month m and $Return_{sm}$ is the total monthly return.

Following Edmans et al. (2012) and Greenwood and Thesmar (2011), we construct

[5]See, `https://finance.yahoo.com/news/jack-bogle-envisions-chaos-catastrophe-markets-everyone-indexed-194610197.html`.

FlowVol as follows:

$$FlowVol_{it} = \left| \sum_{f \in F_{it}} \omega_{fit} \times Flow_{ft} \right| \tag{2.2}$$

where ω_{fit} is fund f's average ownership in stock i, $Flow_{ft}$ is the average fund flows in year t and F_{it} refers to the universe of mutual funds with non-zero holdings in stock i. We use the natural logarithm of *FlowVol* as our primary measure of flow-induced volatility pressure, *FVolatility*, which captures the trading volatility pressure stemming from passive mutual fund flows in a given year [6]. We choose not to use the mutual funds' actual sales and purchases of individual stocks for two reasons. First, we do not observe high frequency trading activities, which might be quite relevant to equity volatility over a certain period[7]. Second, *FVolatility* mainly embodies proportional trading pressure originating from cash inflows and outflows at the fund level, but does not reflect the fund's discretionary selection of stocks, conceivably based on fund managers' views of a firm's riskiness[8]. Since fund flows are strongly driven by fund performance, we also construct *FVolatility_Adj* similar to *FVolatility* but using performance-adjusted fund flows to calculate trading volatility pressure with an aim to more effectively capture liquidity-driven trades [9].

2.2.2 Other volatility measures

Consistent with prior literature (e.g., Coles et al., 2006a; Low, 2009a; Panousi and Papanikolaou, 2006), we define equity volatility (*Volatility*) as the logarithm of the yearly standard deviation of daily stock returns. *Volatility* measures the extent of stock price variation over a certain period, which conveys relevant information on firm risk but also contains noise. Complementing this, we use the CAPM model to decompose equity

[6] Greenwood and Thesmar (2011) propose a similar measure. We use the log-transformation because the unscaled data are strongly right-skewed.

[7] In later sections we propose a crude proxy for actual trading volatility to validate our interpretation.

[8] Note that it is also not directional, meaning that both inflows and outflows lead to higher volatility.

[9] Specifically, for each fund we first estimate a time series regression of net fund flows on the lagged fund return using data from the past 36 months, and then we make adjustments to the fund flows by subtracting expected fund flows based on the lagged performance. As a robustness check, we also use the CAPM risk-adjusted return and obtain similar findings.

volatility into systematic (*Sys Volatility*) and idiosyncratic (*Idio Volatility*) parts[10]. Since equity volatility is at best a noisy signal of firm risk (Gaul and Uysal, 2013), we also use the logarithm of a rolling-window standard deviation of sales growth over the past five years (*SGVolatility*) as a quantity-based measure of firm riskiness. By construction, since *SGVolatility* is not based on prices, it is more closely related to firm fundamentals. To supplement our baseline analysis, we also consider passive mutual fund holding volatility (*HVolatility*) as a crude proxy for funds' actual trading volatility. We calculate *HVolatility* as the natural logarithm of the average annual standard deviation of passive mutual fund ownership in a given firm [11].

2.2.3 Empirical specification

To empirically test whether passive mutual fund flow-induced volatility is priced in the primary bond market, we estimate the following two-stage least squares (2SLS) baseline model where our measures of fund flow-induced volatility pressure are used as instruments for equity volatility:

$$\begin{aligned} ln(Spread_{t+1}) = f(&\widehat{\text{Volatility}}_t, Firm\ Characteristics_t \\ &, Bond\ Attributes_t, Fixed\ Effects) \end{aligned} \tag{2.3}$$

where the dependent variable is the natural logarithm of bond yield spread at issuance and $\widehat{\text{Volatility}}$ denotes the predicted *Volatility* in the second stage of the 2SLS regression where fund flow-induced volatility pressure is used as the instrument variable. Fund flow-induced volatility pressure is measured by either *FVolatility* or *FVolatility_Adj* with the latter adjusted for fund performance. $\widehat{\text{Volatility}}$ is of particular interest to our paper and we expect the coefficient to be positive.

[10] In particular, we estimate a market beta for each stock using daily stock returns and the market value-weighted returns in a given year. We calculate *Sys Volatility* as the natural logarithm of the standard deviation of market returns multiplied by the estimated market beta. We define *Idio Volatility* as the natural logarithm of the standard deviation of residual returns obtained from the CAPM model.

[11] This may underestimate true trading volatility as only quarterly disclosures of funds' positions in stocks are available.

We select a set of firm characteristics consistent with the empirical debt contracting literature and also seek to address omitted variable concerns. We control for several price-based variables such as market capitalization (*ln(ME)*), Tobin's Q (*ln(Q)*) and the annual stock return (*Return*) to mitigate endogeneity concerns about the information embedded in stock prices. Endogeneity is a concern since fund flows may follow fund performance, even though we also consider *FVolatility_Adj* as an alternative measure[12]. Other firm-level characteristics include firm size defined as the natural logarithm of book assets (*Size*), profitability (*ROA*), firm age (*Age*), cash holdings (*Cash*), book leverage (*Leverage*) and Altman's Z-score (*ZScore*).

Bond-level attributes are maturity (*BMaturity*) and bond size (*BSize*) in log form, together with indicators for redeemable options, seniority, and investment grade status [13]. In most specifications, we include both firm and year fixed effects, and adjust standard errors for within-firm clustering because the same firm may issue multiple bonds in the same year. Industry fixed effects are at the two-digit SIC level. Appendix A displays detailed definitions of the variables.

2.2.4 Sample Selection

We construct our samples by combining several data sources: Compustat, CRSP, CRSP Mutual Fund Database, Thomson Reuters Mutual Fund Holdings Database and the Mergent Fixed Income Securities Database (FISD).

We obtain primary data on public corporate bonds offerings from Mergent FISD which provides detailed information on bonds issued by public firms that mature after 1990. Mergent FISD reports the fixed-rate corporate bond spread as the difference between the issue's offering yield and the yield of a benchmark treasury issue expressed in basis points. We require spreads to be positive so that the pricing of risk is well defined.

[12]To be clear, passively managed mutual funds mostly hold large and diversified portfolios. Thus, it is unlikely for investors to use passive mutual funds as a means to trade on private information.

[13]In the baseline model we use an investment grade flag assigned by FISD as a coarse proxy for credit rating. We check for robustness by adding a series of indicators for all available credit ratings issued by the three major credit rating agencies (Moody's, S&P and Fitch) in Section 2.4.1.

Other information on bond characteristics include size of debt issued, bond maturity, and indicators for whether a bond is senior, redeemable, and investment grade [14]. We merge the at-issue bonds data with the CRSP daily equity volatility of offering firms[15]. To compute flow-induced volatility pressure at the stock level as described in Section 2.2.1, we retrieve U.S. passive equity funds flow and holdings data from the CRSP Mutual Fund Database and the Thomson Reuters Mutual Fund Holdings Database.[16] The data on firm fundamentals are from Compustat. We exclude financial firms (SIC codes between 6000 and 6999)[17] and utility firms (SIC codes between 4910 and 4940). After removing observations with missing data, we are left with a merged sample of 5,324 bonds for 1,141 unique borrowing firms issued between 1993 and 2013 [18]. To eliminate the effect of outliers, we winsorize all continuous variables at both tails using 1% cutoff values.

2.2.5 Descriptive Statistics

Table 2.1 presents summary statistics on bonds attributes at issuance for the same set of firms. On average, bond spreads are 229.9 basis points. The average size of bond offerings is around $474.9 million, with an average maturity of 140.8 months. 13.3% of issued bonds are investment grade, while about 82.3% are redeemable bonds. Table 2.1 also reports sample statistics on several baseline firm level variables preceding the bond issue year. Aside from the fact that most bond offering firms are large and mature, the

[14]We exclude perpetual bonds since there is no corresponding benchmark treasury bond. We also drop convertible bonds in order to avoid a mechanical relationship between stocks and bonds issued by the same firm. As with Campbell and Taksler (2003), we further exclude foreign, putable and asset-backed bonds. We keep redeemable bonds as they account for the majority of bond issues in our sample (over 80%), consistent with the recent findings of Elsaify and Roussanov (2016).

[15]We require at least 30 non-missing observations for each year for calculating daily equity volatilities.

[16]In the first step, we use the CRSP Style Code to select domestic equity funds and exclude sector-based funds. Then, following Boone and White (2015), we define a domestic equity fund as passive if its name includes one of the following strings: Index, Idx, Indx, Russell, S & P, S and P, S&P, SandP, SP, DOW, Dow, DJ, MSCI, Bloomberg, KBW, NASDAQ, NYSE, STOXX, FTSE, Wilshire, Morningstar, 100, 400, 500, 600, 900, 1000, 1500, 2000, and 5000.

[17]Financial firms may be mechanically correlated with the mutual fund industry and thus cause endogeneity issues. Another reason for exclusion is that they might employ a different accounting framework, while utility firms are highly regulated.

[18]Our sample period is determined on the basis that some tests involve variables calculated by using year t+1 to year t+5 information and other using t to year t-4 data.

table shows that these firms tend to perform well on paper, that is, they are likely to be very profitable, with an average ROA of about 17.3%. Z-Scores are mostly outside of the distress zone, and they maintain relatively low leverage. For ease of interpretation and comparison we normalize all volatility variables to have zero mean and unit standard deviations[19].

For an initial look at the relationship among flow-induced volatility pressure, equity volatility and the bond spread, we first compute the yearly average of our volatility measures and display these in Figure 2.1 against the yearly average of equity volatility. Panels A and B suggest a positive correlation between the fund flow-induced pressure measures and equity volatility. Panels C depicts the relation between the yearly average of equity volatility and the normalized natural logarithm of bond yield spreads at issuance (red dotted lines) [20]. There seems to be a positive trend in either volatility measures or bond spreads. Therefore, we need to control for year fixed effects in most of our regressions. Moreover, the time-series correlation appears to be stronger during the two major market crashes, namely the 2007-2009 financial crisis and the dot-com bubble bust in the early 2000s. To show that our results are not driven solely by these events, we shall conduct some robustness checks.

2.3 Main Empirical Analysis

2.3.1 Baseline regression results

To study how flow-induced volatility pressure increases the cost of debt through affecting equity volatility, we first examine the relationship between flow-induced volatility pressure and equity volatility in our baseline sample. In Table 2.2, columns (1) and (3), we report OLS regression results where equity volatility (*Volatility*) is the dependent

[19] Since the normalization is a linear transformation, it does not impact the signs and statistical significance of coefficient estimates.

[20] For comparison purpose, we normalize log bond spreads by subtracting the sample mean and dividing them by the sample standard deviation

variable and the key independent variables of interest are the two flow-induced volatility pressure measures, including *FVolatility* and *FVolatility_Adj*, respectively. The marginal effect of flow-induced volatility pressure is small in magnitude: a one standard deviation increase of the flow-induced volatility pressure leads to an increase in *Volatility* equivalent to around 4% of the sample standard deviation. These estimates are reasonable in light of our interpretation that flow-induced volatility pressures mainly drive the uninformative part whereas the majority of equity volatility still reflects firm fundamental risk [21].

Having documented a positive relation between flow-induced volatility pressure and equity volatility, we proceed to explore the implications of increased perceived risks for the cost of debt. Our primary contention is that a stock with higher pressures of fund flow-induced volatility would tend to exhibit a higher level of equity volatility, which in turn may lead to higher costs of debt if creditors use equity volatility as an important stock market signal but have difficulty identifying excessive volatility from the uninformative part of equity volatility.

Specifically, we estimate model (2.3) by treating the fund flow-induced pressure as an instrument variable (IV) for equity volatility and conducting two-stage least squares (2SLS) regressions. If flow-induced pressures affect the cost of debt through increased equity volatility, we would expect a substantial effect of the instrumented equity volatility using flow-induced pressure as an IV in the second-stage estimation. As reported in Table 2.2, we find some support from the data[22]. Columns (2) and (4) show that the coefficients on $V\widehat{olatility}$ are positive and statistically different from zero at the 5% level, regardless of whether we use *FVolatility* or *FVolatility_Adj* as an IV[23]. These results suggest that

[21] Equity volatility has long been widely used as a proxy for firm risk or uncertainty (see, for example, Bulan (2005), Coles et al. (2006b), Bloom et al. (2007), Low (2009b), Bartram et al. (2011), Armstrong and Vashishtha (2012), Panousi and Papanikolaou (2012), Gilchrist et al. (2014) and Kim et al. (2017), among others). Although in theory firm risk and uncertainty are two concepts with subtle differences, empirically it is hard to draw a clear distinction between those two. Therefore in empirical finance or economics literature equity volatility has been either referred to as a measure of firm risk or uncertainty.

[22] For brevity we do not report R-squared as we are primarily interested in the marginal effect and R-squared for 2SLS is not meaningful.

[23] The marginal effect on bond spreads appears to be small in percentage points. For instance, columns (2) and (4) indicate that a one standard deviation increase of the flow-induced volatility pressure is

creditors perceive flow-induced equity volatility as a risk factor.

2.3.2 Perceived risks: systematic vs. idiosyncratic volatility

A natural follow-up question is whether the effect of flow-induced volatility pressure operates differently through the systematic and idiosyncratic parts of equity volatility. We use the CAPM model to decompose total volatility into its systematic (common) and idiosyncratic components. Then we apply the same approach described above and report the results in Table 2.3. Panel A of Table 2.3 shows that the effect for the systematic equity volatility channel remains strong and significant at the 5% level. Panel B shows that the coefficients corresponding to idiosyncratic equity volatility are still positive and significant when using *FVolatility_Adj* as an instrument, while the results become less significant in the case of *FVolatility*. Table 2.3 indicates the common part of equity volatility more robustly drives the increased perceived risk due to heightened flow-induced volatility.

2.3.3 Is flow-induced volatility informative of future firm risk ?

There may still be some concerns that flow-induced volatility might reflect some fundamental information about firm risks. In this subsection, we conduct several validation tests to examine to what extent flow-induced volatility reflects non-fundamental risks.

First, we examine whether flow-induced volatility is associated with future bond defaults[24]. For every bond-year observation in our sample of bond issues, we set Dummy(Bond Default) equal to one if a bond default occurs in the future. We use an IV

associated with a 4.6-6.8 basis points increase in bond spread given that the average bond spread of the sample firms is 229.9 basis points ($229.9 \times e^{0.043 \times 0.46} - 229.9 = 4.6$; $229.9 \times e^{0.038 \times 0.77} - 229.9 = 6.8$). The small marginal impact is consistent with our expectation for the role of non-fundamental equity volatility in bond pricing. But this does not necessarily mean the monetized impact is not economically meaningful. In fact, as the sample average amount of bond issues and time to maturity are $474.9 million and 140.8 months respectively, it follows that a one standard deviation increase in flow-induced volatility pressure translates to about $2.6-$3.8 million worth of additional cost per bond($0.00046 \times 474.9 \times 140.8/12 = 2.6$; $0.00068 \times 474.9 \times 140.8/12 = 6.8$). In aggregate, this is equivalent to around $576-$1508 million per year on average.

[24]We include covenant violations, oftentimes referred to as technical defaults in default classifications.

probit regression model with Dummy(Bond Default) as the dependent variable to estimate the effects of flow-induced volatility on future bond default events. As shown in Table 2.4, we find that passive mutual fund flow-induced volatility has no significant relation with future defaults regardless of whether or not we include controls; but equity volatility is strongly informative of bond defaults (see column (5)). In addition, columns (6) and (7) indicate that measures of both systematic and idiosyncratic volatility contain useful information regarding actual future defaults.

Next, we estimate a 2SLS model for the link between flow-induced volatility and future firm riskiness over a panel of the bond sample firms and report our results in Table 2.5. The dependent variable is the sales growth volatility over the next five years ($SGVolatility_{t,t+5}$) as a proxy for corporate future fundamental risk. The key independent variables of interest are, as before, measures of flow-induced volatility. Firm level controls are the same as in the baseline case. We find that flow-induced volatility is uncorrelated with future firm riskiness, while the corresponding measures of equity volatility strongly predict future firm operating variability.

Taken together, our measures of passive mutual fund flow-induced volatility are valid in the sense that they contain little information about future firm risk that might result in actual defaults. On the one hand, this renders credence to the constructs that we are using to capture the uninformative portion of trading volatility. On the other hand, the perceived risks due to excessive volatility seem to be overpriced in new bond issues. To be sure, it does not necessarily mean our measures are completely immune to any contamination of fundamental factors; rather, it suggests that the fundamental information embedded in the measures, if any, is statistically and economically negligible.

2.3.4 The role of trading volatility

As discussed in section 2.2.1, we deliberately refrain from using actual trading volatility. In addition to our need to address endogeneity, lack of access to high frequency data on mutual funds' trades makes them less useful. Our previous argument was for a perceived risk channel that relies heavily on the premise that our measures of flow-induced volatility pressure are associated with actual trading volatilities, which in turn cause excessive equity volatility. To help strengthen this link, we propose a parsimonious measure of funds' trading volatility at the stock level, *HVolatility*, which measures the average volatility of passive mutual funds' positions on a specific stock within a given year. Since we can only observe portfolio holdings on a quarterly basis, this is at best a crude proxy for actual fund trading volatility.

Column (1) of Table 2.6 shows that *HVolatility* is positively associated with equity volatility with statistical significance at the 1% level. The economic magnitude is larger than our findings regarding the relationship between flow-induced volatility pressure and equity volatility (columns (1) and (3) in Table 2.2), in part because *HVolatility* more directly relates to actual trading activities. As Table 2.6, columns (2) and (4) indicate, *FVolatility* and *FVolatility_Adj* relate positively at the 1% level with *HVolatility*, even though the latter, by construction, does not directly contain information about fund flows. These results validate our measures of flow-induced volatility pressure relating to actual trading volatility. In columns (3) and (5), we use the IV approach again and show that flow-induced volatility pressure affects bond spreads by affecting *HVolatility*.

2.4 Placebo and Robustness Tests

2.4.1 Some placebo tests

The results in section 4.4 indicate that excess equity volatility, driven by passive mutual fund flow-induced volatility pressure and uncorrelated with firm specific fundamental risk, can raise corporate bond spreads at issuance. Since equity volatility also contains fundamental information, we conduct a placebo check by using flow-induced volatility pressure as an instrument for the quantity-based measure of firm risk, *SGVolatility*. If flow-induced volatility pressure only affects price variations, we would expect that it would not increase bond spreads through *SGVolatility*. Panel A of Table

2.7 reports results consistent with this prediction.

Another misspecification concern is that, instead of the second moment price effect, our measures of flow-induced volatility may also capture the first moment price effect as has been studied in Edmans et al. (2012). Columns (1) and (3) in Panel B of Table 2.7 show that neither *FVolatility* nor *FVolatility_Adj* has a significant correlation with the level of stock price (*ln(Q)*). The IV approach yields similar results, showing that there is no evidence that our measures of flow-induced volatility pressure affect bond spreads through stock price levels. Not only does this evidence confirm our interpretations of the results in Table 2.2, but it also helps distinguish our study from the related literature on the real effects of non-fundamental prices (Edmans et al., 2012; Lou and Wang, 2018).

Alternative measures

Our primary measure of flow-induced volatility pressure provides a relatively conservative estimate as two fund flows in opposite directions may not necessarily mean a zero price impact on the underlying stock[25]. As an alternative, we measure the volatility of liquidity demand for fund f in year t by using the annualized variance of monthly fund flows. Standardized flow volatilities aggregated at stock level can be defined as

$$FlowVol1_{it} = \sqrt{\sum_{f \in F_{it}} \omega_{fit}^2 \times FlowVar_{ft}} \tag{2.4}$$

and we define *FVolatility1* as the natural logarithm of *FlowVol1*. This measure is also easy to implement but the downside is that it fails to capture the co-movement of fund flows in a given year[26]. Using this new measure of flow-induced volatility pressure, we

[25]For example, this is the case when flow-induced trading is not executed at exactly the same point of time, because timely execution is dependent on fund managers' liquidity management skills.

[26]The stock fragility measure in Greenwood and Thesmar (2011) has a similar intuition but there is an important but subtle difference. Note that Greenwood and Thesmar (2011) aim to identify a "stable" feature of some stocks, namely vulnerability to non-fundamental shifts in demand. That is why Greenwood and Thesmar (2011) utilize the full historical data to estimate fragility. However, our paper focuses on the short-term presence of fund flow-induced volatility.

re-estimate the baseline regression model and report results in columns (1)-(2) of Table 2.8. Moreover, to adjust fund flows we also construct a performance-adjusted flow-induced volatility pressure measure, *FVolatility_Adj1*. We obtain similar results using these two alternative measures of flow-induced volatility pressure: the estimated coefficient on the instrumented equity volatility is around 0.5, both at the 1 percent level. Overall, these findings show that our main conclusions are robust to various measures of flow-induced volatility pressure.

Omitted variable bias

To mitigate concerns on omitted variables that may bias estimates, we also sequentially add more firm-level characteristics and more detailed bond rating indicators to further control for unknown determinants of bond spreads. As columns (3) and (5) indicate, the extended regression model with interest coverage ratio ($Interest$), payout ratio ($Payout$), physical assets holding ($Tangibility$), current ratio ($Current$), cash flow (CFA) , fire sales pressure ($MFlow$) and mutual fund ownership (MFO) yield similar results. Furthermore, the additional proxies for firm risk or creditworthiness barely affect the explanatory power of non-fundamental equity volatility for the cost of bond issuance.Since the proxy for rating used in the baseline model is coarse (investment grade or not), in columns (4) and (6) we include as categorical variables detailed levels of ratings provided by S&P, Moody's and Fitch as category variables. Our main results still hold. The totality of this evidence reinforces our conclusion that our baseline model is unlikely to be plagued by serious omitted-variable problems.

Subsample analyses

The sample period in our analysis covers several episodes of financial market turmoil, especially the 2007-2009 financial crisis and the bursting of the dot-com bubbles at the beginning of the 2000s. Since spikes in equity volatility are usually associated with severe market crashes, a natural question is whether these special events drive our results. As shown in Table 2.9 our findings still hold after excluding either the 2007-2009 or 2000-2001 data. Together with the previous subsection, it suggests that aggregate factors are not the key driving forces of our results; instead, our measure manages to capture firm-specific determinants of at-issue bond spread.

2.4.2 Evidence from loan pricing

The generality of our analysis is restricted by the fact that not all firms have access to the public bond markets. Therefore, in this subsection we extend our analysis to study the effects of flow-induced volatility on the cost of loan originations by using data from LPC DealScan for the period 1993-2013. The loan sample contains 14,684 loan-year observations. We modify the baseline regression model by replacing the dependent variable with the log of loan spread (all-in spread drawn). We use the same set of firm characteristics but substitute loan maturity, loan size, loan purpose, loan type, and indicators for secured and senior loans for bond attributes in the baseline model. We present the regression results using this loan sample in columns (3) and (4) of Table 2.10, which confirms the positive effect of flow-induced volatility on the cost of borrowing with significance at the 1% level[27].

We next restrict our loan sample to the same set of bond issue firms in our baseline sample. There are 8,266 loans made to our bond sample firms from 1993 to 2013. We report the loan regression results for this restricted sample in Table 2.10, columns (1)-(2). Interestingly, even though Table 2.2 documents a strong impact of our flow-induced volatility on bond spreads, here we find either weak or insignificant effects on loan spreads with the same set of firms. Prior research has shown that bank loan lenders are less sensitive to risk than bond investors (Bharath et al., 2008), and banks are active in

[27]Similarly, Francis et al. (2020) utilize a measure of stock fragility and find it to be positively associated with loan spreads. Although the stock fragility measure is related to our measures of fund flow-induced volatility pressure, they do not directly test the perceived risk channel that we emphasize in this paper.

information acquisition during a loan originating process (Agarwal and Hauswald, 2010). The relatively weaker impact of flow-induced volatility on loan pricing that we have found for bond-issuing firms is largely consistent with the existing findings, and in our case with flow-induced volatility pressure affecting the cost of debt through changing perceived risks.

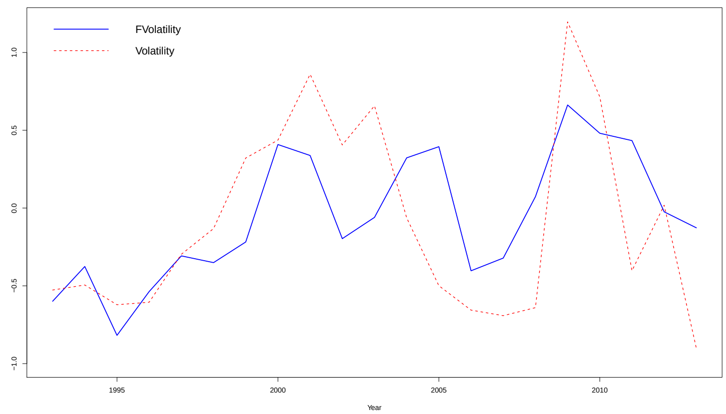
2.5 Conclusion

In this paper, we demonstrate a positive relationship between the yield spread of newly issued bonds and the borrowing firm's exposure to trading volatility pressure imposed by volatile passive equity mutual fund flows. The perceived risk effect of flow-induced volatility pressure to bond investors is driven mainly by an increase in equity volatility that is widely used as a signal for firm future risk. However, we find that fund flow-induced volatility comprises little information about future firm risk unlike the case of equity volatility. Our findings suggest an inefficiency in corporate bond financing caused by equity market inefficiencies.

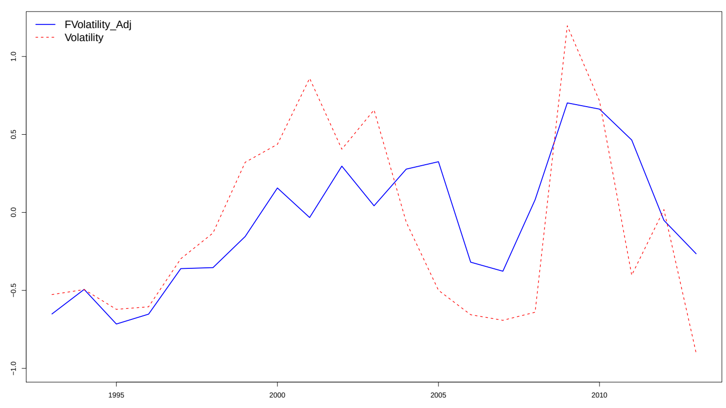
Figure 2.1: Non-fundamental vs. Fundamental Equity Volatility and The Cost of Debt

In Panel A, the blue solid line represents the yearly average *FVolatility*; in Panel B, the blue solid line represents the yearly average *FVolatility_Adj*; in Panel C, the blue solid line represents the yearly average *Volatility*. The red dotted lines in Panels A and Panel B refer to the yearly average *Volatility* and the red dotted line in Panel C refers to the yearly average log bond yield spreads (rescaled to zero mean and unit standard deviation) at issuance.For details about the data sources, see Section 2.2.

Panel A



Panel B



Panel C

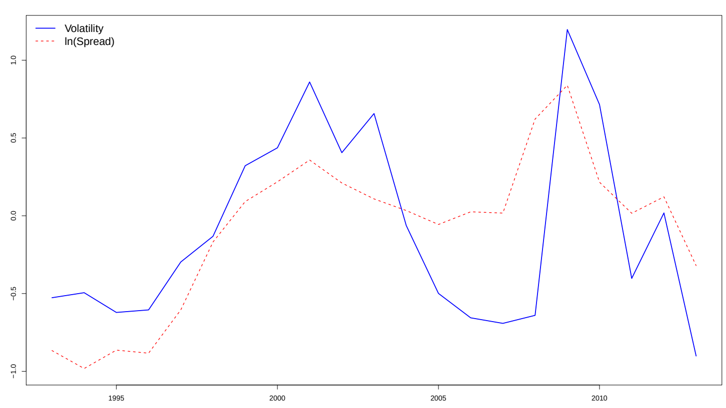


Table 2.1: Descriptive Statistics

This table reports the summary statistics of variables for baseline bond spread analysis that spans from 1993 to 2013.

	Observations	Mean	Std.Dev	10%	50%	90%
Bonds Attributes						
Spread	5,324	229.9	184.7	65	163	502
BMaturity	5,324	140.8	100.3	60	120	360
BSize	5,324	474,886	394,844	150,000	350,000	1,000,000
Invest	5,324	0.133	0.340	0	0	1
Redeem	5,324	0.823	0.381	0	1	1
Senior	5,324	0.00150	0.0387	0	0	0
Firm Level Variables						
Size	5,324	8.901	1.474	6.937	8.951	10.71
Age	5,324	32.24	24.00	6	26	73
Leverage	5,324	0.304	0.165	0.117	0.282	0.515
ROA	5,324	0.173	0.0914	0.0800	0.162	0.280
Cash	5,324	0.0695	0.0844	0.00547	0.0383	0.174
ZScore	5,324	2.985	1.926	0.961	2.686	5.278
ln(ME)	5,324	8.796	1.727	6.455	8.884	11.01
ln(Q)	5,324	0.499	0.391	0.0506	0.430	1.038
FVolatility	5,324	0	1	-0.989	0.00704	0.691
FVolatility	5,324	0	1	-1.038	0.0418	0.723

Table 2.2: Fund Flow-Induced Volatility and the Cost of Debt

This table reports the estimated effect of fund flow-induced volatility on the cost of debt. In columns (2) and (4), the dependent variable is the logarithm of bond spread (ln(*Spread*)). In other columns, the dependent variable is equity volatility (*Volatility*). *FVolatility* and *FVolatility_Adj* are the two measures of passive mutual fund flow-induced volatility pressure where the latter is adjusted for fund performance. Columns (2) and (4) report the second-stage IV regression results where *FVolatility* and *FVolatility_Adj* are used as instruments for *Volatility*, respectively. Bond controls include ln(*BMaturity*), ln(*BSize*) and indicators for bond features. Appendix A provides details on the definitions of variables. The sample period is from 1993 to 2013. We display the standard errors clustered at the firm level in parentheses. We indicate significance at the 10%, 5% and 1% level by *, ** and *** respectively.

Dependent Variable =	Volatility	$\ln(\text{Spread})_{t+1}$	Volatility	$\ln(\text{Spread})_{t+1}$
	OLS	IV (FVolatility)	OLS	IV (FVolatility_Adj)
	(1)	(2)	(3)	(4)
$\widehat{\text{Volatility}}$		0.460**		0.771**
		(0.231)		(0.323)
FVolatility	0.043***			
	(0.014)			
FVolatility_Adj			0.038**	
			(0.015)	
ln(ME)	-0.701***	-0.045	-0.700***	0.175
	(0.074)	(0.168)	(0.074)	(0.229)
ln(Q)	1.099***	-0.304	1.092***	-0.647*
	(0.171)	(0.268)	(0.171)	(0.367)
Return	0.086**	-0.070**	0.089**	-0.099**
	(0.036)	(0.032)	(0.036)	(0.043)
Size	0.676***	-0.129	0.673***	-0.340
	(0.088)	(0.162)	(0.088)	(0.222)
Age	-0.011***	0.002	-0.011***	0.005
	(0.002)	(0.003)	(0.002)	(0.004)
Leverage	-0.304	0.499***	-0.294	0.592***
	(0.208)	(0.146)	(0.209)	(0.187)
ROA	-0.169	-0.554***	-0.198	-0.492***

	(0.244)	(0.139)	(0.242)	(0.187)
Cash	0.495*	0.021	0.505*	-0.125
	(0.268)	(0.225)	(0.268)	(0.280)
ZScore	-0.001	0.005	0.001	0.004
	(0.023)	(0.015)	(0.023)	(0.019)
ln(BMaturity)		0.178***		0.177***
		(0.011)		(0.013)
ln(BSize)		0.095***		0.089***
		(0.017)		(0.022)
Observations	5,324	5,324	5,324	5,324
Adjusted R-squared	0.811	0.796	0.811	0.702
Bond Features FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Table 2.3: Systematic vs. Idiosyncratic Equity Volatility

In columns (2) and (4) of Panel A, the dependent variable is the logarithm of bond spread (ln(*Spread*)). In columns (1) and (3) of Panel A, the dependent variable is systematic equity volatility (*Sys Volatility*). *FVolatility* and *FVolatility_Adj* are the two measures of passive mutual fund flow-induced volatility pressure where the latter is adjusted for fund performance. Columns (2) and (4) of Panel A report the second-stage IV regression results where *FVolatility* and *FVolatility_Adj* are used as instruments for *Sys Volatility* respectively. In columns (2) and (4) of Panel B, the dependent variable is the logarithm of bond spread (ln(*Spread*)). In columns (1) and (3) of Panel B, the dependent variable is idiosyncratic equity volatility (*Idio Volatility*). Columns (2) and (4) of Panel B report the second-stage IV regression results where *FVolatility* and *FVolatility_Adj* are used as instruments for *Idio Volatility* respectively. Firm controls include ln(*ME*), ln(*Q*), *Return*, *Size*, *Age*, *Leverage*, *ROA*, *Cash*, *ZScore*. Bond controls include ln(*BMaturity*), ln(*BSize*) and indicators for bond features. Appendix A provides details on the definitions of variables. The sample period is from 1993 to 2013. We display the standard errors clustered at the firm level in parentheses. We indicate significance at the 10%, 5% and 1% level by *, ** and *** respectively.

Panel A

Dependent Variable =	Sys Volatility	$\ln(\text{Spread})_{t+1}$	Sys Volatility	$\ln(\text{Spread})_{t+1}$
	OLS	IV (FVolatility)	OLS	IV (FVolatility_Adj)
	(1)	(2)	(3)	(4)
Sys $\widehat{\text{Volatility}}$		0.266**		0.578**
		(0.128)		(0.244)
FVolatility	0.075***			
	(0.015)			
FVolatility_Adj			0.050***	
			(0.017)	
Firm Controls	Yes	Yes	Yes	Yes
Bond Controls	Yes	Yes	Yes	Yes
Observations	5,324	5,324	5,324	5,324
Adjusted R-squared	0.725	0.810	0.723	0.714
Bond Features FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes

Firm FE	Yes	Yes	Yes	Yes

Panel B

Dependent Variable =	Idio Volatility	ln(Spread)$_{t+1}$	Idio Volatility	ln(Spread)$_{t+1}$
	OLS	IV (FVolatility)	OLS	IV (FVolatility_Adj)
	(1)	(2)	(3)	(4)
Idio $\widehat{\text{Volatility}}$		0.569*		0.860**
		(0.300)		(0.372)
FVolatility	0.035**			
	(0.014)			
FVolatility_Adj			0.034**	
			(0.014)	
Firm Controls	Yes	Yes	Yes	Yes
Bond Controls	Yes	Yes	Yes	Yes
Observations	5,324	5,324	5,324	5,324
Adjusted R-squared	0.814	0.768	0.814	0.662
Bond Features FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Table 2.4: Non-fundamental Risks: Evidence from Bond Default

This table reports the estimated relationship between fund flow-induced volatility and the likelihood of bond default. The dependent variable is an indicator (Dummy(Bond Default)) that equals to one if the bond defaults in the future and zero otherwise. Columns (1)-(4) report the second-stage IV probit regression results where *FVolatility* and *FVolatility_Adj* are used as instruments for *Volatility*, respectively. Other columns report the probit regression results. *FVolatility* and *FVolatility_Adj* are the two measures of passive mutual fund flow-induced volatility pressure where the latter is adjusted for fund performance. Controls are the same as in the baseline model. We estimate the model by logistic regression. Appendix A provides details on the definitions of variables. The sample period is from 1993 to 2013. We display the standard errors clustered at the firm level in parentheses. We indicate significance at the 10%, 5% and 1% level by *, ** and *** respectively.

Dependent Variable:	Dummy(Bond Default)						
	IV Probit (FVolatility)		IV Probit (FVolatility_Adj)		Probit		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\widehat{\text{Volatility}}$	0.185	-0.806	0.976	0.074			
	(4.399)	(6.599)	(4.697)	(6.829)			
Volatility					0.317***		
					(0.096)		
Sys Volatility						0.236***	
						(0.091)	
Idio Volatility							0.300***
							(0.092)
Controls	No	Yes	No	Yes	Yes	Yes	Yes
Observations	5,324	5,324	5,324	5,324	5,324	5,324	5,324
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.5: Non-fundamental Risks: Panel Analysis

This table reports the predictive power of non-fundamental equity volatility for future firm operating riskiness. The dependent variable is sales growth volatility over the next five-year period. Columns (1)-(4) report the second-stage IV regression results where *FVolatility* and *FVolatility_Adj* are used as instruments for *Volatility*, respectively. *FVolatility* and *FVolatility_Adj* are the two measures of passive mutual fund flow-induced volatility pressure where the latter is adjusted for fund performance. Controls include ln(*ME*), ln(*Q*), *Return*, *Size*, *Age*, *Leverage*, *ROA*, *Cash* and *ZScore*. Appendix A provides details on the definitions of variables. The sample period is from 1993 to 2013. We display the standard errors clustered at the firm level in parentheses. We indicate significance at the 10%, 5% and 1% level by *, ** and *** respectively.

Dependent Variable =	$\text{SGVolatility}_{t+1,t+5}$				
	IV (FVolatility)	IV (FVolatility_Adj)		OLS	
	(1)	(2)	(3)	(4)	(5)
$\widehat{\text{Volatility}}$	0.617	0.052			
	(0.508)	(0.350)			
Volatility			0.057***		
			(0.012)		
Sys Volatility				0.038***	
				(0.010)	
Idio Volatility					0.044***
					(0.011)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	12,442	12,442	12,442	12,442	12,442
Adjusted R-squared	0.003	0.028	0.540	0.539	0.539
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes

Table 2.6: The Role of Trading Pressures

This table reports the estimated effect of flow-induced volatility on the cost of debt. In columns (3) and (6), the dependent variable is the logarithm of bond spread (ln(*Spread*)). In column (1), the dependent variable is equity volatility (*Volatility*). In columns (2) and (4), the dependent variable is a measure of passive mutual fund holding volatility (*HVolatility*). *FVolatility* and *FVolatility_Adj* are the two measures of passive mutual fund flow-induced volatility pressure where the latter is adjusted for fund performance. Columns (3) and (5) report the second-stage IV regression results where *FVolatility* and *FVolatility_Adj* are used as instruments for *HVolatility* respectively. Bond controls include ln(*BMaturity*), ln(*BSize*) and indicators for bond features. Appendix A provides details on the definitions of variables. The sample period is from 1993 to 2013. We display the standard errors clustered at the firm level in parentheses. We indicate significance at the 10%, 5% and 1% level by *, ** and *** respectively.

Dependent Variable =	Volatility	HVolatility	ln(Spread)$_{t+1}$	HVolatility	ln(Spread)$_{t+1}$
	OLS	OLS	IV (FVolatility)	OLS	IV (FVolatility_Adj)
	(1)	(2)	(3)	(4)	(5)
HVolatility	0.068***				
	(0.018)				
$\widehat{\text{HVolatility}}$			0.238*		0.244**
			(0.135)		(0.105)
Fvolatility		0.084***			
		(0.027)			
FVolatility_Adj				0.119***	
				(0.032)	
ln(ME)	-0.690***	-0.223**	-0.314***	-0.214**	-0.313***
	(0.073)	(0.103)	(0.068)	(0.104)	(0.065)
ln(MB)	1.080***	0.275	0.141	0.253	0.139
	(0.169)	(0.226)	(0.123)	(0.228)	(0.122)
Return	0.078**	0.201***	-0.080**	0.203***	-0.082**
	(0.036)	(0.053)	(0.037)	(0.053)	(0.032)
Size	0.686***	-0.055	0.191***	-0.074	0.191***
	(0.087)	(0.147)	(0.067)	(0.148)	(0.067)
Age	-0.010***	-0.012*	-0.000	-0.012*	-0.000
	(0.002)	(0.006)	(0.002)	(0.006)	(0.002)

Leverage	-0.339	0.736*	0.175	0.747*	0.170
	(0.211)	(0.440)	(0.192)	(0.437)	(0.177)
ROA	-0.254	0.826**	-0.829***	0.775**	-0.834***
	(0.241)	(0.364)	(0.167)	(0.355)	(0.158)
Cash	0.525*	-0.450	0.342	-0.418	0.344
	(0.270)	(0.443)	(0.231)	(0.438)	(0.229)
ZScore	0.006	-0.037	0.012	-0.038	0.012
	(0.023)	(0.049)	(0.019)	(0.048)	(0.019)
Observations	4,947	4,947	4,947	4,947	4,947
Adjusted R-squared	0.812	0.571	0.092	0.574	0.084
Bond Controls	No	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes

Table 2.7: Placebo Checks: Sales Growth Volatility and Stock Prices

In columns (2) and (4) of Panel A, the dependent variable is the logarithm of bond spread (ln(*Spread*)). In columns (1) and (3) of Panel A, the dependent variable is sales growth volatility (*SGVolatility*). *FVolatility* and *FVolatility_Adj* are the two measures of passive mutual fund flow-induced volatility pressure where the latter is adjusted for fund performance. Columns (2) and (4) of Panel A report the second-stage IV regression results where *FVolatility* and *FVolatility_Adj* are used as instruments for *SGVolatility* respectively. In columns (2) and (4) of Panel B, the dependent variable is the logarithm of bond spread (ln(*Spread*)). In columns (1) and (3) of Panel B, the dependent variable is the logarithm of market-to-book ratio (*MB*). Columns (2) and (4) of Panel B report the second-stage IV regression results where *FVolatility* and *FVolatility_Adj* are used as instruments for ln(*MB*) respectively. Controls are the same as in the baseline model while *ln(Q)* is excluded if it is used as the dependent variable. Appendix A provides details on the definitions of variables. The sample period is from 1993 to 2013. We display the standard errors clustered at the firm level in parentheses. We indicate significance at the 10%, 5% and 1% level by *, ** and *** respectively.

Panel A				
Dependent Variable =	SGVolatility	$\ln(\text{Spread})_{t+1}$	SGVolatility	$\ln(\text{Spread})_{t+1}$
	OLS	IV (FVolatility)	OLS	IV (FVolatility_Adj)
	(1)	(2)	(3)	(4)
$\widehat{\text{SGVolatility}}$		0.763		1.196
		(0.762)		(1.507)
FVolatility	0.031			
	(0.027)			
FVolatility_Adj			0.028	
			(0.033)	
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Panel B

Dependent Variable =	ln(Q)	ln(Spread)$_{t+1}$	ln(Q)	ln(Spread)$_{t+1}$
	OLS	IV (FVolatility)	OLS	IV (FVolatility_Adj)
	(1)	(2)	(3)	(4)
$\widehat{\ln(Q)}$		58.712		14.209
		(478.099)		(21.556)
FVolatility	0.001			
	(0.003)			
FVolatility_Adj			0.002	
			(0.004)	
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Table 2.8: Robustness

This table reports the estimated effect of passive mutual fund flow-induced volatility on the cost of debt using alternative specifications. The dependent variable is the logarithm of bond spread ($ln(Spread)$). Columns (1) through (2) use alternative measures of flow-induced volatility pressure as instruments; columns (3) through (4) add more firm level controls; columns (5) through (6) add a myriad of indicators for bond ratings from S&P, Moody's and Fitch. Controls are the same as in the baseline model. Appendix A provides details on the definitions of variables. The sample period is from 1993 to 2013. We display the standard errors clustered at the firm level in parentheses. We indicate significance at the 10%, 5% and 1% level by *, ** and *** respectively.

Dependent Variable =	$\ln(\text{Spread})_{t+1}$					
	IV (FVolatility1)	IV (FVolatility2)	IV (FVolatility)	IV (FVolatility_Adj)	IV (FVolatility)	IV (FVolatility_Adj)
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{\text{Volatility}}$	0.497**	0.532***	0.505**	0.761**	0.507**	0.803**
	(0.229)	(0.197)	(0.217)	(0.305)	(0.222)	(0.361)
Interest			-0.001	-0.001	-0.001	-0.001
			(0.001)	(0.001)	(0.001)	(0.001)
Payout			0.018	0.050	0.020	0.057
			(0.043)	(0.053)	(0.044)	(0.060)
Tangibility			-0.351*	-0.471*	-0.383**	-0.531*
			(0.182)	(0.263)	(0.190)	(0.296)
Current			-0.043*	-0.038	-0.037	-0.026
			(0.026)	(0.033)	(0.027)	(0.036)

CF			0.198	0.497	0.263	0.618
			(0.407)	(0.550)	(0.414)	(0.597)
MFO			-0.245	-0.455	-0.206	-0.461
			(0.226)	(0.294)	(0.238)	(0.346)
MFlow			0.001	0.003	0.001	0.004
			(0.002)	(0.003)	(0.002)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Rating Indicators	No	No	No	No	Yes	Yes
Observations	4,953	4,953	3,215	3,215	3,210	3,210
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.9: Subsample Analysis

This table reports the estimated effect of passive mutual fund flow-induced volatility on the cost of debt under subsamples that exclude abnormal times. The dependent variable is the logarithm of bond spread ($ln(Spread)$). $FVolatility$ and $FVolatility\_Adj$ are the two measures of passive mutual fund flow-induced volatility pressure where the latter is adjusted for fund performance. Columns (1)-(3) report estimates under the subsample excluding the financial crisis period (2007-2009). Columns (4)-(6) report estimates under the subsample excluding the dot-com bubble burst period (2000-2001). Bond controls are the same as in the baseline model. Appendix A provides details on the definitions of variables. We display the standard errors clustered at the firm level in parentheses. We indicate significance at the 10%, 5% and 1% level by *, ** and *** respectively.

Dependent Variable =	$\ln(\text{Spread})_{t+1}$			
	Excluding 2007-2009		Excluding 2000-2001	
	IV (FVolatility)	IV (FVolatility_Adj)	IV (FVolatility)	IV (FVolatility_Adj)
	(1)	(2)	(3)	(4)
$\widehat{\text{Volatility}}$	0.442**	0.832**	0.704**	1.110**
	(0.221)	(0.340)	(0.298)	(0.443)
ln(ME)	-0.074	0.203	0.095	0.427
	(0.163)	(0.244)	(0.241)	(0.359)
ln(MB)	-0.302	-0.716*	-0.460	-0.989*
	(0.253)	(0.380)	(0.394)	(0.590)
Return	-0.064*	-0.109**	-0.127***	-0.167***
	(0.036)	(0.052)	(0.044)	(0.062)
Size	-0.104	-0.362	-0.235	-0.545
	(0.154)	(0.231)	(0.226)	(0.338)
Age	0.001	0.005	0.004	0.008
	(0.002)	(0.004)	(0.004)	(0.006)
Leverage	0.546***	0.694***	0.586***	0.772**
	(0.162)	(0.223)	(0.217)	(0.311)
ROA	-0.611***	-0.591***	-0.330	-0.063
	(0.142)	(0.211)	(0.277)	(0.411)
Cash	0.063	-0.105	-0.160	-0.459
	(0.229)	(0.298)	(0.338)	(0.476)

ZScore	0.018	0.020	-0.005	0.001
	(0.017)	(0.022)	(0.020)	(0.029)
Observations	4,495	4,495	4,040	4,040
Bond Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Table 2.10: Loan Sample Results

This table presents the estimated effect of passive mutual fund flow-induced volatility on loan spread. The dependent variable is the logarithm of loan spread ($ln(LSpread)$). *FVolatility* and *FVolatility_Adj* are the two measures of passive mutual fund flow-induced volatility where the latter is adjusted for fund performance. This table the second-stage IV regression results where *FVolatility* and *FVolatility_Adj* are used as instruments for *Volatility* respectively. Firm controls are the same as in the baseline model. Loan controls include loan maturity (log), loan size (log) and indicators for loan purpose, loan type, secured and senior loans. Details on the definitions of variables are provided in Appendix A. The sample period is from 1993 to 2013. Columns (3)-(4) report results based on the baseline bond sample firms only. We display the standard errors clustered at the firm level in parentheses. We indicate significance at the 10%, 5% and 1% level by *, ** and *** respectively.

Dependent Variable =	$\ln(\text{LSpread})_{t+1}$			
	Bond Sample Firms		All Firms	
	IV (FVolatility)	IV (FVolatility_Adj)	IV (FVolatility)	IV (FVolatility_Adj)
	(1)	(2)	(3)	(4)
$\widehat{\text{Volatility}}$	0.261*	0.227	0.325**	0.409**
	(0.153)	(0.141)	(0.154)	(0.160)
Firm Controls	Yes	Yes	Yes	Yes
Observations	8,130	8,130	14,684	14,684
Loan Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

CHAPTER 3

OPTIONS TRADING AND CASH HOLDINGS

3.1 Introduction

Financial derivatives are state-contingent contracts based upon the underlying financial instruments tailored to the demand of investors. The rise of financial derivatives helps complete markets through risk-sharing and facilitate market efficiency. In the United States, the markets for equity options, a derivative used exclusively to trade stocks as the underlying asset, have seen an explosive growth over the last several decades.The Options Clearing Corporation reports that the total number of equity option contracts traded increased by almost 4000% from 1990 to 2018[1]. Equity options allow investors to trade more efficiently on stock price movements for either hedging or speculating purposes. Prior studies show that options trading improves stock market efficiency (Skinner, 1990; Kumar et al., 1998; Chakravarty et al., 2004). However, the implications of options trading for the real activities of underlying firms are still an open question. In this paper, we explore the effects of equity options trading activities on corporate cash holdings, a crucial corporate financial policy that has recently drawn both public attention[2] and academic interest [3].

[1] `https://www.theocc.com/webapps/historical-volume-query`

[2] For example, as reported by the Financial Times, an activist hedge fund manager complained that "Apple has $145 per share of cash on its balance sheet. As a shareholder, this is your money" and tried to change the Apple's capital allocation policies through litigation (see, `https://www.ft.com/content/b4171642-7136-11e2-9d5c-00144feab49a`). In recent years, several financial presses regularly track the evolution of the U.S. corporate cash stockpiling.

[3] See, for example, Dittmar et al. (2003), Faulkender and Wang (2006),Harford et al. (2008), Bates et al. (2009), Denis (2011), Harford et al. (2014), Chen et al. (2015b) and Graham and Leary (2018) among others.

The impact of options activities on the cash policies of underlying firms is *a priori* unclear since there are several channels through which options trading could affect cash holdings; thereby, leading to different predictions. On the one hand, due to low transaction costs and high leverage, stock options provide an ideal opportunity for shareholders to more flexibly manage their exposure to firm specific risk. For corporate officers, whose stakes in their firms disproportionally affect their personal income, this allows them to more actively engage risk-taking activities (Gao, 2010). Alternatively, outside shareholders may benefit from an active option market in terms of hedging[4], and thus, to say the least, be more tolerant to managers pursuing risky projects[5]. In contrast, debtholders have limited access to the upside potential and are exposed to the higher downside risks.

Therefore, there appear to be two competing implications for corporate liquidity management decisions. First, options trading encourages risk-taking leading to *lower* cash holdings. Second, greater risk-taking incentives resulting from active options markets on the firm side may occur at the expense of creditors' interest(Jensen and Meckling, 1976). This likely results in a higher cost to issue new debt, a lower likelihood to renegotiate existing debt agreements (Opler et al., 1999), and a greater incentive to increase cash reserves. Consequently, we expect that firms with more options trading will *increase* their cash reserves.

On the other hand, (Cao, 1999) suggests that options trading aids informed trading and information acquisition, thus improving the information environment of the underlying firms[6]. A better information environment, in turn, lowers the expected cost of capital (Roll et al., 2009; Naiker et al., 2013; Chen et al., 2015a), perhaps resulting in

[4]Several recent studies provide supporting evidence for this view. Using extensive data on derivatives usage, Natter et al. (2016) find that mutual funds use options mainly for hedging via protective puts and covered calls, leading to lower systematic risk and higher risk-adjusted performance. Similarly, Aragon and Martin (2012) find that hedge funds using options deliver higher benchmark-adjusted portfolio returns and lower risk.

[5]Prior research indicates that lower risk exposure of shareholders is associated with more risk-taking by the firms with in institutional portfolios (Amihud and Lev, 1981; Faccio et al., 2011).

[6]Consistent with this view, Skinner (1990), Kumar et al. (1998), Chakravarty et al. (2004) and Cao et al. (2019) among others find that options trading enhances information production and stock price efficiency.

lower demand for cash reserves (Myers and Majluf, 1984). These implications are that a more active options market should *reduce* corporate cash holdings. Taken together, it becomes an empirical question as to how options trading affects cash holdings.

Using a large sample 45,705 firm-year observation for non-financial U.S., we find supporting evidence in line with the prediction that an active option market tends to increase corporate demand for cash savings. In particular, we document that firms that trade a greater volume of options trading volume hold more cash as a fraction of total assets. The relation is statistically significant, and the economic magnitude is sizeable: the baseline results indicate that one standard deviation increase in our options trading measure is associated with an increase in the cash ratio ranging from 7% to 18% of the sample mean.

To address endogeneity concerns, we first follow Roll et al. (2009) and use unsigned moneyness or open interest as an instrument for options trading volume. Second, we employ the Penny Pilot Program as a quasi-natural experiment. The Penny Pilot Program cuts the tick size for selected options classes and thus exogenously increases the liquidity of these pilot options, resulting in higher trading volume. Using a difference-in-differences (DID) framework, we document a relative increase in cash ratio among the pilot firms compared to control firms. To ensure that the channel is through options trading, we instrument the measure of options trading by pilot status in a two-staged least squares (2SLS) model and obtain consistent results. Third, to further alleviate omitted variable and reverse causality concerns[7], we examine the extensive margin of options trading. Specifically, we extend the baseline sample to include firm-year observations without options activities and test whether the option listing status affects future cash holdings. Analyses based on the full sample as well as a matched sample reveal that option listing firms substantially raise cash ratios after initial listings. Overall, these results are

[7]The time-varying intensity of option trading may contain some material information, leading to possible omitted variable problems. As for reverse causality, although in our baseline specification we use lagged option activities, it is possible that past cash policies may affect past options trading.

indicative of a causal interpretation.

We use a myriad of tests to explore possible channels. First, we investigate the effect of option trading on cash holdings conditioned on financial distress risk. If the impact of option trading on firm cash policies is mainly driven by creditors' concerns about asset substitution, then we expect to observe a more pronounced effect among firms that face more financial distress risk since an active option market may exacerbate the agency conflict between firms and outside creditors due to increasing risk-shifting incentives. To test this intuition, we augment the baseline regression model by adding interaction terms that captures the effects of agency conflict. As risk-shifting incentives are particularly high when a firm is in financial distress(Wright et al., 2013), we would expect the effect of option trading on future cash holdings to be more pronounced among firms with high financial distress risk. Using market leverage, Altman's Z-score and Ohlson's O-score as proxies for closeness to distress confirms this conjecture. In addition, we also examine the effects from loan covenant violation events. On the one hand, covenant violations are effectively technical defaults and thus represent realized financial distress states. On the other hand, loan covenant violations allow creditors to more directly influence firm decisions. Since creditors do not benefit from upside potentials, they typically suppress risk-taking. We find that the effects of option trading on cash savings are stronger among firms that have recently violated loan covenants. This suggests that the ability to hedge raises red flags to exacting creditors who would in turn force firms to save more.

Next, we provide more evidence on the plausibility of precautionary saving as a motive for holding more cash with more liquid option markets due to debt financing needs. To this end, we make use of a direct proxy for financial constraints developed by Hoberg and Maksimovic (2014) using 10K disclosures. In particular, we test whether the positive impact of option trading on cash holdings is stronger among firms that have problems funding some projects because they are more concerned about the agency cost of debt. Our findings are generally consistent with view. The effects of options trading are concentrated in firms that have funding needs while facing liquidity issues. More interestingly, since Hoberg and Maksimovic (2014) also provide two financial constraint indices with one indicating a plan to issue debt and the other equity, we find that our results are only significant for debt financing. This validates our hypothesis that the agency cost of debt drives the observed relationship between option trading and cash holdings.

Third, we examine the information channel as an alternative channel to the main results that we document. Although we observe that options trading is positively related to cash savings, this does not necessarily mean that the factors driving the alternative prediction are completely muted. In fact, several previous studies suggest that options activities improve the information environment surrounding the underlying stock, which may help alleviate the agency cost of debt. Tests using several measures of information asymmetry indicate that the positive effects of options trading are significantly weaker in opaque firms where the marginal information efficiency enhancement due to options activities is more pronounced, which tends to mitigate the agency cost of debt and thus decreases the need for cash savings.

We conduct several supplementary analyses to shed more light on our main findings. When the agency conflict due to risk-shifting incentives is severe, it is expected to become more costly to raise debt from outside creditors. Supporting this claim, we find the cost of bank loans and corporate bonds to be positively correlated with option trading activities. Following Faulkender and Wang (2006), we also explore the relation between option trading and the value of cash. We find collaborative evidence that suggests a higher marginal value of cash in a more active option market, consistent with the argument that cash is considered to be more valuable as a buffer for costly debt financing. Lastly, we conduct more robustness tests for the baseline relation using alternative specifications and the results qualitatively remain unchanged.

This study sheds some new insights into the long standing corporate liquidity management literature. In particular, several studies recently focus on the rapid growth of cash holdings in the last decades which has sparked a revived academic interest into what drives corporate cash savings from an empirical perspective (Bates et al., 2009; Denis, 2011; Graham and Leary, 2018). The major innovation of this paper is relating equity option markets to underlying firm cash policies. Our findings suggest that the exponential development of equity option markets may be a contributing factor. Previously, it has been shown by Subrahmanyam et al. (2017) that credit default swaps (CDS) induce CDS-reference firms to hold more cash. Supplementing their study, we find that equity-based financial derivatives also affect corporate liquidity management, and provide multifaceted evidence that points to precautionary motives for cash savings due to increasing agency costs of debt as the driving force.

Our paper also contributes to the burgeoning literature on the real effects of financial markets on firm outcomes (Bond et al., 2012). Despite a prior focus on stocks (Chen et al., 2007; Khan et al., 2012; Edmans et al., 2012; Brogaard et al., 2017), the impact of financial derivative markets on the real decisions of underlying firms is currently under-explored. This paper is meant to help bridge this gap. More closely related to our paper, Roll et al. (2009), Blanco and Wehrheim (2017), Cao et al. (2018) and Cao et al. (2019) find effects of option trading on firm value, patenting activities, debt structure, the cost of bond and stock price informativeness. Our findings complement this line of research.

The remainder of this paper proceeds as follows: Section 3.2 describes the data and variable construction. Section 3.3 contains the baseline results and explores possible channels. Section 3.4 provide additional evidence and discusses alternative interpretations. Section 3.5 concludes.

3.2 Data and Variables

Our initial sample consists of all U.S. common stocks with a share code equal to 10 or 11 from the Center for Research in Security Prices (CRSP) database. We then use the matching table provided by the Wharton Research Data Services (WRDS) to merge this sample with the equity options trading data drawn from the OptionMetrics database. We exclude financial firms [standard industrial classification (SIC) codes 6000-6999] to avoid a potentially mechanical relation to options markets, and also because the liquidity management of financial firms is very different from non-financial firms and is closely regulated by federal agencies. We obtain accounting data from the Compustat database provided through WRDS. After removing observations with missing variables for our baseline analysis, our baseline sample consists of an unbalanced panel of 45,045 firm-years in 5,286 unique non-financial firms.

We define the key independent variable of interest, *Options trading*, as the natural logarithm of total annual dollar options trading volume.*Options trading* is a proxy for the intensity of equity options trading for the underlying stocks. Following Roll et al. (2009), for each stock in our sample, we calculate the annual dollar options trading volume by multiplying the daily trade volume in each option by the end-of-day quote midpoint for that option and aggregate it annually over all trading days and over all options listed on the stock. A higher value of *Options trading* represents a more active options market for the underlying stock[8]. For most of regressions, the main dependent variable is cash ratio (*Cash*), defined as cash and short-term investments divided by total assets.

We closely follow Bates et al. (2009) and Opler et al. (1999) to select our control variables for the baseline regression model that associates options trading intensity to cash ratios. The control variables are motivated by the transaction and precautionary explanations for corporate cash holdings discussed in Bates et al. (2009). The baseline control variables include *Market to book*, *Size*, *Cash flow*, *Net working capital*, *Capital*

[8]In robustness tests we also employ other measures of options trading and obtain similar results.

expenditure, *Leverage*, *Industry sigma*, *Dividend dummy*, *R&D*, *Acquisition*. To ensure that our results are not driven by outliers, we winsorize all continuous variables at the 1st and 99th percentiles. The detailed definitions of our complete set of variables along with their data sources are in Appendix A. Table 3.1 contains summary statistics for the variables involved in the baseline regression. The sample average cash ratio is 19.81%, and the statistics as shown in Table 3.1 are largely comparable to those reported in previous studies (Opler et al., 1999; Bates et al., 2009).

3.3 Main Results

In this section we examine the relationship between equity options trading and cash holdings. Our starting point is a baseline ordinary least squared (OLS) regression model. Next, we proceed to address endogeneity concerns. We first employ the IV approach as in Roll et al. (2009). Then we explore a pilot program initiated by the CBOE as an exogenous shock to options trading. To facilitate a causality interpretation, we also look at the extensive margin of options trading by examining the change in cash holdings before and after options listing. Based on the established relationship, we then proceed to explore possible mechanisms using a set of tests.

3.3.1 Options trading and corporate cash holdings

We test the empirical relation using OLS regression models. The dependent variable is corporate cash holdings captured by *Cash*. The main independent variable of interest is *Options trading* as a proxy for equity options trading intensity. Table 3.2 reports the baseline results of multivariate regression analysis. All the independent variables lag the dependent variable by one year to mitigate reverse causality concerns[9]. Column (1) does not include any fixed effects. From columns (2) through (4) we sequentially add year, industry and firm fixed effects. The coefficients on *Options trading* indicate a positive relation between options trading activities and corporate cash reserves with a

[9]Results remain significant and are actually stronger when using contemporaneous regressions.

statistical significance at the 1% level. As indicated in columns (2) to (4), this relation holds regardless of the presence of various fixed effects[10]. As for the control variables, all these coefficients are signed in the direction suggested in Bates et al. (2009). The economic magnitude is sizeable. The cash ratio increases by 7 to 18 percentages of the sample average following a one standard deviation increase in options trading.

3.3.2 Addressing endogeneity

The baseline estimates may suffer from endogeneity concerns. Although to some extent the reverse causality is less of a concern as we use the lagged independent variables, additional robustness tests are needed to provide better identification. Moreover, options trading may reflect some other information that is not captured by the baseline controls. The potential omitted variables concerns may lead to a spurious relation. In this subsection we seek to tackle these issues using different methods.

Instrumental variables approach

Following Roll et al. (2009), we employ moneyness and open interest in the stock's listed options in turn as the instruments for options trading. Option moneyness is the average absolute difference between the stock's market price and the option's strike price. Roll et al. (2009) contend that moneyness can be linked to options trading activities in various ways. For example, volatility traders may dislike deep in-the-money (ITM) or out-of-the-money (OTM) options because the vega of these options is near zero (Chakravarty et al., 2004). In addition, uninformed traders may gravitate towards ITM options due to risk concerns, while OTM options that are embedded with the largest leverage tend to be more attractive to informed traders. Pan and Poteshman (2006) find some empirical support for this argument. Overall, the relevance requirement is likely to hold given these findings. As for the exclusion restriction, there is no strong argument that

[10] Although firm fixed effects do take away some explanatory power, the estimate of options trading effect remain significant at the 1% level.

unsigned option moneyness directly and unambiguously affects corporate cash policies[11]. Taken together, absolute option moneyness appears to be a valid instrument in this context.

We conduct a two-stage least-squares (2SLS) regression using option moneyness and report the results in Table 3.3. Column (1) reports the estimation result of the first stage regression where *Options trading* is regressed on the unsigned moneyness as an instrumental variable (*Moneyness*) and the baseline control variables with year and industry fixed effects. As with Roll et al. (2009), we find that options trading activities are positively correlated to *Moneyness*. The second stage regression follows the baseline specification except that *Options trading* is replaced by the predicted value from the first stage regression. As indicated in column (2), the 2SLS estimate of the options effect is at the 1% significance level and qualitatively consistent with the OLS result. Columns (3)-(4) contain similar results using year and firm fixed effects. For each IV estimation, We also report tests of both under-identification (Kleibergen-Paap rk LM statistic) and weak identification (Cragg-Donald Wald F-statistic). The two statistics suggest that our IV approach is effective [12].

For robustness, we also use the open interest in options as an alternative instrument suggested by Roll et al. (2009). In particular, *Open interest* is defined as the annual average open interest across all options on a stock. *Open interest* amounts to the number of unsettled put/call contracts and thus inherently correlates to trading volume, while being unlikely to have a mechanical relationship with the corporate decisions on cash savings. We replace *Moneyness* with *Open interest* and report the 2SLS regression results

[11] Exchanges periodically list new options with strike prices close to the recent stock price. So unsigned moneyness may be related to equity volatility which increases the chance that stock prices drift away from the strike price. However, similar to Roll et al. (2009), we find the effects of equity volatility to be insignificant in our robustness tests.

[12] The Kleibergen-Paap rk LM test examines whether the excluded instruments are relevant for identification. A rejection of the null indicates that the model is identified. The Cragg-Donald Wald test is aimed to address weak identification issues. Stock and Yogo (2005) have compiled critical values for the Cragg-Donald F-statistic and suggest that an F-statistic above 16.38 indicates that the weak instruments problem is minimal.

in Table 3.4. We obtain qualitatively similar results using this alternative instrument. In sum, these IV estimation exercises consistently oppose the notion that our baseline results are systemically biased due to endogeneity issues.

The Penny Pilot Program

On Friday, January 26, 2007, the Chicago Board Options Exchange (CBOE) initiated the Penny Pilot Program that cuts the tick size for the options traded on 13 stocks[13]. The pilot program later gradually expanded to include more option classes, with some to replace the delisted pilot options. By 2015, over 350 option classes covering several public firms and ETFs had been added to the pilot program. Since the Penny Pilot Program effectively reduces the trading costs for a set of pilot options only, it serves as a quasi-natural experiment to identify variations in options trading volumes that are likely driven by the cost of trade rather than the underlying firms' fundamentals. This allows us to employ a difference-in-differences (DID) framework to study the casual impact of options trading on corporate cash polices.

We start from our sample firms and match them with the list of pilot option classes through tickers [14]. We are able to identify 289 firms in our sample whose equity options were selected into the Penny Pilot Program. The CBOE did not disclose non-pilot option classes as controls in their experiment. First, we simply treat the rest of firms as the controls and thus the DID analysis is based on all sample firms. But this may lead to a disproportionally large number of control firms. Thus as an alternative method, for each pilot firm in our sample we strive to find a control firm not in the Penny Pilot Program and conduct DID analysis using this matched sample.

[13]More specifically, the Pilot specifies that options trading at less than $3.00 have trading increments of one cent, while those trading at $3.00 or more have trading increments of five cents. Options not in the pilot program have corresponding minimum price increments of $0.05 for options trading below $3.00 and $0.10 for options above $3.00. The pilot program makes an exception for options on the QQQQ, IMW and SPY which trade at or above one cent increments, regardless of price level.

[14]We obtain the pilot option classes tickers from the CBOE website (`https://www.cboe.org/general-info/hybrid-reg-penny-pilot-program`). We also carefully compare the company names to ensure that the match is correct.

Specifically, we model the probability of becoming a pilot firm in a given year as a logit function of firm characteristics along with time and two-digit industry dummies. We include *Options trading* together with all baseline control variables in the logit model to mitigate the concern that the determinants of cash holdings may also affect the propensity of pilot status. As with Subrahmanyam et al. (2017), when estimating the likelihood function we drop the observations of pilot firms after they are included in the program. We lag all explanatory variables in the logit model by one year. We then compute the time-varying predicted likelihood of pilot status. For each pilot firm in the year prior to the program inclusion we match it with a control firm with the nearest estimated probability[15]. The matching process generates a matched sample of 3,854 observations with 432 unique pilot and control firms between 2006 and 2016.

To proceed with DID analysis, we create a dummy variable *Pilot* that equals one if the firm is in the pilot program in the current year and put it in place of *Options trading* in the baseline regression model. Moreover, we also conduct IV estimation by using *Pilot* as an instrument for *Options trading* so as to alleviate the concern that the DID outcomes may not be driven by changes in options trading intensity[16]. Table 3.5 presents the results of DID and IV regressions either based on the baseline sample (Panel A) or the matched sample (Panel B). All models include year fixed effects to capture the common trend among both pilot and control firms. For robustness, we use industry fixed effects in columns (1)-(3), while columns (4)-(6) include firm fixed effects [17].

Column (1) of Panel A shows that the program has a positive and significant effect on cash holdings for pilot firms relative to control firms, and this result is robust to using firm fixed effect, as indicated in column (4). The matched sample results in Panel

[15]Following the literature, when significant discrepancies exist across treated and non-treated samples, a control firm can be matched to multiple pilot firms.

[16]In this case, the exclusion restriction holds because the Penny Pilot Program is designed to evaluate the effects of penny quoting on options markets quality, thus arguably exogenous to managerial decisions of holding more or less cash. As for the relevance requirement, the program effectively reduces the trading costs of pilot classes, which in turn spurs more options trading activities.

[17]When using industry fixed effects we add a "pilot fixed effect" to the regressions in order to control for time invariant differences between the pilot and control firms.

B depict a similar picture even though the sample size substantially shrinks due to the matching process. Turning to IV analysis, as shown in columns (2) and (5), the first stage regressions confirm our conjecture that the options trading activities increase following inclusion into the pilot program regardless of model and sample specifications [18]. More importantly, columns (3) and (6) report that the coefficients on the predicted value of *Options trading* from the second stage regressions are positive and statistically significant at the 1% level, meaning that the DID results can be explained by the exogenous increase in options trading volume. Overall, these findings strongly suggest a casual impact of options trading on the underlying firms' liquidity management policies.

Initial option listing

To further mitigate endogeneity concerns, we also look into the extensive margin of options trading. In particular, we first extend our baseline sample to include firm-year observations without any option listed on exchanges and then identify firms that have an initial option listing but no re-listing afterwards (treatment), along with firms exhibiting no option listing history (control) throughout our sample period[19]. Then we create a dummy variable, *Option listing*, and set it to one for the post-listing period and zero otherwise[20]. The regression model is analogous to the baseline model in section 3.3.1 with *Options trading* being replaced by *Option listing*. The coefficient on *Option listing* thus captures the impact of options trading on the extensive margin (from zero to non-zero). Since the decision to list options is by no means random, we also construct a matched sample where each option listing firm in the month prior to the initial listing is matched to a non-listing firm with the closest estimated likelihood of listing options[21].

[18] We also report tests for instruments validity. Kleibergen-Paap rk LM statistic and Cragg-Donald Wald F-statistic suggest that the null hypotheses that the model is poorly identified are all rejected.

[19] As with Roll et al. (2009), we identify initial option listing by observing the first non-missing trading data in OptionMetrics. As the OptionMetrics data start in 1996, we can only identify initial option listing events since 1997 and thus the extensive margin analysis spans from 1997 to 2016.

[20] For firms that never list any options during the sample period, *Option listing* remains zero.

[21] We follow Mayhew and Mihov (2004) and estimate a logit model that predicts the likelihood of listing. Following Subrahmanyam et al. (2017), we drop the observations of option-listing firms

We present the results of extensive margin analysis in Table 3.6. As expected, we document a positive and significant coefficient on *Option listing* and the results are virtually unchanged if the estimation is based on the matched sample[22]. This suggests that firms choose to hold more cash post-listing. Similar to Nguyen et al. (2018), we also investigate the dynamic effects of option listing as a falsification test. Instead of *Option listing*, we use a number of year dummy variables that trace the changes in cash holdings over a five-year window around the option listing event. Specifically, *Listing year 0* is an indicator that equals one for the year of initial listing for a given firm and zero otherwise. *Listing year - 1* is an indicator that equals one when a listing firm is one year prior to initial listing and zero otherwise. *Listing year + 1* is an indicator that equals one for the first year after initial listing and zero otherwise. *Listing year - 2* and *Listing year + 2* are analogously defined. Column (3) indicate that the coefficients on *Listing year - 2* and *Listing year - 1* are not statistically different from zero, while the coefficients on the year dummies past a given listing event are all positive and significant. In column (6) where the matched sample is used we find very similar estimates. These findings reassure us that, compared to non-listing firms, listing firms only increase cash holdings after the initial option listing, but not before.

Overall, the extensive margin analysis performed in this section corroborates our main findings by offering two important takeaways. First, it helps further alleviate omitted variable concerns because the changing intensity of options trading may partially reflect some private information about firm performance, as suggested by Pan and Poteshman (2006), which our baseline models may fail to capture [23]. Second, by exploring initial

following the initial listing. In addition to the monthly explanatory variables as in Mayhew and Mihov (2004), including annual average daily stock trading volume, annual stock returns volatility, abnormal average daily stock trading volume, abnormal stock returns volatility and the market value of equity, we also include all baseline controls in the prior year in the logit model to mitigate the concern that the determinants of cash holdings also affect the decision to list options. We report the estimation results of the logit model in Appendix B Table B2.

[22]In columns (1) and (4) where the industry fixed effect is used, to control for time invariant differences between listing and non-listing firms we add "listing fixed effect" to the model. We note that including firm fixed effect absorbs the Listing FE.

[23]Pan and Poteshman (2006) find that the ratio of put to call options are predictive of future stock

option listings we are able to more confidently argue that a reverse causality running form cash policies to options trading is unlikely to hold. Even though in our baseline models we use lagged options trading activities, it is still possible that lagged cash policies may cause lagged option options trading to rise. However, since there is only one listing event for each listing firm and thus no past listings[24], such an argument for a potential reverse causality becomes less reasonable. Combining all these tests, we find it difficult to reject the claim that options trading activities tend to cause the underlying firms to save more.

3.3.3 Understanding the mechanisms

So far, we have established a positive relationship between options trading activities and corporate cash holdings, which appears to be causal. In this subsection we proceed to explore the possible channels. We intend to argue that options trading may exacerbate the agency cost of debt by providing more risk-shifting incentives. This is the main channel through which options trading leads to more cash holdings. To this end, we employ regression analyses conditioning on various characteristics to identify situations where the effects of options trading are stronger or weaker. We find support for our argument from different perspectives. By clarifying the channels, these positive results also help alleviate the concern about a spurious correlation.

Heterogeneous effects: conditioning on financial distress risk

We first examine the role of financial distress risk. When a firm becomes financially distressed, managers experience greater risk-shifting incentives to extract wealth from the firm, which may be at the expense of outside debt holders. Several previous studies

returns in very short term (weekly). To be noticed, however, our measure of options trading intensity does not involve any information on directional bets. It simply reflects whether a firm is surrounded by an active or inactive options markets. Therefore, we argue that it is because of more active options markets that exacerbate the risk-shifting incentives that would hurt outside creditors, which in turn causes firms to hold more cash to avoid costly external debt financing. We provide more evidence supportive of this view in the following sections. Moreover, an initial option listing represents a discrete change in option activities, and from Table 3.6 we do observe a jump in cash holdings accordingly when passing the listing event. It is unlikely that this is driven by some sharp changes in other fundamentals, which tend to move slowly.

[24]Subject to data availability, we mean that there is no past listings over the sample period.

provide empirical support for this view (Eisdorfer, 2008; Hotchkiss et al., 2010; Chang et al., 2016). Therefore, this agency problem is likely to escalate during periods of financial distress(Wright et al., 2013). An active options market enables managers to better manage their exposures to firm-specific risk (Gao, 2010), leading to potentially higher agency costs for creditors because of those risk-shifting actions [25]. We expect this expected option-induced agency cost to be more severe when a firm is at risk of financial distress in which case the tendency to take actions against the interest of creditors is strong. Accordingly, the firm may find holding cash especially beneficial in this case due to a higher expected cost of external debt financing.

To test this intuition, we investigate whether the impact of options trading activities is stronger for firms that are relatively more subject to financial distress risk. We first construct several proxies for financial distress risk, including *Market leverage*, *Z-score* and *O-score*. Market leverage is defined as total debt over the market value of assets. Higher Market leverage is indicative of closer distance to insolvency. Altman's *Z-score* and Ohlson's *O-score* are two widely used measures of financial distress risk with lower *Z-score* or higher *O-score* suggesting higher financial distress risk. Then we augment the baseline model to add *Market leverage*, *Z-score* and *O-score* along with the interactions between these variables and *Options trading*. We report the results in Table 3.7. The statistically significant coefficients on the interaction terms suggest that options trading activities have a greater impact for firms that have higher distress risk.

To shed more light on this risk-shifting channel, as a placebo check, we consider loan covenant violations. To do so, we create a dummy variable (*Loan covenant violation*) that equals one if a firm has experienced at least one loan covenant violation in the last three years[26]. Using the interaction between the dummy variable and *Options trading*, we test

[25]Similar to this argument, outside equity holders may be less concerned about risk-taking because equity options provide better protections against stock price movements. Faccio et al. (2011) find that shareholders' ability to manage equity risk is positively related to the underlying firms' risk-taking activities. The implications are about the same.

[26]We obtain covenant violation data from Roberts and Sufi (2009).

whether the effect of options activities is particularly strong for firms following covenant violations. Column (4) of Table 3.7 indicates that the link between options trading and cash holdings is stronger in the case of recent loan covenant violations. This complements the findings in columns (1)-(3) in that loan covenant violations are financial distress events. Moreover, a loan covenant violation leads creditors to scrutinize more closely corporate matters that may hurt them (Acharya et al., 2011). Therefore, the finding in column (4) to some extent validates the proposed risk-shifting channel.

Heterogeneous effects: conditioning on financial constraints

Reliance on external financing is crucial to our interpretation of the baseline results. If there is little demand for additional financing, or it is easy to tap external capital markets, then firms should be less concerned about the agency cost of debt brought by options markets. In contrast, we expect options activities to have a greater impact on cash saving for firms that depend on external sources to finance some projects when funding is difficult. To test this prediction, we follow Hoberg and Maksimovic (2014) and use a text-based measure of financial constraints. In particular, based on textual analysis of the 10K filings[27], the *HM Delay index* quantifies the extent of financial constraints. Firms with a higher *HM Delay index* are deemed to be at risk of delaying their investments due to issues with liquidity. We then interact *HM Delay index* with *Options trading*.

Table 3.8 presents the results. In column (1), the coefficient on the interaction term is positive and statistically significant, which implies that the effects of options activities on cash holdings becomes more pronounced for more financially constrained firms. As a further validation test for our hypothesis and a clarification of the channels, we also make use of two additional text-based proxies for financial constraints as in Hoberg and Maksimovic (2014). Specifically, *HM Debt Delay index* and *HM Equity Delay index* are

[27]The Capitalization and Liquidity Subsection of the MD&A section of the 10-K is parsed using the metaHeuristica software program. For details, see Hoberg and Maksimovic (2014). We thank Professor Gerard Hoberg for making the data available.

analogously defined as with the *HM Delay index* while indicating that there are plans to issue debt and equity, respectively, to address the described liquidity issues. Our hypothesis implies that, when it comes to precautionary motives for cash holdings, the use of equity options should only matter in situations where debt financing is needed, but not as much in the case of equity financing, because options activities provide risk-shifting incentives that may not be in the interest of debt holders. That said, we expect the coefficient on the interaction term involving *HM Debt Delay index* to be significant and positively signed, but not for *HM Equity Delay index*. This is exactly what we find in columns (2)-(3) of Table 3.8.

Heterogeneous effects: conditioning on information asymmetry

As we have argued above, there could be multiple channels through which options activities can affect cash polices. Although we document a positive relationship, that does not necessarily mean other channels that predict a negative relationship have zero effect [28]. Since options markets facilitate information production Cao et al. (2019) and thus have the potential to reduce information asymmetry, we expect this effect to mitigate the equity-debt agency conflict due to the risk-shifting incentives that options trading may cause (Myers and Majluf, 1984). A prediction following this logic is that the positive impact of options activities on cash holdings should be weaker for more opaque firms where the marginal benefit of options trading on improving information efficiency and reducing agency cost of debt should be greater.

To test this prediction, we use the following list of empirical proxies for information asymmetry: analyst forecast error (*Forecast inaccuracy*), a dummy variable indicating the S&P 500 index membership (*S&P500*), probability of information-based trading (*PIN*), a dummy variable indicating the existence of S&P credit rating (*Rating*). *Forecast inaccuracy* is measured by the absolute deviation of median forecasted earnings per share

[28] It is possible that they are net out by the channel that dominates.

(EPS) from the actual EPS. Higher *Forecast inaccuracy* implies greater information asymmetry. We calculate *PIN* following Brown and Hillegeist (2007) who show that greater information asymmetry is associated with higher *PIN*. *S&P500* and *Rating* are dummy variables with a value of one meaning more visibility to the capital market, thus lower information asymmetry, and zero otherwise. We interact these proxies with *Options trading* in the augmented baseline regressions and present the results in Table 3.9. The coefficients on the interaction terms involving *Forecast inaccuracy* and *PIN* are positive and statistically significant. As for *S&P500* and *Rating*, the interaction estimates are negative and significant. These results are in line with our predictions.

3.4 Additional Analyses

3.4.1 Options trading and the cost of debt

We attribute the impact of options activities on cash savings to precautionary motives resulting from concerns about the agency cost of debt financing. To reinforce this argument, we provide additional tests that examine the effects of options trading on the (realized) cost of debt. If options trading activities do intensify creditors' concerns about risk-shifting, then we expect this agency cost (risk) to be priced in newly issued debt. We regress the spread of loan contracts and bonds at issuance on *Options trading* and several standard control variables used in the related literature (Campello et al., 2011a; Hasan et al., 2014). We obtain data on loan contracts from the Thomson Reuters LPC DealScan. We collect information for bond issuance from FISD. After removing missing variables in our regression models we end up with 8,845 loan contracts and 6,562 bond issuances [29]. Table 3.10 presents the estimates. In columns (1) and (2) we find options trading activities to be positively associated with loan spread. Column (3) reports similar result for the cost of bond, though firm fixed effects suppress the statistical significance, as shown in

[29]Loan contracts are at the facility level. A loan package obtained by a firm may include several facilities with varying terms and credit spreads.

column (4). Overall, these results are largely supportive of our prediction, and thus at least partially explain the rationale behind the positive relation between options activities and cash reserves.

3.4.2 Options trading and the marginal value of cash

Although we find that firms tend to hold more cash when options trading is active, the marginal value of cash due to options activities is still unclear. It is entirely possible that as the level of options activities increases, on the margin, the value of one additional dollar in cash reverses may decrease. Theoretically, adding one dollar in cash reverses has both marginal benefits and costs to equity holders and these marginal benefits (or costs) may vary depending on other factors. For firms with a high volume of options activities, the marginal market value of one additional dollar of cash savings is expected to be greater because exacting creditors may lead to foregoing net present value (NPV) projects due to more costly access to external debt capital markets. This can serve as a corollary to our main hypothesis. Following Faulkender and Wang (2006), we empirically test this argument by examining the relationship between excess stock returns and changes in cash holdings at various levels of *Options trading*. Our regression models closely mimics the ones in Faulkender and Wang (2006). We report results in Table 3.11 where column (1) does not include any fixed effect as in Faulkender and Wang (2006), and column (2) adds year and firm fixed effects to the model. The coefficient of interest is the interaction of the change in cash (ΔC) with *Options trading*, which is significantly positive, meaning that the marginal value of cash reserves increases with options activities. These results indirectly support our interpretation of the relation between options activities and cash holdings[30]

[30]To some degree these results also help rule out other explanations and separate our paper from others. For instance, Blanco and Wehrheim (2017) show that options trading facilitates firm innovations. If the mechanism in Blanco and Wehrheim (2017) were the one underpinning our baseline relation, then one should expect the marginal value of cash holdings to be negative at high levels of options activities where the marginal cost of foregoing growth opportunities is likely to outweigh the marginal benefits of storing more cash.

3.4.3 More robustness tests

In this subsection, we add more robustness checks for the stability of the empirical relationship between options activities and corporate cash holdings. In Table 3.12, we report regression results with additional controls. We use these variables to further address omitted variable concerns. For columns (1) to (3), we sequentially add more characteristics related to firm-specific equity (*Equity trading*, *Equity illiquidity*, *Equity return*, *Equity volatility*), option (*Implied volatility*, Put-call ratio) and information environment (*Institutional ownership*, *Analyst coverage*, *Stock price synchronicity*) to the baseline regression models, while the estimated coefficients on *Options trading* are barely affected. In column (4), we further include industry by year fixed effects that control for time varying industry-specific factors, and find similar results. Aside from mitigating omitted variable concerns, these tests also help rule out other explanations. For instance, Cao et al. (2019) find that options trading can change the information environment of the underlying stocks. In columns (3)-(4), however, we show that the coefficient on *Options trading* is robust to adding various empirical proxies for information production (*Institutional* , *Analyst coverage*) and stock price informativeness (*Stock price synchronicity*) as controls. This indicates that our baseline results are unlikely driven by the information production effects of options trading[31].

In addition, we investigate whether the baseline relation holds when we use alternative measures. As with Bates et al. (2009), we use a set of alternative definitions of cash ratio, including cash to assets (*CNA*), log of cash to net asssets and cash to sales (*CS*) as dependent variables. We find qualitatively similar results with statistical significance in all cases (see Table B3 in the Appendix B). Next, we measure the extent of options trading activities, our key independent variable, in alternative ways. Table B4 in the Appendix B reports the results. Given our primary measure using dollar daily volume, as a robustness check we define *Options trading 1* similarly as with *Options trading* while

[31] As we have argued, firms should decrease cash if options activities facilitate information production.

aggregating the daily number of contracts traded instead. Moreover, when constructing the independent variable, if we only include call options trading (*Options trading 2*) or put options trading (*Options trading 3*), our results qualitatively remain the same. To some degree, these tests help strengthen the interpretation of our baseline results[32], where *Options trading* mainly measures how active the option markets are for a given stock, and compared to others, this interpretation is more consistent with the baseline and corroborative results we got so far.

3.4.4 Alternative channels

A caveat to the interpretation of our baseline results is that a governance channel may also be possible. This mechanism emphasizes the agency conflict between managers and shareholders. As we mentioned earlier, a by-product of active options trading is an enhancement of information production through gaining more investor attention, which may serve as a substitute for an external governance mechanism (Yu, 2008; Liu and McConnell, 2013). However, the related literature is inconclusive regarding whether good corporate governance increases or decreases cash savings. Dittmar et al. (2003) find that in countries with weak shareholder protection firms hold more cash, while Harford et al. (2008) document that firms with weaker corporate governance structures actually have smaller cash reserves [33]. Since we find cash ratios to be positively associated with options trading, if this outcome is mainly driven by the governance effect of increasing investor attention, then we would expect to see stronger estimates for firms with poor corporate governance. We use several proxies for governance quality such as the G-index (Gompers et al., 2003), E-index (Bebchuk et al., 2008), board independence and an indicator for

[32] Pan and Poteshman (2006) suggest that put options trading may contain different views compared to calls. This is what prompts us to carry out these robustness tests. Since the results hold regardless of put or call options, these are more in line with the interpretation that documented effects are not merely a reflection of the private information contained in the options trading volume.

[33] Although Jensen (1986) develop the free cash flow hypothesis suggesting that shareholders prefer less cash holdings to prevent mangers from access to free cash flow with the presence of agency conflict, the very existence of agency problem may reduce the likelihood that managers would listen to shareholders with limited control rights.

the CEO being board chairman. We do not find any significant (at the %10 level) results for the coefficient on the interaction between options trading and the aforementioned measures of corporate governance effectiveness. For brevity we report these results in Appendix B, Table B5. Although we are unable to rule out the possibility that the governance effect of options trading may be at play, we deem this channel to be unlikely.

It is also tempting to argue that the relationship between options activities and cash holdings is due to the private information incorporated in options trading. Although we are unable to completely deny the possibility that our primary measure of options trading activities varies across time and firms, and thus may contain some information about firm fundamentals, it is unclear from a theoretical perspective exactly what kind of information is involved because our measure is a simple aggregation of the trading volume of *both* call and put options, regardless of strike prices or maturity, and the measure does not contain any directional information about these trades. Moreover, the robustness tests for identification, especially the ones using the CBOE's pilot program and initial option listing, are not strongly supportive of this view[34]. The estimates reported in Table 3.9 provide additional indirect evidence in that regard, namely that if *Options trading* contains private information that predicts an increasing cash ratio then the relation should be stronger for more opaque firms, while the facts are actually the opposite, as suggested by Table 3.9.

3.5 Conclusion

Equity options enable shareholders to tolerate or even encourage more risk-taking for firms in their portfolios, which may not be in the interest of creditors. Despite other channels that may be also at play, we hypothesize that options trading activities are viewed by the creditors as an increased agency risk, and thus more costly access to

[34]For instance, we base the extensive margin analyses on initial option listings which amount to one-time shocks. In Table 3.6, we find the effects to be persistent, which cannot be explained by informed trading activities.

external debt financing. The resulting impact of options activities on cash holdings then should be positive because of precautionary saving motives. Our finding of a strong positive relationship between the extent of options activities and the cash ratio supports this prediction. In order to minimize the potential endogeneity concerns, we go through three sets of tests, including an IV approach, a quasi-natural experiment and extensive margin analyses, and find robust results that are in favor of a causal interpretation. We also conduct of number of complementary tests that dig deeper into the possible channels. We find the effect to be stronger for firms with more financial distress risk and difficulty to raise additional debt financing despite the existence of investment opportunities. Moreover, options activities are associated with a higher realized cost of loan financing. The marginal value of cash is higher for firms with more active options markets. These findings collectively point to our main hypothesis that options activities tend to increase corporate cash savings mainly through an agency cost of debt channel.

Table 3.1: Descriptive Statistics for Baseline Analysis

This table reports the summary statistics of baseline variables over the full sample between 1996 and 2016. *Cash* refers to cash to assets ratio in year t+1. *Options trading* refers to the natural logarithm of annual equity options trading volume. The baseline controls include *Size*, *Market to book* , *Cash flow* , *Net working capital* , *Capital expenditure* , *Leverage* , *Industry sigma*, *Dividend dummy* , *R&D* and *Acquisition* . Details on the definitions of variables are provided in Appendix A.

	Observations	Mean	Std.Dev	25%	50%	75%
Cash	45,705	0.1981	0.2174	0.0336	0.1127	0.2898
Options trading	45,705	10.9657	2.6401	9.1974	10.9436	12.8035
Market to book	45,705	2.2298	1.7293	1.2160	1.6449	2.5366
Size	45,705	7.1078	1.8369	5.7843	7.0186	8.3411
Cash flow	45,705	0.0368	0.1717	0.0281	0.0718	0.1137
Net working capital	45,705	0.0332	0.1496	-0.0499	0.0202	0.1219
Capital expenditure	45,705	0.0603	0.0630	0.0203	0.0402	0.0757
Leverage	45,705	0.2312	0.2122	0.0260	0.2041	0.3590
Industry sigma	45,705	0.1245	0.1159	0.0561	0.0950	0.1563
Dividend dummy	45,705	0.4040	0.4907	0.0000	0.0000	1.0000
R&D	45,705	0.2820	1.3908	0.0000	0.0034	0.0912
Acquisition	45,705	0.0263	0.0618	0.0000	0.0000	0.0177

Table 3.2: Options Trading and Cash Holdings

This table presents results of OLS regressions that examine the effect of options trading activities on corporate cash holdings. The dependent variable is cash to assets ratio (*Cash*) in year t+1. *Options trading* refers to the natural logarithm of annual equity options trading volume. The baseline controls include *Size*, *Market to book* , *Cash flow* , *Net working capital* , *Capital expenditure* , *Leverage* , *Industry sigma*, *Dividend dummy* , *R&D* and *Acquisition* . The full sample period is from 1996 to 2016. Details on the definitions of variables are provided in Appendix A. The standard errors clustered by firm are displayed in parentheses. Significance at the 10%, 5% and 1% level are indicated by *, ** and *** respectively.

Dependent Variable =	Cash			
	(1)	(2)	(3)	(4)
Options trading	0.0138***	0.0137***	0.0131***	0.0054***
	(0.0007)	(0.0007)	(0.0006)	(0.0005)
Market to book	0.0133***	0.0144***	0.0124***	0.0039***
	(0.0010)	(0.0010)	(0.0010)	(0.0009)
Size	-0.0402***	-0.0406***	-0.0401***	-0.0391***
	(0.0013)	(0.0013)	(0.0014)	(0.0025)
Cash flow	-0.1229***	-0.1217***	-0.1062***	-0.0223**
	(0.0111)	(0.0112)	(0.0111)	(0.0098)
Net working capital	-0.3140***	-0.3074***	-0.3399***	-0.1153***
	(0.0105)	(0.0105)	(0.0119)	(0.0126)
Capital expenditure	-0.6370***	-0.6212***	-0.4810***	-0.2643***
	(0.0200)	(0.0202)	(0.0210)	(0.0185)
Leverage	-0.2427***	-0.2391***	-0.2103***	-0.0743***
	(0.0082)	(0.0082)	(0.0083)	(0.0081)
Industry sigma	0.1876***	0.1837***	0.0385**	-0.0108
	(0.0142)	(0.0145)	(0.0176)	(0.0154)
Dividend dummy	-0.0437***	-0.0424***	-0.0336***	-0.0055*
	(0.0031)	(0.0031)	(0.0030)	(0.0028)
R&D	0.0206***	0.0204***	0.0196***	0.0066***
	(0.0014)	(0.0014)	(0.0014)	(0.0015)

Acquisition	-0.3274***	-0.3187***	-0.3173***	-0.1620***
	(0.0122)	(0.0122)	(0.0117)	(0.0088)
Observations	45,705	45,705	45,705	45,045
Adjusted R-squared	0.5654	0.5685	0.5988	0.8234
Year FE	No	Yes	Yes	Yes
Industry FE	No	No	Yes	No
Firm FE	No	No	No	Yes

Table 3.3: Options Trading and Cash Holdings: Moneyness as Instrumental Variable

This table presents results of 2SLS regressions that examine the effect of options trading activities on corporate cash holdings using the average absolute moneyness as the instrumental variable following Roll et al. (2009). The instrumental variable is the natural logarithm of average absolute moneyness (*Moneyness*). The dependent variable of interest is cash to assets ratio (*Cash*) in year t+1. *Options trading* refers to the natural logarithm of annual equity options trading volume. Details on the definitions of variables are provided in Appendix A. The standard errors clustered by firm are displayed in parentheses. Significance at the 10%, 5% and 1% level are indicated by *, ** and *** respectively.

Dependent Variable =	Options trading	Cash	Options trading	Cash
	IV (1st Stage)	IV (2nd Stage)	IV (1st Stage)	IV (2nd Stage)
	(1)	(2)	(3)	(4)
Options trading (predicted)		0.0145***		0.0118***
		(0.0014)		(0.0014)
Moneyness 0	1.7230***		1.4205***	
	(0.0324)		(0.0266)	
Market to book	0.3011***	0.0117***	0.1982***	0.0015
	(0.0091)	(0.0012)	(0.0085)	(0.0009)
Size	0.7538***	-0.0416***	0.9235***	-0.0484***
	(0.0188)	(0.0019)	(0.0282)	(0.0030)
Cash flow	-0.7869***	-0.1055***	0.3261***	-0.0239**
	(0.1030)	(0.0111)	(0.1016)	(0.0098)
Net working capital	-0.8094***	-0.3392***	0.7260***	-0.1211***
	(0.1284)	(0.0119)	(0.1369)	(0.0127)
Capital expenditure	0.9561***	-0.4843***	1.8320***	-0.2888***
	(0.2730)	(0.0213)	(0.2439)	(0.0192)
Leverage	-0.5120***	-0.2089***	0.0554	-0.0719***
	(0.0895)	(0.0085)	(0.0934)	(0.0081)
Industry sigma	0.9348***	0.0375**	0.8117***	-0.0164
	(0.1947)	(0.0177)	(0.1935)	(0.0154)
Dividend dummy	-0.7702***	-0.0325***	-0.1507***	-0.0049*

	(0.0409)	(0.0031)	(0.0409)	(0.0028)
R&D	0.0732***	0.0195***	0.0294**	0.0064***
	(0.0111)	(0.0015)	(0.0130)	(0.0015)
Acquisition	-0.8719***	-0.3175***	-0.4180***	-0.1613***
	(0.1510)	(0.0117)	(0.1159)	(0.0088)
Observations	45,705	45,705	45,045	45,045
Adjusted R-squared	0.5823	0.5987	0.7831	0.8218
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	No	No
Firm FE	No	No	Yes	Yes
Kleibergen-Paap rk LM-stat	1239.210		1142.212	
Cragg-Donald Wald F-stat	1.2e+04		9027.890	

Table 3.4: Options Trading and Cash Holdings: Open Interests as Instrumental Variable

This table presents results of 2SLS regressions that examine the effect of options trading activities on corporate cash holdings using the average absolute moneyness as the instrumental variable following Roll et al. (2009). The instrumental variable is the average open interests (*Open interests*). The dependent variable of interest is cash to assets ratio (*Cash*) in year t+1. *Options trading* refers to the natural logarithm of annual equity options trading volume. Details on the definitions of variables are provided in Appendix A. The standard errors clustered by firm are displayed in parentheses. Significance at the 10%, 5% and 1% level are indicated by *, ** and *** respectively.

Dependent Variable =	Options trading	Cash	Options trading	Cash
	IV (1st Stage)	IV (2nd Stage)	IV (1st Stage)	IV (2nd Stage)
	(1)	(2)	(3)	(4)
Options trading (predicted)		0.0125***		0.0027***
		(0.0008)		(0.0007)
Open interests	1.1766***		1.0959***	
	(0.0077)		(0.0085)	
Market to book	0.3294***	0.0127***	0.3233***	0.0048***
	(0.0070)	(0.0010)	(0.0070)	(0.0009)
Size	0.4493***	-0.0394***	0.8972***	-0.0353***
	(0.0107)	(0.0015)	(0.0236)	(0.0026)
Cash flow	1.3161***	-0.1065***	0.7429***	-0.0216**
	(0.0744)	(0.0110)	(0.0803)	(0.0098)
Net working capital	0.7134***	-0.3402***	0.9546***	-0.1129***
	(0.0897)	(0.0119)	(0.1104)	(0.0127)
Capital expenditure	2.1565***	-0.4797***	3.2689***	-0.2542***
	(0.1852)	(0.0210)	(0.1783)	(0.0185)
Leverage	-0.8410***	-0.2109***	-0.8317***	-0.0753***
	(0.0603)	(0.0083)	(0.0738)	(0.0082)
Industry sigma	0.0357	0.0388**	0.3590***	-0.0085
	(0.1363)	(0.0176)	(0.1391)	(0.0155)
Dividend dummy	-0.0903***	-0.0340***	0.1230***	-0.0057**

	(0.0250)	(0.0031)	(0.0294)	(0.0028)
R&D	0.0719***	0.0196***	0.0520***	0.0068***
	(0.0077)	(0.0014)	(0.0103)	(0.0015)
Acquisition	1.5658***	-0.3172***	0.7713***	-0.1623***
	(0.1037)	(0.0117)	(0.0896)	(0.0089)
Observations	45,705	45,705	45,045	45,045
Adjusted R-squared	0.7991	0.5988	0.8690	0.8231
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	No	No
Firm FE	No	No	Yes	Yes
Kleibergen-Paap rk LM-stat	2065.232		1876.308	
Cragg-Donald Wald F-stat	7.4e+04		4.4e+04	

Table 3.5: Options Trading and Cash Holdings: Penny Pilot Program

This table presents results of difference-in-differences (DiD) analyses that examine the effect of options trading activities on cash holdings using the Penny Pilot Program as a quasi-natural experiment. The list of stocks in the Penny Pilot Program is obtained from the CBOE website. The treatment group includes 289 pilot stocks during 2007-2015. Panel A and B report full sample results. Panel B report the results based on a matched sample where each pilot firm is matched to a non-pilot firm using a logit model predicting the probability of pilot status. *Pilot* is equal to one if the firm participates in the pilot program in year t, and zero otherwise. Columns (1) and (2) reports DiD estimates. Columns (3) and (6) report IV estimates where options trading volume is instrumented by the pilot status. The dependent variable of interest is cash to assets ratio (*Cash*) in year t+1. *Options trading* refers to the natural logarithm of annual equity options trading volume. The sample period is from 2006 to 2016. Details on the definitions of variables are provided in Appendix A. The standard errors clustered by firm are displayed in parentheses. Significance at the 10%, 5% and 1% level are indicated by *, ** and *** respectively.

Panel A: Full Sample

Dependent Variable =	Cash	Options trading	Cash	Cash	Options trading	Cash
	DiD	IV (1st Stage)	IV (2nd Stage)	DiD	IV (1st Stage)	IV (2nd Stage)
	(1)	(2)	(3)	(4)	(5)	(6)
Pilot	0.0316***	0.5221***		0.0163***	0.3569***	
	(0.0062)	(0.0759)		(0.0051)	(0.0627)	
Options trading (predicted)			0.0604***			0.0456***
			(0.0142)			(0.0164)
Market to book	0.0227***	0.5301***	-0.0094	0.0055***	0.3383***	-0.0099*
	(0.0015)	(0.0155)	(0.0076)	(0.0013)	(0.0142)	(0.0057)
Size	-0.0265***	0.9715***	-0.0852***	-0.0300***	1.4297***	-0.0951***
	(0.0015)	(0.0214)	(0.0140)	(0.0031)	(0.0403)	(0.0237)
Cash flow	-0.1113***	0.2302	-0.1252***	-0.0026	0.4526***	-0.0233
	(0.0151)	(0.1491)	(0.0159)	(0.0122)	(0.1362)	(0.0147)
Net working capital	-0.3321***	-0.7845***	-0.2847***	-0.0869***	0.5957***	-0.1140***
	(0.0157)	(0.1927)	(0.0204)	(0.0146)	(0.1979)	(0.0185)
Capital expenditure	-0.4632***	1.8419***	-0.5745***	-0.1904***	2.3833***	-0.2990***
	(0.0271)	(0.3921)	(0.0422)	(0.0216)	(0.3561)	(0.0485)
Leverage	-0.2159***	-0.6385***	-0.1774***	-0.0472***	-0.1099	-0.0422***
	(0.0104)	(0.1249)	(0.0144)	(0.0108)	(0.1334)	(0.0120)
Industry sigma	0.0143	0.0128	0.0135	-0.0157	0.4655**	-0.0369*
	(0.0211)	(0.2226)	(0.0230)	(0.0164)	(0.2019)	(0.0204)
Dividend dummy	-0.0368***	-0.5783***	-0.0018	-0.0054*	0.0931*	-0.0097**

	(0.0036)	(0.0545)	(0.0093)	(0.0031)	(0.0536)	(0.0040)
R&D	0.0173***	0.1039***	0.0110***	0.0029*	0.0497***	0.0006
	(0.0019)	(0.0146)	(0.0025)	(0.0016)	(0.0188)	(0.0019)
Acquisition	-0.3091***	0.5866***	-0.3445***	-0.1398***	-0.1652	-0.1322***
	(0.0151)	(0.2149)	(0.0195)	(0.0102)	(0.1500)	(0.0118)
Observations	26,124	26,124	26,124	25,697	25,697	25,697
Adjusted R-squared	0.5938	0.5494	0.4251	0.8656	0.8156	0.8079
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pilot FE	Yes	Yes	Yes	No	No	No
Industry FE	Yes	Yes	Yes	No	No	No
Firm FE	No	No	No	Yes	Yes	Yes
Kleibergen-Paap rk LM-stat		40.498			29.623	
Cragg-Donald Wald F-stat		43.803			50.983	

Panel B: Matched Sample

Dependent Variable =	Cash	Options trading	Cash	Cash	Options trading	Cash
	DiD	IV (1st Stage)	IV (2nd Stage)	DiD	IV (1st Stage)	IV (2nd Stage)
	(1)	(2)	(3)	(4)	(5)	(6)
Pilot	0.0341***	0.6136***		0.0133**	0.4731***	
	(0.0080)	(0.1143)		(0.0067)	(0.0978)	
Options trading (predicted)			0.0556***			0.0281**
			(0.0155)			(0.0142)
Market to book	0.0235***	0.3495***	0.0041	0.0037	0.2631***	-0.0037
	(0.0034)	(0.0296)	(0.0059)	(0.0030)	(0.0272)	(0.0046)
Size	-0.0361***	0.6280***	-0.0710***	-0.0416***	0.9805***	-0.0691***
	(0.0054)	(0.0389)	(0.0114)	(0.0078)	(0.0819)	(0.0153)
Cash flow	-0.0499	0.6695*	-0.0871**	-0.0402	0.2352	-0.0468
	(0.0418)	(0.3790)	(0.0407)	(0.0367)	(0.3263)	(0.0338)
Net working capital	-0.3137***	0.4954	-0.3412***	-0.1330***	0.0638	-0.1348***
	(0.0454)	(0.3586)	(0.0504)	(0.0387)	(0.5050)	(0.0423)
Capital expenditure	-0.3815***	2.2634***	-0.5072***	-0.2123***	1.7300**	-0.2609***
	(0.0803)	(0.6811)	(0.0944)	(0.0713)	(0.7307)	(0.0828)
Leverage	-0.1430***	-0.8346***	-0.0967***	-0.0438	-0.1035	-0.0409
	(0.0301)	(0.2471)	(0.0322)	(0.0328)	(0.2763)	(0.0323)
Industry sigma	-0.0102	-0.0533	-0.0073	-0.0069	0.5159	-0.0214
	(0.0397)	(0.3325)	(0.0436)	(0.0368)	(0.3267)	(0.0418)
Dividend dummy	-0.0159	-0.2416**	-0.0025	-0.0009	0.2272**	-0.0073

	(0.0106)	(0.0945)	(0.0111)	(0.0087)	(0.1025)	(0.0099)
R&D	0.0143**	0.1349***	0.0068	-0.0045	0.1444**	-0.0085
	(0.0071)	(0.0471)	(0.0069)	(0.0060)	(0.0683)	(0.0060)
Acquisition	-0.2732***	0.0534	-0.2762***	-0.1677***	-0.3095	-0.1590***
	(0.0435)	(0.4113)	(0.0503)	(0.0307)	(0.3063)	(0.0314)
Observations	3,854	3,854	3,854	3,853	3,853	3,853
Adjusted R-squared	0.6093	0.4972	0.5411	0.8483	0.7047	0.8355
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pilot FE	Yes	Yes	Yes	No	No	No
Industry FE	Yes	Yes	Yes	No	No	No
Firm FE	No	No	No	Yes	Yes	Yes
Kleibergen-Paap rk LM-stat		25.706			21.400	
Cragg-Donald Wald F-stat		83.908			81.192	

Table 3.6: Option Listing and Cash Holdings

This table examines the effects of initial option listing on corporate cash holdings. The dependent variable is cash to assets ratio (*Cash*). *Option Listing* is a dummy variable that equals one if the firm has equity options traded in year t and zero otherwise. *Listing Year-2*, *Listing Year-1*, *Listing Year 0*, , *Listing Year 1*, *Listing Year 2* and *Listing Year 3* are dummy variables that equal one if the option-listing firm is -2, -1, 0, 1, 2, and 3 year away from the initial option listing, and zero otherwise. The baseline controls include lagged *Size*, *Market to book* , *Cash flow* , *Net working capital* , *Capital expenditure* , *Leverage* , *Industry sigma*, *Dividend dummy* , *R&D* and *Acquisition* . Columns (1)-(2) report results based on a full sample of firms with and without option listing. Columns (3)-(6) report results based on a matched sample where each option listing firm is matched to a non-options firm using a logit model predicting the probability of option listing. Details on the definitions of variables are provided in Appendix A. For brevity baseline control coefficients are not reported. The standard errors clustered by firm are displayed in parentheses. Significance at the 10%, 5% and 1% level are indicated by *, ** and *** respectively.

Dependent Variable =	Cash					
	Full Sample			Matched Sample		
	(1)	(2)	(3)	(4)	(5)	(6)
Option listing	0.0316***	0.0093***		0.0454***	0.0094***	
	(0.0035)	(0.0029)		(0.0041)	(0.0035)	
Listing year - 2			-0.0000			0.0004
			(0.0040)			(0.0046)
Listing year - 1			0.0056			0.0065
			(0.0038)			(0.0043)
Listing year 0			0.0253***			0.0260***
			(0.0034)			(0.0040)
Listing year +1			0.0128***			0.0138***
			(0.0026)			(0.0032)
Listing year +2			0.0084***			0.0106***
			(0.0021)			(0.0025)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	70,763	70,763	70,763	45,191	45,191	45,191

Adjusted R-squared	0.4937	0.7776	0.7779	0.5381	0.7875	0.7879
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Listing FE	Yes	No	No	Yes	No	No
Industry FE	Yes	No	No	Yes	No	No
Firm FE	No	Yes	Yes	No	Yes	Yes

Table 3.7: Conditioning on Financial Distress Risk

This table presents results of OLS regressions that examine the effect of options trading activities on cash holdings across firms with different degree of financial distress and risk shifting incentives. The dependent variable is cash to assets ratio (*Cash*) in year t+1. *Options trading* refers to the natural logarithm of annual equity options trading volume. *Market leverage* is defined as the book value of debt divided by the market value of assets. *Loan covenant violation* is a dummy variable that is set to one if there exists a loan covenant violation in the past three years and zero otherwise. *Z-score* refers to the Altman's Z-score as a measure of financial health, with a higher value meaning better financial health. *O-score* refers to the Ohlson's O-score as a measure of financial distress risk, with a higher value meaning higher financial distress risk(Ohlson, 1980). The baseline controls include lagged *Size*, *Market to book* , *Cash flow* , *Net working capital* , *Capital expenditure* , *Leverage* , *Industry sigma*, *Dividend dummy* , *R&D* and *Acquisition* . Coefficients on the baseline controls are not reported for brevity. Details on the definitions of variables are provided in Appendix A. The standard errors clustered by firm are displayed in parentheses. Significance at the 10%, 5% and 1% level are indicated by *, ** and *** respectively.

Dependent Variable =	Cash			
	(1)	(2)	(3)	(4)
Options trading × Market leverage	0.0088***			
	(0.0020)			
Market leverage	-0.1108***			
	(0.0260)			
Options trading × Z-score		-0.0004***		
		(0.0001)		
Z-score		0.0075***		
		(0.0008)		
Options trading × O-score			0.0004**	
			(0.0002)	
O-score			-0.0103***	
			(0.0020)	
Options trading × Loan covenant violation				0.0052***
				(0.0017)
Loan covenant violation				-0.0516***

				(0.0168)
Options trading	0.0038***	0.0071***	0.0062***	0.0052***
	(0.0007)	(0.0006)	(0.0006)	(0.0005)
Controls	Yes	Yes	Yes	Yes
Observations	45,045	43,358	41,238	45,045
Adjusted R-squared	0.8236	0.8284	0.8244	0.8235
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Table 3.8: Conditioning on Financial Constraints

This table presents results of OLS regressions that examine the effect of options trading activities on cash holdings across firms with different degree of financial constraints. The dependent variable is cash to assets ratio (*Cash*) in year t+1. *Options trading* refers to the natural logarithm of annual equity options trading volume. *HM Delay index* is a text-based measure of financial constraints. Higher values of *HM Delay index* means firms are at risk of delaying their investments due to liquidity issues. *HM Debt delay index* is similar to *HM Delay index* while indicating debt issuance plans to address their liquidity issues. *HM Equity delay index* is similar to *HM Delay index* while indicating equity issuance plans to address their liquidity issues. The baseline controls include lagged *Size*, *Market to book* , *Cash flow* , *Net working capital* , *Capital expenditure* , *Leverage* , *Industry sigma*, *Dividend dummy* , *R&D* and *Acquisition* . Coefficients on the baseline controls are not reported for brevity. Details on the definitions of variables are provided in Appendix A. The standard errors clustered by firm are displayed in parentheses. Significance at the 10%, 5% and 1% level are indicated by *, ** and *** respectively.

Dependent Variable =	Cash		
	(1)	(2)	(3)
Options trading × HM Delay index	0.0108**		
	(0.0052)		
HM Delay index	-0.0676		
	(0.0601)		
Options trading × HM Debt delay index		0.0095*	
		(0.0056)	
HM Debt delay index		-0.1667***	
		(0.0644)	
Options trading × HM Equity delay index			0.0059
			(0.0056)
HM Equity delay index			-0.0025
			(0.0642)
Options trading	0.0058***	0.0057***	0.0058***
	(0.0006)	(0.0007)	(0.0007)
Controls	Yes	Yes	Yes
Observations	28,968	28,968	28,968

Adjusted R-squared	0.8263	0.8262	0.8263
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

Table 3.9: Conditioning on Information Asymmetry

This table presents results of OLS regressions that examine the effect of options trading activities on cash holdings across firms with different degree of information asymmetry. The dependent variable is cash to assets ratio (*Cash*) in year t+1. *Options trading* refers to the natural logarithm of annual equity options trading volume. *Forecast inaccuracy* is a measure of average analyst forecasting errors. *S&P500* is a dummy variable that is set to one if a firm belongs to the S&P500 index the and zero otherwise. *PIN* refers to the probability of informed trading as a measure of information asymmetry. *Rating* is a dummy variable that is set to one if a firm has credit rating index the and zero otherwise. The baseline controls include lagged *Size*, *Market to book* , *Cash flow* , *Net working capital* , *Capital expenditure* , *Leverage* , *Industry sigma*, *Dividend dummy* , *R&D* and *Acquisition* . Coefficients on the baseline controls are not reported for brevity. Details on the definitions of variables are provided in Appendix A. The standard errors clustered by firm are displayed in parentheses. Significance at the 10%, 5% and 1% level are indicated by *, ** and *** respectively.

Dependent Variable =	Cash			
	(1)	(2)	(3)	(4)
Options trading × Forecast inaccuracy	-0.0009**			
	(0.0004)			
Forecast inaccuracy	0.0104**			
	(0.0042)			
Options trading × S&P500		0.0024*		
		(0.0013)		
S&P500		-0.0295*		
		(0.0160)		
Options trading × PIN			-0.0279***	
			(0.0059)	
PIN			0.1636***	
			(0.0623)	
Options trading × Rating				0.0019**
				(0.0008)
Rating				-0.0185**
				(0.0091)
Options trading	0.0058***	0.0052***	0.0084***	0.0046***

	(0.0005)	(0.0005)	(0.0011)	(0.0007)
Observations	42,403	45,089	29,192	45,089
Adjusted R-squared	0.8278	0.8236	0.8257	0.8236
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Table 3.10: Options Trade and The Cost of Debt

This table presents estimates of the effects of options trading activities on the cost of debt. Columns (1)-(2) report the results for the logarithm of loan spread. Columns (3)-(4) report the results for the logarithm of bond spread. *Options trading* refers to the natural logarithm of annual equity options trading volume. In columns (1)-(2), fixed effects indicating senior loans, secured loans, loan types and loan purposes are included. In columns (3)-(4), bond seniority, fixed effects indicating putable bonds, callable bonds, convertible bonds and private bonds. Details on the definitions of variables are provided in Appendix A. The standard errors clustered by firm are displayed in parentheses. Significance at the 10%, 5% and 1% level are indicated by *, ** and *** respectively.

	Loan spread		Bond spread	
	(1)	(2)	(3)	(4)
Options trading	0.0196***	0.0319***	0.0294***	0.0145
	(0.0047)	(0.0065)	(0.0075)	(0.0108)
Size	-0.0800***	-0.0792***	-0.3282***	-0.1291***
	(0.0106)	(0.0263)	(0.0159)	(0.0298)
Leverage	0.5025***	0.5143***	0.7402***	0.6550***
	(0.0615)	(0.0940)	(0.1096)	(0.1647)
Tangibility	-0.0873*	-0.2405*	-0.0889	-0.1652
	(0.0476)	(0.1348)	(0.0859)	(0.1818)
Cash	0.1056	-0.0838	0.2704*	0.1355
	(0.0802)	(0.1280)	(0.1435)	(0.1686)
Z-score	0.0033	0.0105	-0.0061	0.0127
	(0.0045)	(0.0074)	(0.0122)	(0.0143)
Market to book	-0.1292***	-0.1323***	-0.1896***	-0.1072***
	(0.0137)	(0.0222)	(0.0216)	(0.0249)
ROA	-0.5477***	-0.4208***	-1.3901***	-0.9830***
	(0.1045)	(0.1209)	(0.2288)	(0.2379)
Earnings volatility	0.6006***	0.7425***	1.5602***	0.5327
	(0.1271)	(0.2020)	(0.3134)	(0.3514)
Maturity	-0.0614***	-0.0616***	0.1555***	0.1975***
	(0.0187)	(0.0198)	(0.0150)	(0.0132)

Offering amount	-0.0798***	-0.0786***	0.2071***	0.1381***
	(0.0081)	(0.0090)	(0.0191)	(0.0206)
Observations	8,845	8,336	6,562	6,239
Adjusted R-squared	0.6824	0.7927	0.5370	0.6418
Loan/Bond Characteristics FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes

Table 3.11: Options Trading and the Marginal Value of Cash

This table presents results of OLS regressions that examine the effect of options trading activities on the value of corporate cash holdings. The dependent variable is annual excess stock return over the Fama-French benchmark (*Excess equity return*). *Options trading* refers to the natural logarithm of annual equity options trading volume. ΔC denotes the change of cash scaled by lagged market capitalization. The full sample period is from 1996 to 2016. Details on the definitions of variables are provided in Appendix A. The standard errors clustered by firm are displayed in parentheses. Significance at the 10%, 5% and 1% level are indicated by *, ** and *** respectively.

Dependent Variable =	Excess equity return	
	(1)	(2)
Options trading × Δ C	0.0553***	0.0525***
	(0.0193)	(0.0196)
Options trading	0.0088***	0.0013
	(0.0011)	(0.0029)
Δ C	0.3792*	0.4337**
	(0.1957)	(0.1992)
Δ E	0.3587***	0.2817***
	(0.0293)	(0.0292)
Δ NA	0.1501***	0.0783***
	(0.0170)	(0.0184)
Δ RD	-0.1138	0.4655
	(0.3408)	(0.3600)
Δ I	-1.5433***	-0.5536
	(0.3823)	(0.4128)
Δ D	0.2935	-0.1988
	(0.3607)	(0.3846)
C	0.2742***	0.8626***
	(0.0259)	(0.0463)
L	-0.3779***	-1.1815***
	(0.0176)	(0.0400)
NF	-0.0213	0.1131***

	(0.0358)	(0.0407)
Observations	18,402	17,706
Adjusted R-squared	0.1585	0.2552
Year FE	No	Yes
Firm FE	No	Yes

Table 3.12: Additional Controls

This table presents results of OLS regressions that examine the effect of options trading activities on corporate cash holdings. The dependent variable is cash to assets ratio (*Cash*) in year t+1. *Options trading* refers to the natural logarithm of annual equity options trading volume. The baseline controls include lagged *Size*, *Market to book* , *Cash flow* , *Net working capital* , *Capital expenditure* , *Leverage* , *Industry sigma*, *Dividend dummy* , *R&D* and *Acquisition* . The full sample period is from 1996 to 2016. Details on the definitions of variables are provided in Appendix A. The standard errors clustered by firm are displayed in parentheses. Significance at the 10%, 5% and 1% level are indicated by *, ** and *** respectively.

Dependent Variable =	Cash			
	(1)	(2)	(3)	(4)
Options trading	0.0052***	0.0062***	0.0060***	0.0063***
	(0.0007)	(0.0008)	(0.0008)	(0.0009)
Equity trading	0.0046**	0.0026	0.0033	0.0006
	(0.0021)	(0.0023)	(0.0024)	(0.0025)
Equity illiquidity	0.0118**	0.0069	0.0117	0.0055
	(0.0059)	(0.0081)	(0.0081)	(0.0087)
Equity return	0.0039***	0.0039***	0.0036***	0.0049***
	(0.0013)	(0.0014)	(0.0014)	(0.0015)
Equity volatility	0.0162	-0.0162	-0.0053	-0.0095
	(0.0140)	(0.0163)	(0.0164)	(0.0173)
Implied volatility		0.0363***	0.0333***	0.0274***
		(0.0098)	(0.0100)	(0.0103)
Put-call ratio		-0.0002***	-0.0002***	-0.0003***
		(0.0001)	(0.0001)	(0.0001)
Institutional ownership			0.0082	0.0077
			(0.0057)	(0.0059)
Analyst coverage			-0.0008	-0.0023
			(0.0023)	(0.0025)
Stock price synchronicity			-0.0095***	-0.0082***
			(0.0019)	(0.0021)

Controls	Yes	Yes	Yes	Yes
Observations	38,344	32,957	32,655	32,621
Adjusted R-squared	0.8251	0.8288	0.8296	0.8301
Year FE	Yes	Yes	Yes	Yes
Industry-Year FE	No	No	No	Yes
Firm FE	Yes	Yes	Yes	Yes

CHAPTER 4

SHORT-SELLING CONSTRAINTS AND CORPORATE HEDGING

4.1 Introduction

Financial derivatives can help offset declining cash flows in times of economic adversity, and therefore are widely used as a means of firm risk-reduction policy. A recent survey documents that about 60.3% of large companies around the world[1] use some types of derivatives (Bartram et al., 2009). Despite its pervasiveness, neoclassical theory (Modigliani and Miller, 1958) suggests that risk management is not necessary. Therefore, the question as to why firms engage in hedging activities has spurred a number of theoretical and empirical studies on the determinants of corporate risk management. Meanwhile, there is a burgeoning literature that looks into the real effects of financial markets on corporate real activities (Bond et al., 2012). Despite the fact that prior theoretical and empirical research emphasize *primary* capital market imperfections as a key motive for managing risk (Smith and Stulz, 1985; Froot et al., 1993; Holmstrom and Tirole, 2000; Campello et al., 2011b), little is known about the role of *secondary* market frictions in corporate risk management decisions. In this paper, we bridge these two strands of literature and empirically explore whether short-selling restrictions matter for corporate hedging decisions.

We are particularly interested in short selling because of a long-lasting debate among market participants and regulators about the implications of restrictions on short sales

[1] The sample covers 7,319 nonfinancial firms that account for 82.2% of global market capitalization. More recently, ISDA said 94% of top 500 companies use derivatives.

given the controversial role that short sellers typically play in stock markets (Bris et al., 2007). Adding to this debate, there is a growing academic literature that suggests that the impact of short-selling constraints goes beyond stock markets. Contrary to the traditional view that secondary markets are merely a sideshow to the real economy, several studies find that relaxing short-selling restrictions has real effects on corporate decision making[2]. We complement these discussions by studying the impact of short-selling frictions on firm risk-taking behavior.

While we are not aware of any theoretical models that directly link short-selling constraints to corporate hedging behavior, we hypothesize that relaxing restrictions on short selling increases the demand for more corporate risk management through a financial distress channel (Smith and Stulz, 1985). Specifically, as short sellers are able to profit from informed trading on firm downside risks, an increase in short sales resulting from a relaxation of short-selling constraints may increase the shorted firm's financial distress risk due to the negative signal it sends to outside creditors (Kecsk et al., 2013; Henry et al., 2015). In response, the managers are incentivized to enhance risk management in order to reduce the expected cost of financial distress and thus enhance the firm value. We provide theoretical motivations and empirical evidence in line with this mechanism.

The extent of risk management is difficult to measure. Although derivative usage is presumably a natural proxy for risk management (Beatty, 1999), detailed information about derivative holdings are hard to obtain due to limited disclosure. Following Rajgopal and Shevlin (2002), Jin and Jorion (2006) and Kumar and Rabinovitch (2013), we focus on a sample of upstream oil and gas producers (Standard Industrial Classification [SIC] = 1311) that usually provide abundant details of derivative contracts in their annual reports. This allows us to measure more accurately firm level hedging intensity. An additional advantage of using firms within a narrowly-defined industry is that they are likely to

[2]The impact of short sales constraints has been found on investment (Grullon et al., 2015), earnings management (Massa et al., 2015; Jin et al., 2018), executive compensation structure (De Angelis et al., 2017), audit fees (Hope et al., 2017) and mergers and acquisitions (Chang et al., 2018), among others

be homogeneous in terms of risk environment, which can help control for a myriad of unobservable confounding factors.

To overcome identification challenges, we take advantage of a pilot program under the Regulation SHO that suspended short-sale price tests for a set of randomly selected stocks in U.S. equity markets from 2005 to 2007. This randomized experiment, which is tantamount to a pure exogenous shock to the barrier on short sales, provides an ideal empirical setting that enables us to examine the real effects of short-selling frictions on corporate risk management. We use a difference-in-differences (DiD) framework comparing the change in corporate hedging intensity in a treatment group of firms that experienced a relaxation of short sales restrictions to a control group of firms that did not.

Using a hand-collected dataset on derivatives contracts, we calculate firm-specific hedge ratios as a proxy for hedging intensity, and then employ a DiD approach to study the causal impact of short-selling frictions on corporate risk management. Our main results indicate that firms hedge more when short-selling activities become easier. Compared to non-pilot (control) firms, the hedge ratios of pilot firms experience a significant *relative* increase during the pilot period when short-sale constraints are relaxed.

We use several empirical tests to explore the underlying channel. First, we find that incremental short interest in the pilot firms was relatively higher during the experiment period. Second, if more short sales are perceived to be an indicator for higher default risk, managers should have greater motives to reduce cash flow volatility when the firm is closer to insolvency. To test this prediction, we use several measures of financial distress risk such as market leverage, the Altman Z-score and the Merton (1974) expected default frequency computed as in Bharath and Shumway (2008). Based on difference-in-difference-in-differences (DDD) analysis, we find consistent results using different proxies, namely that the effect of short-selling friction reduction on corporate risk management is larger for firms with poorer financial health.

Third, since lowering financial distress risk tends to enhance firm value (Smith and

Stulz, 1985), our argument implies that managers whose incentives are more aligned with shareholders would be more responsive to the change in short-selling constraints. Consistent with this view, we employ a DDD analysis and find a larger increase in hedging intensity following the short-selling friction decrease among firms where CEO compensation is more tied more closely to firm value[3].

Lastly, to validate further the role of short sales in our findings, we exploit the cross-sectional variations among stocks in terms of their exposure to short-selling threats. On the one hand, since short sellers mainly profit from a potential stock price decrease, we expect the effects of short-selling on risk management to be concentrated in firms with relatively high downside equity risk. The evidence supports this prediction. On the other hand, more importantly, the bulk of returns on short sales are supposed to stem from the ability to explore some private information that is yet to be reflected in stock prices. Implicitly, we argue that the documented effect should be more pronounced for firms with less informative stock prices. Based on two commonly used proxies for stock price informativeness, namely price non-synchronicity (1-R2) (Roll, 1988), and the probability of informed trading (PIN) (Easley et al., 2002; BrownStephen and Hillegeist, 2007), we find that in both cases low stock price informativeness firms in the treatment group are engaged in risk management more aggressively than those in the control group following the reduction in short-selling constraints.

Overall, our study is among the first to provide evidence that short-selling friction in the *secondary* market has a real effect on corporate risk management policies. Prior hedging literature has developed explanations for the extent of corporate risk management based on costly financial distress (Smith and Stulz, 1985), the underinvestment problem (Froot et al., 1993), signalling managerial skill (DeMarzo and Duffie, 1995) and managerial risk aversion (Smith and Stulz, 1985). Our empirical findings are more consistent with the financial distress argument as in Smith and Stulz (1985), while highlighting the unique

[3]In untabulated tests we consider other explanations based on CEO personal interest but could not find support in the data.

role of short-selling constraints in shaping corporate risk reduction strategies. Models of corporate risk management in the presence of secondary market imperfections are rare in the current hedging literature. Our study suggests a potential avenue for future theoretical research in this area.

More broadly speaking, our paper contributes to the growing literature on the real effects of financial markets (Edmans et al., 2012). In particular, as with Grullon et al. (2015), Massa et al. (2015), Fang et al. (2016), He and Tian (2016) and Chang et al. (2018), we focus on the impact of secondary-market short-selling constraints on corporate real decisions. This paper, however, departs from those studies in terms of channels through which short-selling activities affect real outcomes. While most of the related studies in the past emphasize that short-sellers act as a disciplining device to firms [4], our overall findings are supportive of a financial distress channel, where managers' concerns about risks of insolvency are associated with short-selling activities in the face of costly financial distress. This, in turn, leads to a variation in the extent of risk management strategies. In that regard, our paper resonates with Kecsk et al. (2013) and Henry et al. (2015) who find a linkage between short sales and credit risk, and with Smith and Stulz (1985) as to the importance of financial distress and managerial incentives in hedging policies.

The remainder of the paper is organized as follows. Section 4.2 develops the hypotheses. Section 4.3 lays out the empirical research design. Section 4.4 presents the baseline results and analyses the channel. Section 4.5 conducts several cross-sectional tests to further support the hypothesized channel. Section 4.6 provides some robustness tests for the baseline results. Section 4.7 attempts to rule out some alternative explanations. Section 4.8 concludes.

[4]For example, see Massa et al. (2015), Fang et al. (2016) and Chen et al. (2018) among others. Exceptions are Grullon et al. (2015) and De Angelis et al. (2017), where short sales affect firm outcomes through a stock price channel.

4.2 Hypotheses Development

Prior work indicates that short sellers have the capability to detect downside risk (Karpoff and Lou, 2010; Christophe et al., 2010; Callen and Fang, 2015; Fang et al., 2016; Boehmer et al., 2018), and to predict financial distress events. For example, both Kecsk et al. (2013) and Henry et al. (2015) find that short-selling pressures substantially increase prior to a credit rating downgrade. Accordingly, Henry et al. (2015) posit that outside lenders view an increase in short interest as a strong negative signal about the financial health of the firm, and therefore may demand a higher credit premium. Consistent with this prediction, they document empirically that greater short interest is associated with significantly higher bond spreads.

The hedging literature, on the other hand, has long recognized financial distress risk as a key determinant in corporate risk management. In a seminal paper, Smith and Stulz (1985) develop a financial distress model of risk management and argue that firms are more likely to hedge against operating income volatility when the risk of financial distress is high because hedging can reduce the cost of financial distress. An implication of this theory is that corporate risk management can reduce the cost of borrowing. Both Campello et al. (2011b) and Chen and King (2014) find support for this view in the data.

Based on these two lines of research, we anticipate that firms prefer more risk management when there is a rise in short-selling activities. More specifically, the *perceived* risk of default increases as outside creditors interpret an increase in short interest as indicative of deteriorating financial health, which in turn pushes the cost of debt for the shorted firm higher. Aside from an informative role of short sales, there could be a self-fulling process as well, namely that higher credit spreads may further increases the probability of financial distress. In turn, managers respond by increasing the intensity of corporate risk management to reduce the expected costs of financial distress. Since relaxing a binding short-sale constraint comes with more short-selling pressures, our main hypotheses, in alternative form, are as below.

H1: Firms hedge more when the short-selling constraints are relaxed.

H2: The effect of relaxing short-selling constraints on corporate risk management is stronger at higher levels of financial distress risk.

According to Smith and Stulz (1985), corporate risk management can enhance firm value by reducing the expected cost of financial distress. This suggests that the motive for hedging under short-selling pressures should be higher among managers with high incentive alignment with shareholders. The third hypothesis expresses this in alternative form as the following.

H3: The effect of relaxing short-selling constraints on corporate risk management is stronger when managers' incentives are more aligned with firm value.

To complement our main hypotheses, we also develop some cross-sectional predictions in terms of the tendency to be a target for shorting. Since short sellers profit from stock price downturns and are better informed than the public, they are likely to use their informational advantage to earn abnormal returns on stocks with less informative prices. Therefore, stocks that have more downside risk (thus more sensitive to bad news) and less price informativeness, are more likely to be targeted by short sellers and firms may react to the short-selling constraint shock differently. we summarize this in the following two additional hypotheses stated in alternative form.

H4a: The effect of relaxing short-selling constraints on corporate risk management is stronger at higher levels of downside equity risks.

H4b: The effect of relaxing short-selling constraints on corporate risk management is stronger at lower levels of stock price informativeness.

4.3 Research Design

4.3.1 Identification strategy and empirical model

We exploit a randomized experiment to identify the causal effect of short-selling constraints on corporate risk management. To evaluate the effects of short-sale price tests on trader behavior and market quality, Securities and Exchange Commission (SEC) introduced a pilot program under Regulation SHO (Reg SHO) that temporarily suspended price tests for a set of designated pilot securities (Rule 202T–Pilot Program). Roughly one-third of the Russell 3000 Index constituents were randomly drawn as pilot stocks: the SEC first ranked the 2004 Russell 3000 Index firms based on trading volume and then selected every third company into the pilot program. From May 2005 to August 2007, the SEC exempted pilot stocks from short-sale price tests. These price tests are designated as the uptick rule on the NYSE and the bid test on Nasdaq [5], which were designed to prevent short sellers from excessively forcing prices down in a declining market. The experiment effectively relaxed short-selling constraints for pilot firms. Previous studies show that this regulatory change led to higher short-selling pressure during the experiment period (SEC's OEA 2007; Alexander and Peterson, 2008; Grullon et al., 2015). As the selection of pilot stocks is completely random, and there is no clear evidence that the experiment was anticipated by any individual firm[6], we use this experiment as a plausibly exogenous shock to the short-selling constraints in this paper.

Since the Reg SHO embodies an exogenous shock to short-selling constraints, we employ a DiD research design to examine the relation between the implementation of Reg SHO pilot program and corporate risk management strategies. To be more specific, we use OLS to estimate the following baseline model:

$$Hedge\ Ratio = \alpha_1 Pilot \times During + \alpha_2 Pilot + \alpha_3 During + \beta \cdot Controls + \epsilon \tag{4.1}$$

[5]The uptick rule mandates that short sales cannot be made at a lower price than the most recently traded price, known as a plus tick at a price above the most recently traded price, or at the most recently traded price if that price is lower than the last different price (zero-plus tick). The bid test, formally known as NASD Rule 3350 and implemented in 1998, prevents short sales by NASD members at or below the current best bid when that bid is lower than the previous best bid. The temporary suspension of these two price tests was originally set to expire on April 28, 2006, but was extended to August 6, 2007.

[6]Several prior studies, for example, Alexander and Peterson (2008), Grullon et al. (2015) and Fang et al. (2016), use the pilot program as an exogenous shock to short-selling constraints.

where *Hedge Ratio* is a specific measure of corporate hedging intensity, and *Pilot* is an indicator variable for whether firm i is selected as a pilot stock by the Reg SHO pilot program (treatment group). *During* indicates the 2005 to 2007 period (treatment period) when the pilot stocks faced less short-selling restrictions than the non-pilot stocks, whereas such a difference did not exist in both pre and post experiment eras. *Pilot* controls for the differences between pilot and non-pilot firms, while *During* controls for the differences between treatment and control periods that equally affect all the sample firms. The coefficient α_1 on the interaction term, *Pilot* $\times$ *During*, then captures the DiD effect of Reg SHO on corporate risk management. *Controls* represents a vector of control variables. Standard errors are two-way clustered at both firm and year levels.

4.3.2 Data

We begin the empirical analysis with a sample of U.S. oil and gas producers with SIC code 1311 in the Compustat universe. SIC code 1311 is comprised of firms that primarily engage in crude petroleum and natural gas production, where oil and gas prices volatility constitutes the largest risk. Businesses can manage this risk by diversifying business operations (operational hedge), or by entering into commodity derivative contracts. Risk management in the latter form is much easier to quantify in that the details of derivative contracts are usually disclosed in the annual reports, which allows us to more accurately measure hedging intensity. In addition, operational hedges tend to be capital intensive for oil and gas producers, and thus is less likely to be used as a means to manage risk over the short run [7]. Therefore, the potential bias caused by neglecting operational hedge is minimal. Overall, focusing on SIC 1311 firms can greatly mitigate a wide variety of issues commonly seen in empirical studies, such as measurement errors, omitted variables or spurious correlations [8].

[7]The pilot program lasted about three years. If such a temporary regulatory change does affect corporate risk-taking, we would expect firms to react by first adjusting their portfolios of financial derivatives instead of capital expenditure which is more costly and takes a longer time to take effect.

[8]Previous studies on corporate risk management that draw upon SIC 1311 industry include Rajgopal and Shevlin (2002), Jin and Jorion (2006), Kumar and Rabinovitch (2013) and Bakke et al. (2016) among

Next, we restrict the sample to oil and gas producers that took part in the Reg SHO pilot program over the 2005-2007 period when a third of 2004 Russell 3000 index members were randomly drawn as pilot stocks that were exempted from price tests for short sales, while the rest were assigned into the non-pilot (control) group. The SEC published the list of pilot firms[9]. Since the SEC did not disclose the final list of non-pilot stocks, we identified those firms by following the SEC's procedure (Securities and Exchange Commission, 2007; Fang et al., 2016) [10]. We then combine those two lists and merge them with the aforementioned sample of oil and gas producers to ensure that the sample firms are either in the treatment or control group.

Since the major risk of upstream oil and gas producers is from oil and gas price movements, we measure the extent of corporate risk management by using disclosures of commodity derivative contracts, and sometimes fixed-price physical delivery contracts, in firms' 10-K filings. The quantitative information about various hedging instruments are usually reported in item 7A or footnotes to the consolidated financial reports, including, for example, contract types, contract amounts, contract maturity, weighted average settlement prices for forwards and futures, weighted average strike prices for options or collars. we first hand-collect these data through the SEC's EDGAR [11]. Then we collect the stated prices for each product (oil, gas or gas liquid) from annual reports, and use them to standardize the unit of either production or contract size as *barrels*[12]. Since most firms in the oil and gas industry engage in hedging activities over a short horizon (Jin

others. Although the gold mining industry has also been used in some studies, for example, Tufano (1996), the resulting sample is too small as our analysis requires those firms to be in the experiment.

[9]See, `http://www.sec.gov/rules/other/34-50104.htm`.

[10]We start with 2004 Russell 3000 index constituents and delete those that were not traded on NYSE, Amex, or NASDAQ-NM, went public, or had spin-offs after April 30, 2004. Then we obtain the control group by excluding the pilot stocks.

[11]Following Jin and Jorion (2006), we only consider directional positions on oil and gas prices and thus ignore, for instance, basis contracts. The most commonly used hedging instruments in the sample are swaps and collars. The two combined constitute over 83% of derivative usage in terms of volume on average (see Table C1, Appendix C for more details).

[12]We do so because we need to aggregate data on hedging instruments over different products (oil, gas or gas liquid) for each firm. When firm-level output price data are not available, we use the sample cross-sectional average prices as replacements.

and Jorion, 2006), we focus on hedging instruments deployed for the next year in our baseline analysis[13]. A further reason for such a focus is that the pilot program, when first introduced by the SEC in 2004, was publicly known to be ending in the near future; therefore, if the pilot firms did respond to the regulatory change, they were more likely to adjust short-term hedging .

Following Tufano (1996) and Jin and Jorion (2006), to more accurately measure hedging intensity, we calculate delta for each non-linear derivative contract such as a call option, put option and collar by using Black's option pricing model[14], while for linear contracts delta is set to -1 for short positions and 1 otherwise[15]. Then we obtain firm-year level total delta by multiplying the notional volume of each contract by its delta and summing them up over all hedged positions that mature within one year. Lastly, our primary measure of corporate risk management, *Hedge Ratio*, is defined as negative total delta scaled by annual production[16]. *Hedge Ratio* indicates the intensity of corporate hedging: a larger number means less loss in revenue given a certain drop in output prices. *Hedge Ratio* is used as the main dependent variable in the baseline analysis [17].

For robustness, we control for additional independent variables when necessary. As a placebo check, we add *Post* and the interaction term, *Post*×*Pilot*, where *Post* is a indicator variable for the period after the experiment ended[18]. The coefficient on *Post*×*Pilot* reflects a comparison between the differences in the extent of hedging among pilot and non-pilot firms before the start and after the termination of the experiment. Because the pilot and non-pilot firms are equally treated in the absence of the experiment, the coefficient on the interaction term should not be significantly different from zero.

In addition, we select the baseline controls for firm characteristics by drawing on

[13]We include long-term hedging (up to three years) in the robustness check and find similar results.
[14]Some inputs such as implied volatility and price are obtained from the Bloomberg terminal.
[15]Details on calculating delta can be found in the Appendix B of Jin and Jorion (2006).
[16]We include more details regarding the construction of hedging intensity in Appendix C.
[17]We conduct several robustness checks with regard to alternative dependent variables and the main results still hold.
[18]Fang et al. (2016) employ a similar specification.

the previous hedging literature[19]. We control for firm size by using the log of total assets (*log(Assets)*) as size has been known to be a key factor in risk management (Dolde, 1993). As several studies have associated financial distress with corporate hedging (Fehle and Tsyplakov, 2005; Rampini et al., 2014), we include a measure of financial distress (*Altman Z-score*) in the model as well. Following Froot et al. (1993) and Geczy et al. (1997), we also add *Market-to-Book* ratio to capture the role of growth opportunity in corporate decisions on risk management. Last but not least, we use *Institutional Ownership* as a proxy for information symmetry, which is deemed to be related to hedging activities (DeMarzo and Duffie, 1995).

The sample period starts from three years prior to the experiment, and ends three years after it. We require that firms have data to compute baseline variables in at least one fiscal year during both the treatment and control periods. After removing all observations with missing variables, Our final sample for the baseline analysis consists of 343 firm-year observations over the 2002 to 2010 period. To mitigate the influence of outliers, we winsorize all continuous variables at the 1st and 99th percentiles. The definitions of a complete set of variables along with their data sources are summarized in Appendix A.

Panel A of Table 4.1 presents summary statistics for the baseline variables. Despite a focus on the oil and gas industry, the sample descriptive statistics indicate substantial variations in firm size, valuation, financial soundness and institutional ownership. More importantly, Panel B of Table 4.1 compares variable means for pilot and non-pilot firms *prior* to the experiment[20]. All variables are statistically similar across the two samples. This evidence provides further support for the validity of the randomized experiment pertinent to the identification strategy.

[19] As with Grullon et al. (2015), we use beginning-of-year firm characteristics. Using the contemporaneous ones yield similar results in terms of statistical significance.

[20] We also test and find no significant difference in their medians using non-parametric methods. For brevity the results are not tabulated but available upon requests.

4.4 Main Empirical Analysis

4.4.1 Univariate analyses

From a theoretical perspective, if short-selling constraints are not binding *ex ante*, then a relaxation of those constraints may not have any incremental impact. To mitigate this concern, we first examine whether pilot stocks in the sample faced more incremental short-selling pressures during the Reg SHO experiment period. For each oil and gas producer in the sample, we create a proxy for incremental short-selling pressure, *Short Interest Innovation* , defined as the monthly first difference in the average number of shares held short scaled by the previous month shares outstanding [21]. The univariate difference-in-differences test results are reported in the Panel A of Table 4.2. Row 1 compares the short interest innovation from the during- and pre-period. As shown in columns 1 and 2, when moving from the pre to during-period, the pilot firms experienced a significant increase in short-selling pressures whereas the incremental short interests on the non-pilot firms slightly declined. The difference-in-differences estimator in column 3 further indicates that the short-selling pressures increased more on the pilot firms than the non-pilot ones during the experiment. Row 2 conducts a comparison between during- and post-period, showing that, relative to the post-period when firms were equally treated, the positive spread in short-selling pressures between pilot and non-pilot firms was significantly larger during the experiment period. Row 3 reports a placebo test and finds no significant change of the differences in short-selling pressures on pilot and non-pilot in the post-period compared to the pre-period.

Given an exogenous relative decrease in short-selling frictions under Reg SHO, do firms adjust their corporate risk management policies ? To address this question, we first employ univariate analyses on the extent of corporate hedging. Panel B of Table 4.2 reports the results of the univariate difference-in-differences tests. Using either the pre- or

[21]Shares held short are reported by exchanges on the 15th and the end of each calendar month. Data on historical short positions are obtained from Compustat. Taking first difference is meant to capture the incremental short-selling pressure; meanwhile it can filter out the unit root embedded in the time series.

post-period as control period, we observe a higher hedging intensity in the pilot firms than the non-pilot firms during the Reg SHO program period. We attribute this hedging gap between pilot and non-pilot firms to differential short-selling pressures. As all the sample firms faced identical short-selling constraints either before or after the during-period, we expect that such a gap should not exist between the pre and post-period with statistical significance. The difference-in-differences estimator in column 3 of row 3 is consistent with this prediction. In what follows we will provide more evidence in a multivariate regression framework.

4.4.2 Baseline regression results: Reg SHO and corporate hedging

In this section, we conduct empirical analysis based on the baseline regression model (4.1). Table 4.3 presents the results of the analysis examining the effect of Reg SHO pilot program on corporate hedging in a multivariate difference-in-differences framework. Column (1) does not include any additional control variables and shows a positive relation between the experiment and hedging intensity with statistical significance at the 1% level. As a placebo check, in column (2) we add *Post*, an indicator for post-experiment period, along with an interaction term, $Pilot\times Post$. The estimated coefficient on $Pilot\times Post$ is not statistically different from zero, meaning that the differences between pilot and non-pliot firms in terms of hedging intensity are similar across the pre and post experiment eras.

This evidence also suggests a reversal effect when the experiment ended. To better illustrate this interpretation we calculate the differences of average *Hedge Ratio* between treatment and control groups over three time periods: before, during and after the pilot program. Figure 4.1 shows that the gap widens during the pilot program period, whereas the trend reverts after the repeal of price tests for both groups. Although the magnitude of reversion is not as strong, the pattern is largely supportive of the identification strategy[22].

Column (3) further augments the model with firm characteristics. The results are

[22] A possible explanation for the weak reversion is that the termination of the Reg SHO pilot program was well anticipated.

similar. This relation is also economically meaningful. The estimated coefficients on *Pilot* $\times$ *During* indicate that, on average, *Hedge Ratio* is between 0.0438 and 0.0544 higher due to the relaxation of short sales constraints. This finding represents between 16.31% and 20.27% of mean hedging intensity (0.2684). Overall, the estimation results of the baseline model are in line with the alternative form of our main hypothesis (*H1*), suggesting that lower short-selling frictions lead firms to hedge more.

4.4.3 Understanding the mechanism

Reg SHO, financial distress and corporate hedging (*H2*)

For oil and gas producers, crude oil and natural gas prices are the key determinants of their cash flows because these firms are mainly involved in the upstream of the oil and gas industry. During the sample period, the volatilities of crude oil and natural gas prices were at high levels. Figure 4.2 depicts the daily market oil and gas average price (left scale), along with the historical volatility of daily market oil and gas average price (right scale) computed as the trailing standard deviation of prices over the past 250 trading days[23]. Interestingly, despite that oil and gas prices were mostly on the rise at the time, Figure 4.2 also shows that the Reg SHO pilot program happened to accompany a volatility spike in the oil and gas prices. Moreover, during that time period some market observers were aware of a crash risk in oil and gas prices. The OPEC secretary general at the time, Abdalla Salem El-Badri, said in a 2007 statement: " the rising oil prices which we are currently witnessing are, however, largely being driven by market speculators"[24], the prolonged bull market over the past years has led to concerns about a possible price bubble given the slowing economy prior to the great recession.

Our explanation for the baseline results relies on a financial distress argument, namely that hedging policies can be used to smooth cash flows and thus reduce the cost

[23] The market oil and gas prices is constructed by averaging the WTI spot crude oil and Henry Hub natural gas prices. We download oil and gas price data from the FRED website and assume 1 barrel = 5.8 mmbtu.

[24] For the context of this quote, see the 10/17/2007 New York Times article, available at https://www.nytimes.com/2007/10/17/business/worldbusiness/17oil.html

of financial distress (Smith and Stulz, 1985). However, if the uncertainty of commodity prices is not as high, the oil and gas producers' demand for corporate hedging, which is costly in itself, may be very low due to negligible marginal benefits. The anecdotal evidence for the substantial commodity market downside risk, as mentioned above, helps alleviate this concern. Since an unexpected market crash will inevitably push unhedged oil and gas firms closer to financial distress, corporate risk management becomes especially valuable when there is a deteriorating credit condition due to a change in the risk attitude of outside creditors when observed short sales pick up. The primary prediction of this argument is that the effect of relaxing short-selling constraints on corporate hedging should be larger among firms that are less closer to financial distress.

We test this prediction (*H2*) by exploiting cross-sectional variation in financial distress risk to estimate DDD regression models. We sort the sample firms into terciles based on a proxy of financial distress risk and create an indicator, *High Distress Risk*, which is set to one for firms in the top tercile, and zero otherwise [25]. We then extend the baseline regression model by adding *High Distress Risk* and its interactions with *Pilot* and *During*. For robustness, we use several alternative proxies of financial distress risk. *Market Leverage* is defined as the ratio of total debt to market value of assets. A higher *Market Leverage* is associated with more risk of insolvency. *Altman Z-score* follows standard definitions (Altman, 1968). We use negative *Altman Z-score* to construct *High Distress Risk* because lower *Altman Z-score* means poorer financial health and therefore higher default risk. Finally, *Expected Default Frequency* measures the probability of default based on the distant to default model of Merton (1974), and thus is a more direct proxy for future financial distress risk . We compute *Expected Default Frequency* following Bharath and Shumway (2008).

Table 4.4 presents the estimation results where *Market Leverage*, *Altman Z-score* and *Expected Default Frequency* are used as proxies for financial distress risk in columns

[25]We use data from the control period to construct the cross-sectional indicators in this paper.

(1), (2) and (3) respectively. Regardless of alternative specifications, the coefficients on the interaction term, *Pilot×During×High Distress Risk* are positive and statistically significant at the 1% level, suggesting that the positive effect of the Reg SHO experiment on corporate hedging is larger for firms more subject to a financial distress risk. This finding is consistent with the prediction that firms with a weak financial standing are more likely to be negatively affected by a short-selling constraint reduction that could further increase the probability of financial distress, leading firms to hedge more to counteract this negative impact.

4.4.4 Reg SHO, managerial incentives and corporate hedging (*H3*)

Smith and Stulz (1985) claim that risk management can enhance firm value if the purpose is reducing expected cost of financial distress. Following this logic, the hypothesized channel, if true, implies that the firm-value-maximization motives of managers should play an important role in hedging decisions (Span, 2007). That is, the effect of the Reg SHO pilot program on hedging intensity should be greater for firms where the incentives of managers are aligned more closely with shareholders.

To investigate this mechanism, we use an indicator, *High Incentive Alignment*, which is set to one to represent a firm with high incentive alignment between shareholders and managers. To calculate *High Incentive Alignment*, we construct three alternative measures of the extent of chief executive officer (CEO) wealth vested in firm equity. The first measure is the value of the CEO's restricted stock grants as a fraction of total compensation (*Stock Grants*). If the form of CEO pay is tilted towards stock grants, then the CEO should be more concerned about firm value in a financial distress state. Similarly, the second measure is the value of CEO stock holdings (*Stock Holdings*). Lastly, following Coles et al. (2006c), we use CEO pay-performance sensitivity (delta), defined as change in CEO wealth associated with one percent change in the firm's stock price (*Delta*).

We sort firms into terciles based on each of the aforementioned measures of managerial incentive alignment, and set *High Incentive Alignment* equal to one for firms in the top tercile, and zero otherwise. We estimate DDD regression models using *High Incentive Alignment* based on all three alternative proxies and present the results in columns (1) through (3) in Table 4.5, respectively. The coefficient on the triple-interaction term is positive with statistical significance, suggesting that the positive effect of the Reg SHO experiment on corporate hedging is concentrated in firms where CEO personal wealth is more closely tied to shareholders'. This evidence provides additional support for relating the baseline results to the Smith and Stulz (1985) model.

4.5 More Cross-Sectional Tests of the Effect of the Reg SHO on Corporate Hedging

So far, the findings suggest that a relaxation of short-selling constraints leads to more corporate risk management through a financial distress channel. In this section, we conduct additional cross-sectional tests under a DDD framework. These tests are important because not only do they provide further evidence to support the main hypothesis, but also serve to alleviate concerns that the relation between Reg SHO and corporate hedging is generated by chance.

4.5.1 Reg SHO, downside equity risk and corporate hedging (*H4a*)

While attributing the change in corporate hedging policies to the regulatory experiment because of its effect on short selling as shown in Table 4.2, now we exploit some cross-sectional tests to shed more lights on the role of short sellers in the underling mechanism. These exercises can help mitigate concerns about a spurious relationship, rather than a causal one that we believe in.

Since short sellers mainly profit from stock price downturns[26], managers should be more responsive to the Reg SHO experiment when the company's stock is more susceptible

[26] Supporting this view, Callen and Fang (2015) document a positive relation between short sales and stock crash risk.

to downside equity risk, but not as much to upside potential. In Table 4.6, we test this intuition by examining the effect of Reg SHO on corporate risk management conditioning on the cross-sectional variation in downside equity risk.

We use three variables as proxies for downside equity risk. First, we calculate the annual standard deviation of daily stock returns that are below the annual sample mean, and refer to it as *Downside Volatility*. Second, we sort market returns into terciles in each year, and then estimate *Downside Beta* by regressing daily stock returns on the value-weighted market returns during bearish market days (lowest tercile). The third proxy is *Downside Return*, defined as the negative annual average daily stock returns when the value-weighted market returns are in the bottom tercile. Overall, we intend to quantify the left tail risk of stock returns with these three proxies.

Based on each of these proxies, we define a corresponding indicator for high downside equity risk, *High Downside Risk* , which is set to one if the proxy is in the top tercile, and zero otherwise[27]. For each proxy, we interact the indicator with the Reg SHO experiment indicators. In columns (1) through (3), the DDD coefficients are all positive and significant. This evidence suggests that firms with larger downside equity risk are more reactive to the experiment, thus consistent with the notion that short-selling pressures impact firms through a price channel.

To further validate the conjectured channel, we also create a dummy variable, *High Upside Risk* based on each of three different proxies for upside equity risk, similar to the ones for downside equity risk, but in the opposite direction. The first proxy is Upside Volatility, defined as the annual standard deviation of daily stock returns that are above the annual sample mean. The second one is Upside Beta, which is estimated by regressing daily stock returns on the value-weighted market returns during bullish market days (highest tercile). Lastly, we measure Upside Return by taking the annual

[27]For the third measure of downside equity risk, since we use negative daily stock returns for the convenience of interpretation, the top tercile represents bad returns. Therefore, in this case *High Downside Risk* $= 1$ still indicates a high downside equity risk.

average of daily stock returns while the value-weighted market returns are in the top tercile. Taken together, upside volatility, upside beta and upside return all capture the upside components of equity risk.

We set *High Upside Risk* equal to one when each of these proxies are in the top tercile, and zero otherwise. So *High Upside Risk* $= 1$ indicates high upside equity risk. we run similar regressions as in Table 4.6, except for using *High Upside Risk* to replace *High Downside Risk* , and accordingly, columns (1) to (3) use upside volatility, upside beta and upside return as proxies, respectively. Columns (1) and (2) of Table 4.7 show that there is no significant difference in reactions to the Reg SHO experiment between firms with high and low upside volatility or beta. In column (3), the coefficient on the triple-interaction term is negative and significant. It indicates that firms with more upward potential in stock returns in a bull market more *less* active in risk management. This evidence complements the result in column (3) of Table 4.6. As hedging tends to impair earnings in a good market, it is not surprising that firms with more upward potential in stock returns during bullish market days have fewer incentives to hedge because in that case the threats of potential short sales are small. In sum, comparing Table 4.6 and 4.7 suggests that short-selling activities appear to be a primary driving force for the relation between the Reg SHO experiment and corporate hedging.

4.5.2 Reg SHO, stock price informativeness and corporate hedging (*H4b*)

In this subsection we continue to test the relevance of short selling by exploring hypothesis *H4b*. Numerous studies have shown that short sellers are capable of using an informational comparative advantage to trade on bad news, which improves the informativeness of stock prices (Boehmer and Wu, 2012; Drake et al., 2015). Accordingly, stocks that reflect less private information are more likely to become a shorted target in which case the chance that short sellers have an informational edge is high, which can translate into higher expected shorting returns. So the prediction is that the Reg SHO experiment should have a larger impact on firms with less informative stock prices.

As before, we use a DDD regression model to test this prediction. Following Roll (1988), we use stock price non-synchronicity (*1-R2*) to measure stock price informativeness. This measure is based on the idea that stock prices with more private information are less correlated with aggregate market or industry level factors. High *1-R2* means high stock price informativeness. For each firm and year, we calculate *1-R2* as one minus R^2, where the R^2 is obtained from a within firm-year regression of daily stock returns on the daily CRSP value-weighted market and Fama-French 48 industry returns. As an alternative, the second measure of stock price informativeness we use is the probability of information-based trading (*PIN*) based on a market microstructure model (Easley et al., 2002; BrownStephen and Hillegeist, 2007). Since informed trading is likely to incorporate information into stock prices, high *PIN* is associated with high stock price informativeness. Sorting firms into terciles based on stock price informativeness, we create an indicator, *Low Price Informativeness* equal to one for firms in the bottom tercile, and zero otherwise.

We report the results of DDD analysis based upon stock price informativeness are reported in Table 4.8. We use *1-R2* and *PIN* to compute *Low Price Informativeness* in columns (1) and (2) respectively. In both cases, we find that the coefficients on the *Pilot*$\times$*During*$\times$ *Low Price Informativeness* are positive and significant at the 5% level. These results support the hypothesis that firms with less informative stock prices hedge more as they are impacted by the rising short interest. Overall, the evidence suggests that short-selling activities appear to contribute to the documented change in corporate hedging policies due to the regulatory experiment.

4.6 Sensitivity Tests of the Baseline Specification

4.6.1 Omitted variables

While Angrist and Pischke (2008) caution against including additional controls in DiD estimation, to further mitigate omitted variable concerns and ensure the randomness of treatment (Roberts and Whited, 2013), we conduct a variety of sensitivity tests to see whether more controls affect the results. Since the exploitation of oil and gas, which are essentially natural resources, may face geography-based risk, in column (1) we add year-by-state dummies to capture time-varying region-specific factors. In this case, *During* is subdued by the time indicators. Column (1) shows a significantly higher hedge ratio for pilot firms relative to control firms during the experiment period, suggesting that the results are not driven by aggregate or location-specific factors. Next, in column (2) of Table 4.9 we control for measures of operating risk that may drive hedging decisions, namely, *Equity Volatility* defined as the standard deviation of daily stock returns, *Operating Volatility* defined as the standard deviation of quarterly return on assets. The coefficient on *Pilot* $\times$ *During* is still positive at the 1% level. Column (3) includes other firm characteristics that pertain to financial distress and taxation, , market leverage (*Leverage*) and its squared (*Leverage*^{2}) , *Net Worth* defined as market value of equity scaled by assets and *Marginal Tax* indicating marginal tax rate (Purnanandam, 2008; Fehle and Tsyplakov, 2005; Rampini et al., 2014; Bakke et al., 2016). The results, as reported in column (3), are robust to the alternative specification.

4.6.2 Limited samples

In this section we examine the robustness of the baseline estimation using alternative limited samples and report the results in Panel A of Table 4.10. As the Reg SHO experiment was announced in late 2004, in column (1) we drop the 2004 observations to address concerns about dating the treatment period. Column (2) restricts the sample to the pre-crisis years from 2002 to 2007 in order to see whether the results are driven by the financial crisis. In the last column of Panel A, we require that firms have data to compute baseline variables throughout the full sample period. We find the baseline results to hold in each of the limited samples.

4.6.3 Alternative measures

Panel B of Table 4.10 reports the results of using alternative measures of hedging intensity. In column (1) we include all derivative contracts that will expire in the next three years when calculating total delta, and thus compared to the baseline measure (*Hedge Ratio*), *Hedge Ratio 1* considers both short-term and long-term hedges. Column (2) still focuses on short-term hedging but the total delta is scaled by total reserves instead of total production. The third alternative measure of hedging intensity, as indicated in column (3), is based on hedge accounting data. Effective in 2001, SFAS 133 required that unrealized gains and losses from financial hedging are recorded as a component of equity ((accumulated other comprehensive income). Thus as a measure of hedging intensity, we create *Hedge Ratio 3* by using the absolute value of accumulated other comprehensive income – derivatives unrealized gains/loss (*aocidergl*) scaled by total assets[28]. The drawback of this measure is that it tends to underestimate overall financial hedging (Huang et al., 2013). Panel B shows that the baseline results are unaffected under alternative measures of hedging intensity.

4.7 Alternative Explanations

Although our findings are consistent with higher short-selling pressures inducing firms to hedge more due to concerns about costly financial distress, some other explanations to the empirical relation between the Reg SHO experiment and corporate risk management are also possible because the observed increase in hedging intensity may reflect other actions that firms take in response to Reg SHO. We proceed to discuss these possibilities.

4.7.1 Investment and equity issuance

Grullon et al. (2015) find that small firms react to the Reg SHO experiment by reducing corporate investment and equity financing. On the one hand, it is possible that a decrease in capital expenditure enables firms to have more liquidity to engage in risk

[28] The sample correlation between *Hedge Ratio* and *Hedge Ratio 3* is over 40%.

management. On the other hand, a decrease in equity financing could also encourage more risk management due to concerns about volatilities in internal cash flows. Since corporate hedging, investment and financing decisions are known to be jointly determined (Bolton et al., 2011), we cannot rule out the possibility of such indirect effects. However, to show that the results are not entirely driven by investment and equity financing, we re-estimate the baseline model by adding controls for capital expenditure and equity issuance. As indicated in column (1) of Table 4.11, the main results still hold. In addition, in untabulated tables we split the sample into small and large firms, and find that the effect on hedging is concentrated in large firms, suggesting that the mechanisms in Grullon et al. (2015) may not be the same as the one in this paper.

4.7.2 Earnings management

Prior accounting literature has shown that earnings management through discretionary accruals and derivatives usage are partial substitutes in smoothing earnings (Barton, 2001; Pincus and Rajgopal, 2002). As Fang et al. (2016) document a decrease in discretionary accruals among pilot firms following the Reg SHO shock, it is possible that our findings are merely due to a substitution effect given that financial derivatives information is used to construct the measure of hedging intensity. To mitigate this concern, we conduct a robustness test controlling for discretionary accruals. We follow Fang et al. (2016) and calculate *Discretionary Accruals* as a firm's discretionary accruals minus the corresponding discretionary accruals of a matched firm from the same fiscal year and industry with the closest return on assets. The test result is reported in column (2) of Table 4.11. The coefficient on *Discretionary Accruals* is negative, suggesting a substitution between derivatives hedging and discretionary accruals consistent with Barton (2001) and Pincus and Rajgopal (2002), while it is not statistically significant. More importantly, the coefficient on *Pilot*$\times$*During* is still positive and significant at 1% level. Taken together, the hypothesized substitution channel receives little support from the data.

4.7.3 Compensation structure and the FAS 123R

Another possibility is that the effect of the Reg SHO experiment on corporate risk management may be a result of changes in executive compensation structures, as De Angelis et al. (2017) find that the proportion of stock options in new equity grants increases significantly for pilot firms during the experiment. We argue that this is unlikely the case. Otherwise, firms should hedge less in response to the experiment because more option grants tend to increase the convexity of the compensation (Tufano, 1996; Bakke et al., 2016). This prediction is, however, inconsistent with our findings. Despite that, we control for the convexity structure of CEO equity grants defined as CEO option grants divided by stock grants in the baseline model.

Another related concern is a regulatory change in the accounting treatment of stock options known as FAS 123R that might have a confounding effect through a compensation structure channel. In 2004, the FASB issued a revised version of accounting rule, known as FAS 123R, that changed the accounting treatment of equity-based compensation. Under FAS 123R, however, the cost of employee stock options is required to be measured by their fair value[29]. Due to higher accounting charges following the adoption of FAS 123R in 2005, firms reduced their reliance on stock options in equity-based compensations (Hayes et al., 2012), which in turn might have affected corporate hedging policies (Tufano, 1996; Bakke et al., 2016). As with Hayes et al. (2012), We define accounting impact as option expense scaled by diluted shares (*xintopt/cshfd*). We create an indicator *FAS123R* set to one if the average accounting impact prior to 2005 is in the top tecile. Then we interact *FAS123R* with a post-FAS 123R indicator (*Post04*) and include the interactions terms in the baseline regression model.

Column (3) of Table 4.11 report the results of controlling for these potential confounding factors related to managerial compensation structure. It can seen that

[29]Prior to FAS 123R, since no compensation expense is recorded for stock option grants when using intrinsic value method and setting the exercise price of fixed stock options to the stock price on the grant date, most firms avoid the use of fair values in the income statements.

the relation between Reg SHO and firm hedging intensity is unchanged and remains statistically significant at 5% level. The evidence suggests that the change in the structure of CEO compensation, if any, is not the driving force of the main results. Our findings, therefore, are unlikely a rediscovery of De Angelis et al. (2017).

4.8 Conclusion

We investigate how short-selling constraints relates to corporate hedging polices. To avoid endogeneity issues, the analysis relies on a regulatory experiment conducted by SEC, known as Reg SHO pilot program that removed some restrictions on short sales for a set of randomly selected firms. By hand-collecting data on derivatives usage disclosed by oil and gas firms, we construct a measure of hedging intensity, and employ a DiD framework to examine how an exogenous reduction in short-selling frictions affect corporate risk management decisions.

We empirically document that the treated group on average hedges more than the control group does. Exploring the channel, we find that short-selling pressures increase more for pilot firms, and the Reg SHO experiment tends to have a larger impact on corporate hedging for firms with higher financial distress risk. These facts point to a financial distress channel that drives the relation between short selling and corporate risk management. We expand our investigation by exploiting more additional cross-sectional tests under a DDD framework and find that the effect is concentrated in firms with higher managerial incentive alignment, higher downside equity risk and lower stock price informativeness.

Ultimately, we conclude that a relaxation of short-selling constraints leads to more corporate risk management in anticipation of costly financial distress due to the informational role of short sales in credit markets. Although the real effect of short-selling pressures on firm hedging policies appears to be value maximizing for an individual firm, it remains unclear whether it is optimal from a broader prospective. To be more specific, risk management using derivatives, which consumes a firm's liquidity and involves transaction costs, is expensive, but there is no strong evidence that creditors perfectly understand the informational content of short-selling activities. Even though hedging is supposed to be a rational response to the increasing financial distress risk as a result of short selling, one cannot rule out the possibility that the short selling might be a false alarm because at least in theory not all short sales are informative (Goldstein and Guembel, 2008). We leave this question to future research.

Figure 4.1: Gaps in Average Hedging Intensity between Pilot and Non-pilot Firmss

This figure shows differences in the mean *Hedge Ratio* between pilot and non-pilot firms over three periods: Pre Experiment (2002-2004), During Experiment (2005-2007) and Post Experiment (2008-2010).

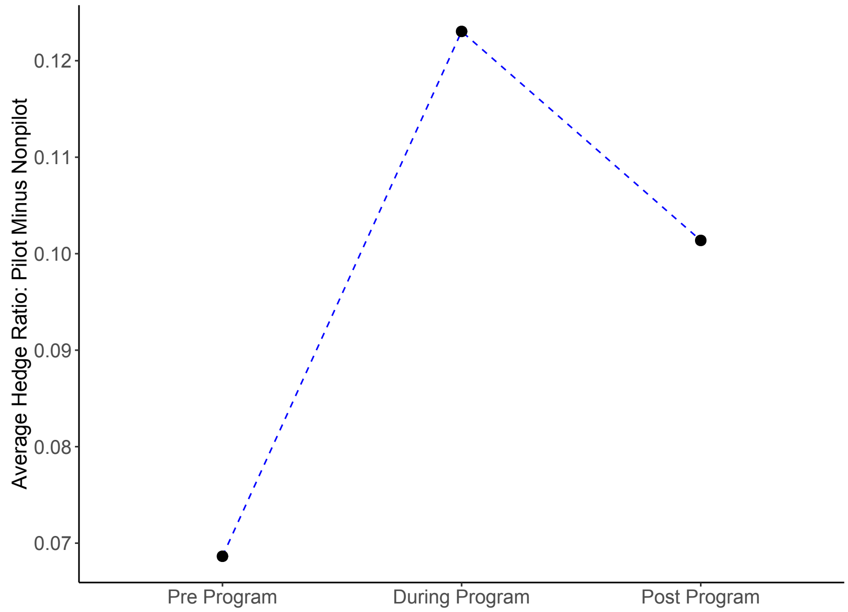


Figure 4.2: Oil & Gas Price Level and Historical Volatility

This figure shows the daily average of market oil and gas prices (left scale) and the 250-day trailing historical volatility of daily average market oil and gas prices (right scale) over 2002-2010. Price is in dollar per million BTU.

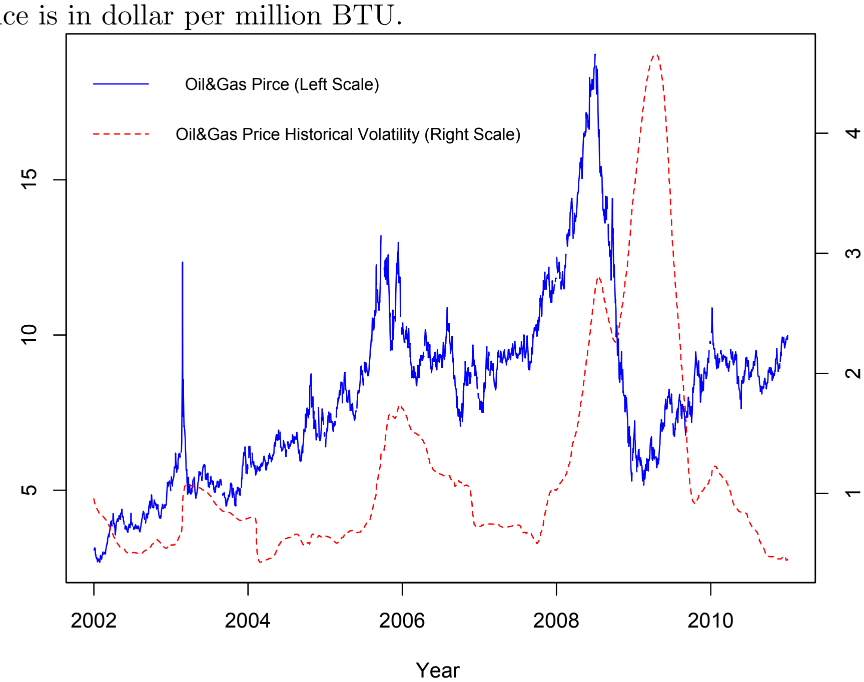


Table 4.1: Descriptive Statistics for Baseline Analysis

Panel A reports the summary statistics of baseline variables over the full sample between 2002 and 2010. Panel B compares the sample means of treatment and control firms before the Regulation SHO's pilot program, and reports tests for differences of means between *Pilot* = 1 and *Pilot* =0 equal to zero, where *Pilot* is a dummy variable that equals one for firms that are selected as Regulation SHO pilot stocks (treatment group) and zero for the remaining Russell 3000 Index constituents (control group). Details on the definitions of variables are provided in Appendix A. Standard errors are clustered at the firm and year level. Significance at the 10%, 5% and 1% level are indicated by *, ** and *** respectively.

Panel A: Summary Statistics for Full Sample

	Observations	Mean	Std.Dev	25%	50%	75%
Hedge Ratio	343	0.2684	0.2325	0.0578	0.2356	0.4212
Assets	343	5,608.8036	9,346.1392	586.2920	1,796.3690	5,282.7980
Market-to-Book	343	1.9759	1.5594	1.1829	1.5749	2.1561
Altman Z-score	343	2.3163	2.6164	1.3076	1.9370	2.6447
Institutional Ownership	343	0.7067	0.2305	0.5943	0.7689	0.8869

Panel B: Tests for Preprogram Differences between Treatment and Control Groups

	Treatment Firms (Pilot=1)	Control Firms (Pilot=0)		
	Mean	Mean	Difference	T-stat
Hedge Ratio	0.3029	0.2342	0.0686	1.09
Assets	4108.2260	3311.0670	797.1591	0.43
Market-to-Book	1.8076	2.0556	-0.2479	-0.88
Altman Z-score	2.4783	2.8967	-0.4184	-0.61
Institutional Ownership	0.6444	0.6405	0.0039	0.07

Table 4.2: Univariate Difference-in-differences Analyses

The Panel A and Panel B in this table present the univariate results of difference-in-differences tests for short interest innovation and hedge ratio, respectively. *Pilot* is a dummy variable that equals one for firms that are selected as Regulation SHO pilot stocks (treatment group) and zero for the remaining Russell 3000 Index constituents (control group). *During* refers to years 2005 to 2007 when the pilot program is effective (treatment period). *Post* refers to years 2008 to 2010 and *Pre* refers to years 2002 to 2004, both of which can be viewed as control period. *Short Interest Innovation* is computed as the monthly first difference of the ratio of monthly average shares held short to the share outstanding at the start of the month. *Hedge Ratio* is defined as total delta of hedges scaled by total production. Details on the definitions of variables are provided in Appendix A. The The standard errors two-way clustered by both firm and date are displayed in parentheses. Significance at the 10%, 5% and 1% level are indicated by *, ** and *** respectively.

Panel A: Short Interest Innovation

	Pilot=0	Pilot=1		
	Time-Series Difference	Time-Series Difference	Difference-in-Differences	T-stat
During-Pre	-0.0002	0.0011*	0.0013***	2.98
During-Post	0.0002	0.0018*	0.0016**	2.64
Post-Pre	-0.0003	-0.0008	-0.0005	-0.86

Panel B: Hedge Ratio

	Pilot=0	Pilot=1		
	Time-Series Difference	Time-Series Difference	Difference-in-Differences	T-stat
During-Pre	-0.0246*	0.0298	0.0544***	9.17
During-Post	-0.0652***	-0.0435	0.0217***	4.96
Post-Pre	0.0405	0.0733*	0.0327	0.97

Table 4.3: Reg SHO Pilot Program and Corporate Hedging

This table presents results from the difference-in-differences (DiD) estimations for the effect of Regulation SHO's pilot program on corporate risk management. The dependent variable is *Hedge Ratio*, defined as total delta of hedges scaled by total production. *Pilot* is a dummy variable that equals one for firms that are selected as Regulation SHO pilot stocks (treatment group) and zero for the remaining Russell 3000 Index constituents (control group). *During* is a time dummy variable that equals 1 from 2005 to 2007 when the pilot program is effective (treatment period) and 0 otherwise (control period). The baseline controls include *Pilot×Post*, *Post*, *log(Assets)*, *Market-to-Book* , *Altman Z-score* , *Institutional Ownership*. *Post* is an indicator for post-program period. Details on the definitions of variables are provided in Appendix A. The standard errors two-way clustered by both firm and year are displayed in parentheses. Significance at the 10%, 5% and 1% level are indicated by *, ** and *** respectively.

Dependent Variable =	Hedge Ratio		
	(1)	(2)	(3)
Pilot×During	0.0438***	0.0544***	0.0462***
	(0.0071)	(0.0121)	(0.0091)
Pilot	0.0793	0.0686	0.0671
	(0.0567)	(0.0550)	(0.0544)
During	-0.0444***	-0.0246*	-0.0074
	(0.0110)	(0.0125)	(0.0340)
Pilot×Post		0.0327	0.0352
		(0.0350)	(0.0274)
Post		0.0405	0.0242
		(0.0259)	(0.0344)
log(Assets)			-0.0005
			(0.0191)
Market-to-Book			-0.0056
			(0.0143)
Altman Z-score			-0.0200*
			(0.0096)
Institutional Ownership			0.0319
			(0.1407)

Observations	343	343	343
Adjusted R-squared	0.0328	0.0355	0.0859

Table 4.4: Reg SHO, financial distress and corporate hedging

This table presents OLS estimations showing how the effect of Regulation SHO's pilot program on corporate risk management varies in the cross section with different degree of firm financial distress risk. The dependent variable is *Hedge Ratio*, defined as total delta of hedges scaled by total production. *Pilot* is a dummy variable that equals one for firms that are selected as Regulation SHO pilot stocks (treatment group) and zero for the remaining Russell 3000 Index constituents (control group). *During* is a time dummy variable that equals 1 from 2005 to 2007 when the pilot program is effective (treatment period) and 0 otherwise (control period). *High Distress Risk* is a dummy variable that equals one if the a firm is more exposed to financial distress risk and zero otherwise. Three proxies are used for identifying cross-sectional variation in the financial distress risk. In column (1), *High Distress Risk* is set to 1 if *Leverage* (total debt over the market value of assets) is in the highest tercile. In column (2), *High Distress Risk* is set to 1 if *Altman Z-score* (Altman, 1968) is in the lowest tercile. In column (3), *High Distress Risk* is set to 1 if *EDF* (Merton (1974) expected default frequency calculated as in Bharath and Shumway (2008)) is in the highest tercile. Additional control variables includes *Pilot×Post*, *Post*, *log(Assets)*, *Market-to-Book* , *Altman Z-score* , *Institutional Ownership*. Details on the definitions of variables are provided in Appendix A. The standard errors two-way clustered by both firm and year are displayed in parentheses. Significance at the 10%, 5% and 1% level are indicated by *, ** and *** respectively.

Dependent Variable =	Hedge Ratio		
Proxy for High Distress Risk:	High Leverage	Low Z-Score	High EDF
	(1)	(2)	(3)
Pilot×During×High Distress Risk	0.1356***	0.1219***	0.0851***
	(0.0133)	(0.0156)	(0.0250)
Pilot× High Distress Risk	-0.0139	-0.0084	0.0270
	(0.1077)	(0.1174)	(0.0959)
During×High Distress Risk	-0.1023***	-0.0865***	-0.1575***
	(0.0177)	(0.0249)	(0.0121)
Pilot×During	-0.0014	0.0029	0.0239
	(0.0085)	(0.0079)	(0.0257)
High Distress Risk	0.1189	0.1099	0.1371*
	(0.0650)	(0.0771)	(0.0627)
During	0.0046	0.0044	0.0166
	(0.0287)	(0.0301)	(0.0370)

Pilot	0.0762	0.0739	0.0438
	(0.0732)	(0.0750)	(0.0715)
Controls	Included	Included	Included
Observations	343	343	343
Adjusted R-squared	0.1128	0.1094	0.1298

Table 4.5: Cross-sectional Tests: The Role of Managerial Incentives

This table presents OLS estimations showing how the effect of Regulation SHO's pilot program on corporate risk management varies in the cross section with different degree of managerial incentive alignment. The dependent variable is *Hedge Ratio*, defined as total delta of hedges scaled by total production. *Pilot* is a dummy variable that equals one for firms that are selected as Regulation SHO pilot stocks (treatment group) and zero for the remaining Russell 3000 Index constituents (control group). *During* is a time dummy variable that equals 1 from 2005 to 2007 when the pilot program is effective (treatment period) and 0 otherwise (control period). *High Incentive Alignment* is a dummy variable that equals one if the CEO compensation is more closely tied to firm value, and zero otherwise. Three proxies are used for identifying cross-sectional variation in the sensitivity to stock price changes for CEO. In column (1), *High Incentive Alignment* is set to 1 if *Stock Grant* (CEO's restricted stock grants scaled by total compensation) is in the highest tercile. In column (2), *High Incentive Alignment* is set to 1 if *Stock Holdings* (CEO's dollar stock ownership) is in the highest tercile. In column (3), *High Incentive Alignment* is set to 1 if *Delta* (dollar change in CEO's wealth given one percent change in stock price) is in the highest tercile. Additional control variables includes *Pilot×Post*, *Post*, *log(Assets)*, *Market-to-Book* , *Altman Z-score* , *Institutional Ownership*. Details on the definitions of variables are provided in Appendix A. The standard errors two-way clustered by both firm and year are displayed in parentheses. Significance at the 10%, 5% and 1% level are indicated by *, ** and *** respectively.

Dependent Variable =	Hedge Ratio		
Proxy for High Incentive Alignment:	High Stock Grants	High Stock Holdings	High Delta
	(1)	(2)	(3)
Pilot×During×High Incentive Alignment	0.1350***	0.1035***	0.0923**
	(0.0320)	(0.0255)	(0.0321)
Pilot× High Incentive Alignment	-0.0560	0.1948	0.0830
	(0.1324)	(0.1442)	(0.1202)
During×High Incentive Alignment	-0.0606**	-0.0141	0.0176
	(0.0248)	(0.0333)	(0.0681)
Pilot×During	0.0225	0.0112	0.0036
	(0.0246)	(0.0269)	(0.0415)
High Incentive Alignment	0.0188	-0.1313	0.0411
	(0.0692)	(0.0764)	(0.0635)
During	0.0254	0.0046	0.0258

	(0.0299)	(0.0434)	(0.0575)
Pilot	0.0647	-0.0194	0.0474
	(0.0904)	(0.1050)	(0.1042)
Controls	Included	Included	Included
Observations	264	264	241
Adjusted R-squared	0.2004	0.2473	0.2726

Table 4.6: Cross-sectional Tests: The Role of Downside Risk

This table presents OLS estimations showing how the effect of Regulation SHO's pilot program on corporate risk management varies in the cross section with different degree of downside risk. The dependent variable is *Hedge Ratio*, defined as total delta of hedges scaled by total production. *Pilot* is a dummy variable that equals one for firms that are selected as Regulation SHO pilot stocks (treatment group) and zero for the remaining Russell 3000 Index constituents (control group). *During* is a time dummy variable that equals 1 from 2005 to 2007 when the pilot program is effective (treatment period) and 0 otherwise (control period). *High Downside Risk* is a dummy variable that equals one for stocks that are more subject to downside risk and zero otherwise. Three proxies are used for identifying cross-sectional variation in downside risk. In column (1), *High Downside Risk* is set to one if *Downside Volatility* is in the highest tercile. In column (2), *High Downside Risk* is set to one if *Downside Beta* is in the highest tercile. In column (3), *High Downside Risk* is set to one if *Downside Return* is in the lowest tercile. Additional control variables includes *Pilot×Post*, *Post*, *log(Assets)*, *Market-to-Book* , *Altman Z-score* , *Institutional Ownership*. Details on the definitions of variables are provided in Appendix A. The standard errors two-way clustered by both firm and year are displayed in parentheses. Significance at the 10%, 5% and 1% level are indicated by *, ** and *** respectively.

Dependent Variable =	Hedge Ratio		
Proxy for High Downside Risk:	High Downside Volatility	High Downside Beta	Low Downside Return
	(1)	(2)	(3)
Pilot×During×High Downside Risk	0.1220***	0.0805**	0.1220***
	(0.0315)	(0.0257)	(0.0184)
Pilot×High Downside Risk	-0.1246	0.1829	0.1192
	(0.0927)	(0.1085)	(0.1132)
During×High Downside Risk	-0.0560**	-0.0890***	-0.0602***
	(0.0195)	(0.0155)	(0.0135)
Pilot×During	0.0074	0.0102	0.0040
	(0.0119)	(0.0172)	(0.0056)
High Downside Risk	0.0653	0.0294	-0.0207
	(0.0646)	(0.0639)	(0.0645)
During	0.0156	0.0087	0.0134
	(0.0325)	(0.0335)	(0.0342)
Pilot	0.1007	0.0143	0.0410

	(0.0706)	(0.0612)	(0.0691)
Controls	Included	Included	Included
Observations	334	343	343
Adjusted R-squared	0.0825	0.1318	0.0992

Table 4.7: Cross-sectional Tests: The Role of Upside Risk

This table presents OLS estimations showing how the effect of Regulation SHO's pilot program on corporate risk management varies in the cross section with different degree of upside risk. The dependent variable is *Hedge Ratio*, defined as total delta of hedges scaled by total production. *Pilot* is a dummy variable that equals one for firms that are selected as Regulation SHO pilot stocks (treatment group) and zero for the remaining Russell 3000 Index constituents (control group). *During* is a time dummy variable that equals 1 from 2005 to 2007 when the pilot program is effective (treatment period) and 0 otherwise (control period). *High Upside Risk* is a dummy variable that equals one for stocks that are more subject to upside risk and zero otherwise. Three proxies are used for identifying cross-sectional variation in upside risk. In column (1), *High Upside Risk* is set to one if *Upside Volatility* is in the highest tercile. In column (2), *High Upside Risk* is set to one if *Upside Beta* is in the highest tercile. In column (3), *High Upside Risk* is set to one if *Downside Return* is in the highest tercile. Additional control variables includes *Pilot×Post*, *Post*, *log(Assets)*, *Market-to-Book* , *Altman Z-score* , *Institutional Ownership*. Details on the definitions of variables are provided in Appendix A. The standard errors two-way clustered by both firm and year are displayed in parentheses. Significance at the 10%, 5% and 1% level are indicated by *, ** and *** respectively.

Dependent Variable =	Hedge Ratio		
Proxy for High Upside Risk:	High Upside Volatility	High Upside Beta	High Upside Return
	(1)	(2)	(3)
Pilot×During×High Upside Risk	0.0386	-0.0696	-0.1044***
	(0.0375)	(0.0520)	(0.0188)
Pilot×High Upside Risk	-0.2194**	0.3140**	0.1924
	(0.0831)	(0.1188)	(0.1248)
During×High Upside Risk	-0.0248	0.0324	0.0259
	(0.0206)	(0.0210)	(0.0144)
Pilot×During	0.0304*	0.0534**	0.0711***
	(0.0143)	(0.0182)	(0.0088)
High Upside Risk	0.0563	-0.1003	-0.0111
	(0.0700)	(0.0691)	(0.0642)
During	0.0139	-0.0179	-0.0200
	(0.0314)	(0.0326)	(0.0260)
Pilot	0.1245	-0.0289	0.0124
	(0.0690)	(0.0625)	(0.0568)

Controls	Included	Included	Included
Observations	334	343	343
Adjusted R-squared	0.1036	0.1533	0.1046

Table 4.8: Reg SHO, stock price informativeness and corporate hedging

This table presents OLS estimations showing how the effect of Regulation SHO's pilot program on corporate risk management varies in the cross section with different degree of stock price informativeness. The dependent variable is *Hedge Ratio*, defined as total delta of hedges scaled by total production. *Pilot* is a dummy variable that equals one for firms that are selected as Regulation SHO pilot stocks (treatment group) and zero for the remaining Russell 3000 Index constituents (control group). *During* is a time dummy variable that equals 1 from 2005 to 2007 when the pilot program is effective (treatment period) and 0 otherwise (control period). *Low Price Informativeness* is a dummy variable that equals one if the firm's stock price is less informative, and zero otherwise. Three proxies are used for identifying cross-sectional variation in stock price informativeness. In column (1), *Low Price Informativeness* is set to 1 if *1-R2* (stock price non-synchronicity) is in the lowest tercile. In column (2), *Low Price Informativeness* is set to 1 if *PIN* (probability of informed trading) is in the lowest tercile. Additional control variables includes *Pilot×Post*, *Post*, *log(Assets)*, *Market-to-Book* , *Altman Z-score* , *Institutional Ownership*. Details on the definitions of variables are provided in Appendix A. The standard errors two-way clustered by both firm and year are displayed in parentheses. Significance at the 10%, 5% and 1% level are indicated by *, ** and *** respectively.

Dependent Variable =	Hedge Ratio	
Proxy for Low Price Informativeness:	Low 1-R2	Low PIN
	(1)	(2)
Pilot×During× Low Price Informativeness	0.1730**	0.1751***
	(0.0676)	(0.0189)
Pilot× Low Price Informativeness	-0.2063	-0.2118*
	(0.1121)	(0.1120)
During×Low Price Informativeness	-0.0615***	-0.1015***
	(0.0137)	(0.0151)
Pilot×During	-0.0142	-0.0184
	(0.0343)	(0.0113)
Low Price Informativeness	0.0477	0.1357
	(0.0853)	(0.0752)
During	0.0020	0.0336
	(0.0381)	(0.0341)
Pilot	0.1379*	0.1492*
	(0.0662)	(0.0732)

Controls	Included	Included
Observations	343	343
Adjusted R-squared	0.1011	0.1105

Table 4.9: Sensitivity Tests for the Relation between Reg SHO and Corporate Hedging

This table presents results from models estimating the statistical robustness of the hedging intensity and Reg SHO relation. The dependent variable is *Hedge Ratio*, defined as total delta of hedges scaled by total production. *Pilot* is a dummy variable that equals one for firms that are selected as Regulation SHO pilot stocks (treatment group) and zero for the remaining Russell 3000 Index constituents (control group). *During* is a time dummy variable that equals 1 from 2005 to 2007 when the pilot program is effective (treatment period) and 0 otherwise (control period). All specifications include the baseline controls: *Pilot×Post*, *Post*, *log(Assets)*, *Market-to-Book* , *Altman Z-score* , *Institutional Ownership*. Column (1) contains state-by-year fixed effect. Column (2) contains additional controls: *Equity Volatility*, *Operating Volatility*. Column (3) contains additional controls: *Leverage*, *Leverage*^{2} , *Net Worth* and *Marginal Tax*. Details on the definitions of variables are provided in Appendix A. The standard errors two-way clustered by both firm and year are displayed in parentheses. Significance at the 10%, 5% and 1% level are indicated by *, ** and *** respectively.

Dependent Variable =	Hedge Ratio		
	State×Year FE	More Controls	More Controls
	(1)	(2)	(3)
Pilot×During	0.0604***	0.0473***	0.0571***
	(0.0107)	(0.0085)	(0.0170)
Pilot	0.0609	0.0669	0.0657
	(0.0550)	(0.0564)	(0.0553)
During		-0.0095	0.0073
		(0.0375)	(0.0316)
Equity Volatility		0.0739	
		(0.0623)	
Operating Volatility		0.3350	
		(0.2467)	
Leverage			1.1125*
			(0.5564)
Leverage^2			-1.1750
			(0.7383)
Net Worth			0.0060

			(0.2136)
Marginal Tax			0.1285
			(0.2935)
Controls	Included	Included	Included
Observations	335	339	343
Adjusted R-squared	0.0323	0.0858	0.1237

Table 4.10: More Sensitivity Tests for the Relation between Reg SHO and Corporate Hedging

This table presents additional results from models estimating the statistical robustness of the hedging intensity and Reg SHO relation. *Pilot* is a dummy variable that equals one for firms that are selected as Regulation SHO pilot stocks (treatment group) and zero for the remaining Russell 3000 Index constituents (control group). *During* is a time dummy variable that equals 1 from 2005 to 2007 when the pilot program is effective (treatment period) and 0 otherwise (control period). In Panel A we present results from various limited samples. The dependent variable is *Hedge Ratio*, defined as total delta of hedges scaled by total production. Column (1) excludes observations in year 2002. Column (2) restricts sample to the pre-crisis era (2002-2007). Column (3) requires that firms have data to compute baseline variables over 2002-2010. In Panel B we present results using alternative measures of hedging intensity as dependent variables. Column (1) uses *Hedge Ratio 1*, defined as total delta of hedges for the next three years scaled by total production. Column (2) uses *Hedge Ratio 1*, defined as total delta of hedges scaled by total reserves. Column (3) uses *Hedge Ratio 3*, defined as the absolute derivatives unrealized gains/loss scaled by total assets. All specifications include the baseline controls: *Pilot×Post*, *Post*, *log(Assets)*, *Market-to-Book* , *Altman Z-score* , *Institutional Ownership*. Details on the definitions of variables are provided in Appendix A. The standard errors two-way clustered by both firm and year are displayed in parentheses. Significance at the 10%, 5% and 1% level are indicated by *, ** and *** respectively.

Panel A: Limited Samples			
Dependent Variable =	Hedge Ratio		
	Excluding 2002	Pre-Crisis Era	Balanced Panel
	(1)	(2)	(3)
Pilot×During	0.0445**	0.0485***	0.0814***
	(0.0142)	(0.0035)	(0.0158)
Pilot	0.0656	0.0716	0.0322
	(0.0478)	(0.0567)	(0.0564)
During	-0.0032	-0.0264	0.0320
	(0.0456)	(0.0291)	(0.0466)
Controls	Included	Included	Included
Observations	301	239	261
Adjusted R-squared	0.0853	0.0792	0.0863

Panel B: Alternative Measures of Hedging Intensity			
Dependent Variable =	Hedge Ratio 1	Hedge Ratio 2	Hedge Ratio 3
	(1)	(2)	(3)
Pilot×During	0.0844***	0.0064***	0.0066***
	(0.0172)	(0.0013)	(0.0014)
Pilot	0.1099	0.0013	-0.0018
	(0.0980)	(0.0055)	(0.0023)
During	0.0552	-0.0063**	0.0013
	(0.0665)	(0.0025)	(0.0026)
Controls	Included	Included	Included
Observations	343	343	343
Adjusted R-squared	0.0676	0.0557	0.0088

Table 4.11: Alternative Explanations

This table presents additional results from models estimating the statistical robustness of the hedging intensity and Reg SHO relation controlling for alternative channels. The dependent variable is *Hedge Ratio*, defined as total delta of hedges scaled by total production. *Pilot* is a dummy variable that equals one for firms that are selected as Regulation SHO pilot stocks (treatment group) and zero for the remaining Russell 3000 Index constituents (control group). *During* is a time dummy variable that equals 1 from 2005 to 2007 when the pilot program is effective (treatment period) and 0 otherwise (control period). Column (1) controls for *Investment* (capital expenditure over total assets) and *Security Issue* (equity and debt issues over total assets). Column (2) controls for *Discretionary Accruals* (discretionary accruals minus the corresponding discretionary accruals of a matched firm from the same fiscal year and industry with the closest return on assets (Fang et al., 2016)). All specifications include the baseline controls: *Pilot×Post*, *Post*, *log(Assets)*, *Market-to-Book* , *Altman Z-score* , *Institutional Ownership*. Details on the definitions of variables are provided in Appendix A. The standard errors two-way clustered by both firm and year are displayed in parentheses. Significance at the 10%, 5% and 1% level are indicated by *, ** and *** respectively.

Dependent Variable =	Hedge Ratio		
	Investment&Financing	Earnings Management	Executive Compensation
	(1)	(2)	(3)
Pilot×During	0.0483***	0.0453**	0.1496**
	(0.0117)	(0.0147)	(0.0471)
Pilot	0.0559	0.0651	-0.0613
	(0.0548)	(0.0528)	(0.0680)
During	-0.0257	-0.0270	-0.0178
	(0.0297)	(0.0407)	(0.0732)
Investment	0.1520		
	(0.1281)		
Equity Issue	0.0480		
	(0.1223)		
Discretionary Accruals		-0.0089	
		(0.0059)	
Option/Equity			-0.0204
			(0.0522)

FAS123R×Post04			-0.0086
			(0.0509)
FAS123R			-0.0194
			(0.0649)
Post04			0.0191
			(0.0929)
Controls	Included	Included	Included
Observations	298	307	197
Adjusted R-squared	0.1075	0.0737	0.2312

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APPENDIX A

Table A1: Definitions of Variables

Variable	Definition and Calculation
AT	Total assets (AT)
Age	Firm age: Years after a firm's first appearance in CRSP database
$Cash$	Cash holdings: Cash and Short-Term Investments (CHE)/ total assets (AT)
CFA	Cash flow: (Income Before Extraordinary Items (IB) + Depreciation and Amortization (DP))/ lagged total assets (AT)
$Leverage$	Book leverage ratio: (Long-term debt (DLTT) + current debt (DLC))/ Total assets (AT)
ROA	Profitability: Earnings before interest, tax, depreciation and amortization (EBITDA) / lagged total assets (AT)
Q	Tobin's Q: (Stock price (PRCC)$\times$shares outstanding (CSHO) + total assets (AT) $-$book equity (CEQ))/total assets (AT)
ZS	Z-score: (1.2*Working capital (WCAP) +1.4*retained earnings (RE)+3.3*pre-tax income (PI)+.999*sale (SALE))/total assets (AT)
$Interest$	Interest coverage ratio: Earnings before interest, tax, depreciation and amortization (EBITDA) / interest expense (XINT)
$Payout$	Payout ratio: (Dividend-preferred (DVP)+ dividend common (DVC) / net income (NI)
$Tangibility$	Fixed assets holding: Property, Plant and Equipment (PPENT)/ AT
$Current$	Current ratio: Current Assets (ACT)/ Current Liabilities (LCT)
$MFlow$	Fire sale pressure at stock level, as calculated in Edmans et al. (2012)

Size	Firm size: Logarithm of total assets (AT)
ME	Market capitalization: Stock price (PRCC) × shares outstanding (CSHO)
FlowVol	Measure of stock-level trading pressure induced by holding mutual funds' flow volatilities as defined in (2.4).
FlowVol_Adj	Measure of stock-level trading pressure induced by holding mutual funds' flow volatilities where fund flows are adjusted for fund raw performance as defined in (2.4).
FlowVol1	Measure of stock-level trading pressure induced by holding mutual funds' flow volatilities as defined in (2.2).
FlowVol_Adj1	Measure of stock-level trading pressure induced by holding mutual funds' flow volatilities similar to *FlowVol_Adj* but fund flows are adjusted for fund CAPM excess returns.
Spread	Bond spread: Spread between bond offering yield and benchmark Treasury bond yield
Volatility	Equity volatility: Logarithm of the yearly standard deviation of the daily stock returns.
IdioVolatility	Idiosyncratic equity volatility: Logarithm of the yearly standard deviation of the daily CAPM idiosyncratic stock returns.
SysVolatility	Idiosyncratic equity volatility: Logarithm of the yearly standard deviation of the daily CAPM idiosyncratic stock returns.
FVolatility	Fund flow-induced volatility pressure: Logarithm of *FlowVol* normalized to zero mean and unit standard deviation (see Section 2.2.2)
FVolatility_Adj	Adjusted fund flow-induced volatility pressure: Logarithm of *FlowVol* normalized to zero mean and unit standard deviation (see Section 2.2.2)
SGVolatility	Firm operating riskiness: Logarithm of rolling-window standard deviation of corporate sales growth rate over the past five years.
HVolatility	Passive mutual fund holding volatility: Logarithm of the average annual standard deviation of passive mutual fund ownership in a given firm.
Invest	Dummy variable equal to one for investment-grade bonds and zero otherwise
Senior	Dummy variable equal to one for senior bonds and zero otherwise
Redeem	Dummy variable equal to one for callable bonds and zero otherwise

$BMaturity$	Time to maturity of bonds at issuance
$BSize$	Offering size of bonds at issuance
$LSpread$	All-draw-in spread of new loans
$LMaturity$	Time to maturity of new loans
$LSize$	Offering size of new loans

Table A2: Definitions of Variables

Variable	Definition	Data Sources
Z-score	3.3*(EBIT/AT) +0.99*(SALE/AT) +0.6*(ME/LT) +1.2*(ACT/AT) +1.4*(RE/AT)	Compustat
Δ *C*	Change in cash and short-term investments divided by the lagged market value of equity ((CHE-CHE$_{t-1}$)/(PRCC_F*CSHO)$_{t-1}$	Compustat
Δ *D*	Change in dividend payments divided by the lagged market value of equity ((DVC-DVC$_{t-1}$)/(PRCC_F*CSHO)$_{t-1}$	Compustat
Δ *E*	Change in income before extraordinary items divided by the lagged market value of equity ((IB-IB$_{t-1}$)/(PRCC_F*CSHO)$_{t-1}$	Compustat
Δ *I*	Change in interest payments divided by the lagged market value of equity ((XINT-XINT$_{t-1}$)/(PRCC_F*CSHO)$_{t-1}$	Compustat
Δ *NA*	Change in net assets divided by the lagged market value of equity ((AT-CHE-(AT$_{t-1}$-CHE$_{t-1}$))/(PRCC_F*CSHO)$_{t-1}$	Compustat
Δ *RD*	Change in R&D expenditures divided by the lagged market value of equity ((XRD-XRD$_{t-1}$)/(PRCC_F*CSHO)$_{t-1}$	Compustat
Acquisition	Acquisition expenditures divided by total assets (AQC/AT)	Compustat
Analyst coverage	The number of analyst followings	IBES
C	Cash and short-term investments divided by the market value of equity at period beginning ((CHE$_{t-1}$)/(PRCC_F*CSHO)$_{t-1}$	Compustat
Capital expenditure	Capital expenditures divided by total assets (CAPX/AT)	

Cash flow	Operating income before depreciation minus interest, taxes, and common dividends, all divided by total assets ((OIBDP-XINT-TXT-DVC)/AT)	Compustat
Cash	Cash and short-term investments divided by total assests (CEH/AT)	Compustat
Dividend dummy	A dummy variable that equals one if DVC is positive, and zero otherwise	Compustat
Earnings volatility	The standard deviation of *ROA* in the past 10 years	Compustat
Equity illiquidity	The average ratio of the equity daily absolut ereturn to the dollar trading volume	CRSP
Equity return	The annual stock return	CRSP
Equity trading	The natural logarithm of dollar stock trading volume	CRSP
Equity volatility	The annual standard deviation of stock rerturns	CRSP
Forecast inaccuracy	The absolute deviation of median forecasted earnings per share (EPS) from the actual EPS	IBES
HM Debt delay index	A text-based measure similar to *HM Delay index* while indicating debt issuance plans to address their liquidity issues	Hoberg and Maksimovic (2014)
HM Delay index	A text-based measure of financial constraints with a higher value meaning that firms are at risk of delaying their investments due to liquidity issues	Hoberg and Maksimovic (2014)
HM Equity delay index	A text-based measure similar to *HM Delay index* while indicating equity issuance plans to address their liquidity issues	Hoberg and Maksimovic (2014)
Implied volatility	The average implied volatility of options	OptionMetrics
Industry sigma	The standard deviation of *Cash flow* in the past 10 years at two digit industry levels	Compustat
Institutional Ownership	Total shares held by 13F filers divided by total share outstanding	TR-13F, CRSP

L	Long term and short term debts divided by the market value of equity at period beginning ($(\text{DLTT} + \text{DLC})_{t-1}/(\text{PRCC\_F*CSHO})_{t-1}$	Compustat
Leverage	Total debt divided total assets ((DLTT+DLC)/AT)	Compustat
Loan covenant violation	A dummy variable that is set to one if there exists a loan covenant violation in the past three years and zero otherwise	CRSP
Market leverage	Total debt divided by the market value of total assets ((DLTT+DLC)/(PRCCF*CSHO+AT-CEQ-TXDB)	Compustat
Market to book	Market value of assets divided by total assets ((PRCC_C*CSHO-CEQ+AT)/AT)	Compustat
Moneyness	The average absolute difference between the stock's market price and the option's strike price.	OptionMetrics
Net working capital	Working capital minus cash and short-term investments, all divided by total assets ((WCAP-CHE)/AT)	
NF	Net financing divided by the market value of equity at period beginning ($(\text{SSTK-PRSTKC+DLTIS-DLTR})_{t-1}/(\text{PRCC\_F*CSHO})_{t-1})$	Compustat
Open interest	the annual average open interest across all options on a stock	OptionMetrics
Option listing	A dummy variable that equals one if at least one option has positive trading volume in the current year, and zero otherwise	OptionMetrics
O-score	$-1.32-.407*\log(\text{AT})+6.03*\text{LT/AT}-1.43*\text{WCAP/AT}+.076*\text{LCT/ACT}-1.72*\mathbf{1}\{\text{LT}>\text{AT}\}-2.37*\text{NI/AT} -1.83* \text{FOPT/LT} +.285*\mathbf{1}\{\text{NI}<0\ \& \ \text{NI}_{t-1} <0\}-.521*(\text{NI-NI}_{t-1})/(\|\text{NT}\|+\|\text{NI}_{t-1}\|)$	Compustat

Pilot	An indicator equal to one for firms that are selected as CEBO pilot option classe, and zero otherwise	CEBO
PIN	Probability of informed trading	Brown and Hillegeist (2007)
Put-call ratio	The average put-call ratio of options	OptionMetrics
R&D	R&D expenditures divided by sales (XRD/SALE)	Compustat
Rating	A dummy variable that equals one for the existence of an S&P credit rating, and zero otherwise	Compustat
ROA	Operating income before depreciation divided by total assets (OIBDP/AT)	Compustat
S&P500	A dummy variable that equals one for the S&P 500 index membership, and zero otherwise	Compustat
Size	Natural log of total assets	Compustat
Stock price synchronicity	Price synchronicity computed as in Roll (1988)	CRSP
Tangibility	Fixed assets divided by total assets (PPENT/AT)	Compustat

Table A3: Definitions of Variables

Variable	Definition	Data Sources
Altman Z-score	3.3*(EBIT/AT) +0.99*(SALE/AT) +0.6*(ME/LT) +1.2*(ACT/AT) +1.4*(RE/AT)	Compustat
1-R2	Price non-synchronicity computed as in Roll (1988)	CRSP
Age	Number of years that the firm has been listed in CRSP	CRSP
Assets	Total assets (AT)	Compustat
Delta	Dollar change in CEO's wealth given one percent change in stock price	Execucomp
Discretionary Accruals	A firm's discretionary accruals minus the corresponding discretionary accruals of a matched firm from the same fiscal year and industry with the closest return on assets, computed as in Fang et al. (2016)	Compustat
Downside Beta	Annual estimates of beta from a regression of daily stock returns on the value-weighted market returns during bad market days (lowest tercile)	CRSP
Downside Return	Negative annual average daily stock returns when the value-weighted market returns are in the bottom tercile	CRSP
Downside Volatility	Annual standard deviation of daily stock returns that are below the annual sample mean	CRSP
During	An indicator equal to 1 for the time period over 2005-2007 when the pilot program is effective (treatment period) and 0 otherwise (control period)	
EDF	The Merton (1974) expected default frequency computed as in Bharath and Shumway (2008)	Compustat, CRSP
Equity Issue	Equity issues divided by total assets (SSTK/AT)	Compustat

Equity Volatility	Annual standard deviation of daily stock returns	CRSP
FAS123R	An indicator equal to 1 if the pre-FAS 123R accounting impact (XINTOPT/CSHFD) is in the top tercile and 0 otherwise	Compustat
Hedge Ratio 1	Negative total delta of hedged positions that mature within three years divided by total production	10K filings
Hedge Ratio 2	Negative total delta of hedged positions that mature within one year divided by total reserves	10K filings
Hedge Ratio 3	Absolute value of accumulated other comprehensive income – derivatives unrealized gains/loss scaled by total assets (AOCIDERGL/AT)	Compustat
Hedge Ratio	Negative total delta of hedged positions that mature within one year divided by total production	10K filings
Institutional Ownership	Total shares held by 13F filers divided by total share outstanding	TR-13F, CRSP
Investment	Capital expenditure divided by total asssets (CAPX/AT)	Compustat
Leverage	Total debt divided by the market value of total assets ((DLTT+DLC)/(PRCCF*CSHO+AT-CEQ-TXDB)	Compustat
Leverage^2	Squared *Leverage*	Compustat
log(Assets)	Natural log of total assets	Compustat
Marginal Tax	Non-parametric marginal tax rate (BCG_MTRINT)	Compustat
Market-to-Book	Market value of equity divided by book value of equity (PRCC_C*CSHO/(SEQ+TXDB+ITCB -PREF))	Compustat
Net Worth	Total equity divided by total assets (SEQ/AT)	Compustat

Operating Volatility	Annual standard deviation of quarterly operating income divided by total assets (OIBDP/AT)	Compustat
Option/Equity	CEO option grants divided by stock grants	Execucomp
Payout	Total payout divided by total assets (DVC+DVP+PRSTKC)/AT)	Compustat
Pilot	An indicator equal to one for firms that are selected as Regulation SHO pilot stocks (treatment group) and zero for the remaining Russell 3000 Index constituents (control group)	SEC, Russell
PIN	Probability of informed trading	Dr. Brown's website
Post	An indicator equal to 1 for the time period after 2007 when the pilot program is closed and 0 otherwise	
Post04	An indicator equal to 1 for the post-FAS 123R period and zero otherwise	
Short Interest Innovation	Monthly first difference of he ratio of monthly average shares held short to the share outstanding at the start of the month	Compustat
Stock Grants	CEO stock grants divided by CEO total compensation (RSTKGRNT /TDC1 or STOCK_AWARDS_FV/TDC1)	Execucomp
Stock Holdings	CEO stock holdings (SHROWN_EXCL_OPTS*PRCC_F)	Execucomp
Upside Beta	Annual estimates of beta from a regression of daily stock returns on the value-weighted market returns during good market days (highest tercile)	CRSP
Upside Return	Annual average daily stock returns when the value-weighted market returns are in the top tercile	CRSP
Upside Volatility	Annual standard deviation of daily stock returns that are above the annual sample mean	CRSP

APPENDIX B

Table B1: The logit model for pilot status

This table presents results of logit model that predicts the probability of entering the CBOE's Penny Pilot Program next year. *Options trading* refers to the natural logarithm of annual equity options trading volume. The baseline controls include lagged *Size*, *Market to book* , *Cash flow* , *Net working capital* , *Capital expenditure* , *Leverage* , *Industry sigma*, *Dividend dummy* , *R&D* and *Acquisition* . Details on the definitions of variables are provided in Appendix A. The standard errors clustered by firm are displayed in parentheses. Significance at the 10%, 5% and 1% level are indicated by *, ** and *** respectively.

	Probability of Pilot Status
	(1)
Options trading	1.868***
	(0.110)
Market to book	−0.032
	(0.064)
Size	0.273***
	(0.081)
Cash flow	−3.551***
	(0.729)
Industry sigma	−1.054

	(1.307)
Net working capital	-1.418^{*}
	(0.818)
Capital expenditure	0.077
	(1.625)
Leverage	0.302
	(0.498)
Dividend dummy	-0.552^{***}
	(0.207)
R&D	0.073
	(0.077)
Acquisition	0.606
	(1.741)
Observations	26,400
Year FE	Yes
Industry FE	Yes

Table B2: The logit model for initial option listing

This table presents results of logit model that predicts the probability of option listing in the next month. *Volume* is average daily trading volume over the previous 250 trading days, *Volatility* is the standard deviation of stock returns over the same period, *Abnormal volume* is the ratio of 30-day to 250-day average daily trading volume, *Abnormal volatility* is the analogous measure for volatility, and *Market capitalization* is the monthly market value of equity. The baseline controls include lagged *Size*, *Market to book* , *Cash flow* , *Net working capital* , *Capital expenditure* , *Leverage* , *Industry sigma*, *Dividend dummy* , *R&D* and *Acquisition* . Details on the definitions of variables are provided in Appendix A. Coefficients on year and industry dummies are not reported for brevity. The standard errors clustered by firm are displayed in parentheses. Significance at the 10%, 5% and 1% level are indicated by *, ** and *** respectively.

	Probability of Initial Option Listing
	(1)
Volume	0.001
	(0.002)
Abnormal volume	0.126^{***}
	(0.017)
Volatility	0.090^{**}
	(0.037)
Abnormal volatility	0.416^{***}
	(0.057)
Market capitalization	-0.018^{**}
	(0.008)
Market to book	0.330^{***}
	(0.008)
Size	1.252^{***}

	(0.018)
Cash flow	-0.396^{***}
	(0.096)
Industry sigma	-0.279
	(0.270)
Net working capital	-0.248^{**}
	(0.123)
Capital expenditure	3.124^{***}
	(0.266)
Leverage	-2.427^{***}
	(0.101)
Dividend dummy	-0.869^{***}
	(0.047)
R&D	0.032^{***}
	(0.007)
Acquisition	1.010^{***}
	(0.229)
Observations	417,255
Year-Month FE	Yes
Industry FE	Yes

Table B3: Alternative measure of cash holdings

This table presents results of OLS regressions that examine alternative measures of corporate cash holdings. *CNA* refers to cash and short-term investments divided by net assets (total assets minus cash and short-term investments). log(*CNA*) refers to the natural logarithm of *CNA*. *CS* refers to cash and short-term investments divided by total sales. *Options trading* refers to the natural logarithm of annual equity options trading volume. The baseline controls include *Size*, *Market to book* , *Cash flow* , *Net working capital* , *Capital expenditure* , *Leverage* , *Industry sigma*, *Dividend dummy* , *R&D* and *Acquisition* . The full sample period is from 1996 to 2016. Details on the definitions of variables are provided in Appendix A. The standard errors clustered by firm are displayed in parentheses. Significance at the 10%, 5% and 1% level are indicated by *, ** and *** respectively.

Dependent Variable =	CNA	log(CNA)	CS
	(1)	(2)	(3)
Options trading	0.0137***	0.0590***	0.0319***
	(0.0041)	(0.0046)	(0.0097)
Controls	Yes	Yes	Yes
Observations	44,933	44,933	44,825
Adjusted R-squared	0.7166	0.7993	0.6847
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

Table B4: Alternative measures of options trading

This table presents results of OLS regressions that examine the effect of options trading activities on corporate cash holdings. The dependent variable is cash to assets ratio (*Cash*) in year t+1. *Options trading 1* refers to the natural logarithm of annual equity options trading volume in terms of number of contracts. *Options trading 2* refers to the natural logarithm of annual put equity options trading volume. *Options trading 3* refers to the natural logarithm of annual call equity options trading volume. The baseline controls include *Size*, *Market to book* , *Cash flow* , *Net working capital* , *Capital expenditure* , *Leverage* , *Industry sigma*, *Dividend dummy* , *R&D* and *Acquisition* . The full sample period is from 1996 to 2016. Details on the definitions of variables are provided in Appendix A. The standard errors clustered by firm are displayed in parentheses. Significance at the 10%, 5% and 1% level are indicated by *, ** and *** respectively.

Dependent Variable =	Cash		
	(1)	(2)	(3)
Options trading 1	0.0050***		
	(0.0006)		
Options trading 2		0.0050***	
		(0.0005)	
Options trading 3			0.0046***
			(0.0005)
Controls	Yes	Yes	Yes
Observations	45,045	45,045	45,045
Adjusted R-squared	0.8231	0.8233	0.8233
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

Table B5: Conditioning on Corporate Governance

This table presents results of OLS regressions that examine the effect of options trading activities on cash holdings across firms with different degree of information asymmetry. The dependent variable is cash to assets ratio (*Cash*) in year t+1. *Options trading* refers to the natural logarithm of annual equity options trading volume. *G-index* refers to the governance index as in Gompers et al. (2003). *E-index* refers to the governance index as in Bebchuk et al. (2008). *Board independence* refers to the fraction of outside directors on board. *CEO chair* is a dummy variable that is set to one when CEO is the chairman, and zero otherwise. The baseline controls include *Size*, *Market to book* , *Cash flow* , *Net working capital* , *Capital expenditure* , *Leverage* , *Industry sigma*, *Dividend dummy* , *R&D* and *Acquisition* . Coefficients on the baseline controls are not reported for brevity. Details on the definitions of variables are provided in Appendix A. The standard errors clustered by firm are displayed in parentheses. Significance at the 10%, 5% and 1% level are indicated by *, ** and *** respectively.

Dependent Variable =	Cash			
	(1)	(2)	(3)	(4)
Options trading × G-index	0.0003			
	(0.0002)			
G-index	-0.0045			
	(0.0028)			
Options trading × E-index		0.0004		
		(0.0004)		
E-index		-0.0067		
		(0.0052)		
Options trading × Board independence			0.0024	
			(0.0024)	
Board independence			-0.0057	
			(0.0274)	
Options trading × CEO chair				0.0001
				(0.0009)
CEO chair				0.0025
				(0.0107)
Options trading	0.0034*	0.0054***	0.0049**	0.0064***
	(0.0020)	(0.0013)	(0.0020)	(0.0010)

Controls	Yes	Yes	Yes	Yes
Observations	26,087	26,242	20,430	18,811
Adjusted R-squared	0.7941	0.7936	0.7905	0.7908
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

APPENDIX C

This appendix explains the computation of hedge ratio in more details. We closely follow Jin and Jorion (2006). The procedures are summarized as below.

1. For each firm-year observation, we read through the annual report (10K form) and hand-collect information on all commodity derivatives and fixed price contracts, including contract type, notional quantity and average maturity.

2. Contract types with non-zero notional quantity include oil swap, two-way oil collar, three-way oil collar, oil put, oil call, oil fixed price contract, gas swap, two-way gas collar, three-way gas collar, gas put, gas call, gas fixed price contract, gas liquid fixed price contract. We collect the stated prices for each product (oil, gas or gas liquid) from annual reports, and use them to standardize the unit of notional quantity as *barrels*. Table C1 reports the sample average notional quantity for each type of derivatives.

3. We calculate delta, defined as the sensitivity of derivative value to the underlying asset price, for each contract. For the short (long) position of swaps, delta is set to -1 (+1). For the short (long) position of calls, delta is set to $-e^{rT}N(d)$ ($e^{rT}N(d)$). For the long (short) position of puts, delta is set to $-e^{rT}N(-d)$ ($e^{rT}N(-d)$). A two-way collar is a short position in a call combined with a long position in a put, in which case delta is set to $-e^{rT}N(d_1) - e^{rT}N(-d_2)$. A three-way collar is a short position in a call combined with a long position in a put and a short position in a

different put, and the delta is computed analogously. For the delta of non-linear contracts (collars, calls and puts), r denotes risk-free interest rate; T is the average maturity of the contract; $d = \frac{ln(F/X)+\sigma^2 T/2}{\sigma\sqrt{T}}$, where X refers to the strike price of the underlying call or put contract soled short or long, while F and σ are the price of exchange-traded oil or gas futures option contract and the corresponding implied volatility. We obtain information on the exchange-traded commodity futures option from the Bloomberg terminal. As Jin and Jorion (2006) provide a specific numerical example in the appendix (page 918), we manage to replicate their results using the data we collect.

4. We aggregate the deltas across the associated contracts. The total delta is equal to $\sum_k Delta_k Vol_k$, where $Delta_k$ is the delta of contract k and Vol_k is the notional quantity of commodity underlying the contract.

5. Finally, we scale the *negative* total delta by total production to obtain *Hedge Ratio*. The resulting *Hedge Ratio* are positive for all sample firms, meaning that commodity derivatives are mainly used to insure against declining prices, and thus for hedging purposes.

Table C1: The Distribution of Derivatives Usage

	Oil Swap	Two-way Oil Collar	Three-way Oil Collar	Oil Put	Oil Call	Oil Fixed Price
Ave. Quantitiy (barrels)	1441503	1342416	633144.5	453430.1	198070.6	0
(%)	14.98%	13.95%	6.58%	4.71%	2.06%	0.00%
	Gas Swap	Two-way Gas Collar	Three-way Gas Collar	Gas Put	Gas Call	Gas Fixed Price
Ave. Quantitiy	2763905	1643311	503084.9	309512.2	293885.5	35050.31
(%)	28.73%	17.08%	5.23%	3.22%	3.05%	0.36%
	Gas Liquid Swap	Two-way Gas Liquid Collar	Three-way Gas Collar	Gas Liquid Put	Gas Liquid Call	Gas Liquid Fixed Price
Ave. Quantitiy	0	0	0	0	0	2980
(%)	0.00%	0.00%	0.00%	0.00%	0.00%	0.01%