Enhancement in a Firm's Information Environment via Options Trading

and the Efficiency of Corporate Investment

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Abstract

We examine the association between enhancement in a firm's information environment via options trading and firm investment efficiency. Investment inefficiency is partly driven by information asymmetries between firm managers and capital providers, aggravating moral hazard concerns. We test whether enhancement in a firm's information environment through higher volumes of options trading (including a natural experiment involving exogenous shocks via the Penny Pilot Program) is positively related to more efficient firm investment decisions. Our results confirm that enhanced informational efficiency via higher volumes of options trading is positively related to improvements in firm-level investment efficiency. Our findings are in line with the enhancement in the information environment stemming from options trading reducing agency and moral hazard concerns (an agency channel) and are not driven by alternative explanations such as managerial learning from informed traders or the lower cost of capital. Overall, our findings suggest that an enhanced information environment via more options trading benefits firms' investment decisions.

JEL Classifications: G12, G31, D81

Keywords: Information environment enhancement, option trading activity, corporate investment efficiency, under- or over-investment, information asymmetry, agency costs, managerial learning.

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1. Introduction

In efficient markets, firms in theory make their financing and investment decisions independently (Modigliani and Miller, 1958), undertaking all projects with positive net present value (Modigliani and Miller, 1958; Hayashi, 1982; Biddle et al., 2009). In the presence of capital market frictions, however, firms deviate from optimal levels of investment by either over- or under-investing because of conflicts of interest between firm insiders and outsiders and the associated financing constraints (Jensen and Meckling, 1976; Myers and Majluf, 1984). Prior literature (e.g., Biddle et al., 2009; Jung et al., 2014) has identified frictions associated with information asymmetries, adverse selection and moral hazard as triggering factors leading to sub-optimal levels of corporate investing. The above research has suggested that investment inefficiency —measured in terms of deviations from 'normal' or optimal levels of investment— can be mitigated by enhancing a firm's information environment, which should reduce moral hazard concerns through more effective monitoring by shareholders and outside stakeholders (Cheng et al., 2013; Chen et al., 2017b).

In this paper, we examine the association between enhancement in a firm's information environment via an increase in the firm's options trading activity and the efficiency of its corporate investment. More options trading activity stimulates information production and acquisition leading to more informed trades (Cao et al., 2022) and reduces information asymmetries between firm managers and outsiders, which potentially lowers the cost of capital and increases firm value (Ross, 1976; Kumar et al., 1998; Pan and Poteshman, 2006; Naiker et al., 2013; Blanco and Wehrheim, 2017; Chen et al., 2021; Roll et al., 2009). Options trading increases the participation of informed traders (Chakravarty et al., 2004; Hu, 2018) and helps make the environment of markets and firms more informationally efficient. These benefits are accrued mainly to firms with substantial options trading activity and they increase with a higher volume of options trading (Chen et al., 2021).

In light of the above, our paper examines whether enhancement in the firm's information environment via a higher volume of options trading—a key factor that reduces information asymmetry and differential access to firm-specific information on the part of outsiders—is associated with a significant improvement in the efficiency of firm-level investment decisions. We expect that an improved firm information environment proxied by a higher intensity of options trading should have a positive association with the efficiency of corporate investment decision-making thus reducing deviations from optimal investment levels.

Managers may deviate from optimal levels of investment when their private interests differ from those of firm shareholders because of adverse selection (Biddle and Hilary, 2006; Biddle et al., 2009; Benlemlih and Bitar, 2018). With agency conflicts and moral hazard frictions, deviating incentives between managers and shareholders would exacerbate over- or under-investment depending on the availability of capital (Biddle et al., 2009). Concurrently, a firm's trading in the options markets increases the informational efficiency of stock prices (Pan and Poteshman 2006; Cremers and Weinbaum 2010, Chen et al., 2021), reduces informed trading asymmetries (Hu, 2018), and helps correct stock overvaluation (Diamond and Verrecchia, 1987). Also, when informed investors trade more frequently in the options market, information may be transferred to the stock market facilitating price discovery (Cremers and Weinbaum, 2010; Jin et al., 2012; Johnson and So, 2012; Chen et al., 2021). As stock prices become more informative, information asymmetry between firm insiders and outside investors is reduced (Chen et al., 2021). For this reason, more options trading improves the firm's informational efficiency and reduces asymmetries with capital providers. Both information asymmetry and moral hazard concerns lead to managers and capital suppliers having different levels of access to information and prevent outsiders from efficiently assessing and predicting a firm's prospects and impeding their monitoring role.

We, thus, hypothesize that an enhanced firm information environment induced by a higher intensity of options trading should be positively associated with corporate investment efficiency. We further expect that benefits arising from improvements in firms' information environments stemming from higher options trading volumes should be relatively more important for promoting efficient investing for investments that are less tangible and more uncertain, specifically non-capital expenditures (NonCapex) in contrast to capital expenditure (Capex) investments. Regarding the mechanisms that could drive our main prediction, as a main channel, enhanced firm information environment via higher options trading activity should help alleviate adverse selection and moral hazard concerns that drive investment inefficiency. We anticipate that when alternative mechanisms with similar power to improve firms' information environments are also present, the enhancing effect on efficient investment stemming from options trading volume would be less strong due to a substitution effect. Thus, we expect that when substitutive mechanisms of external monitoring are stronger, the impact of active options trading on promoting investment efficiency should be weaker in the presence of this kind of substitutive mechanism which should also help towards achieving optimal levels of investment.

We examine the above research question using data on US firms with traded options in Optionmetrics during the 1996-2019 period. In our baseline analysis, we follow extant literature (see Biddle et al., 2009) and measure investment efficiency using firm-specific residuals from a model predicting the level of investment in growth opportunities based on sales growth. We additionally extend the baseline model of Biddle et al. (2009) beyond sales growth to directly account for growth opportunities a) in line with the measure of growth options proposed by Cao et al. (2008) and Trigeorgis and Lambertides (2014), and b) using Tobin's Q based on standard macroeconomics theory to infer the right level of investment. We find that an enhanced firm information environment stemming from a higher volume of options trading is positively associated with firm-level investment efficiency. Our results are moderately stronger for non-capital expenditures (NonCapex) consisting of R&D investments and acquisitions that mostly involve growth options, compared to capital expenditures (Capex) focused on assets-in-place (AIP). Our results hold for both components of NonCapex investment on a stand-alone basis, i.e., for R&D investment and for acquisition outlays separately. These results support the notion that an enhanced firm information environment via a higher volume of options trading helps mitigate information asymmetries and moral hazard concerns (an agency channel).

Results are robust to using ex ante firm-specific characteristics such as cash levels and leverage to identify investment (in)efficiency (Biddle et al., 2009; Cheng et al., 2013; Chen et al., 2017b), and to using alternative measures of options trading activity (options volume based on the number of contracts rather than their dollar value, when considering call options volume and put options volume separately or when measuring option market activity through delta-weighted option volumes as in Lakonishok et al. (2007)).

We carefully address endogeneity concerns, as the production of corporate information stems from factors which may be unobservable but may correlate with the volume of options trading. We cannot preclude the possibility that options trading volume is endogenously determined by the efficiency of firm investment, or that both options volume and efficient investing are (co)determined by the effectiveness of firms' information environment or by managerial quality characteristics linked to options awareness. We take several measures to mitigate potential endogeneity concerns. We use firm fixed effects in all our estimations to account for unobserved firm-specific heterogeneity. Importantly, we apply a generalized method of moments (GMM) estimation in the context of a quasi-natural experiment involving a positive exogenous shock to option trading liquidity resulting in exogenous increases in option trading volumes for select firms that participated for the first time in the Options Penny Pilot Program that was initiated by the U.S. Securities and Exchange Commission in January 2007.[1] In line with Blanco and García (2021) and Cao et al. (2022), we instrument options trading volume by a binary variable taking value one from the first time a firm trading in the Chicago Board Options Exchange (CBOE) was included in the Options Pilot Program. Our main results continue to hold and are actually somewhat stronger following this instrumentation.

We further employ propensity score matching (PSM) procedures, in which our treatment firms have enhanced firm information environment stemming from high volumes of options trading (above industry-year median options volume) with control firms being otherwise comparable firms with weaker information environment as proxied by low volumes of options trading (below industry-year median). The average treatment effect between the two groups of firms indicates higher investment efficiency for firms with higher informational efficiency proxied by options trading volumes. We also re-estimate our baseline model specification for firms with high options trading volume and their propensity-score matched low-volume counterparts, confirming that our main findings hold for our treatment and control-matched samples. We conclude that our main finding is not driven by endogenous firm characteristics.

[1] The Penny Pilot Program allows some stocks to trade their options in increments of $0.01 for option series with a premium below $3 (and $0.05 for option series with a premium of $3 and above). While stocks had been quoted in pennies since 2001, options on stocks prior to the pilot program in 2007 were quoted in nickels and dimes.

We further examine whether the efficacy of external monitoring works as an underlying mechanism and find that our main result is weaker for firms (a) with a higher-than-average external threat to takeovers (indicating a lower degree of insulation from the disciplining effect of the market for corporate control) and (b) with stronger institutional monitoring, and is stronger for firms without a credit rating. The above mechanism suggests that options trading activity may substitute for the aforementioned factors and may be positively associated with investment efficiency as these allow for a more accurate inference of firms' investment opportunities. The above support an agency channel explanation for our findings, in line with our theoretical predictions.

We also examine whether our results might be explained by alternative mechanisms, such as managerial learning and lower cost of capital, but find little support for these alternative channels. Managerial learning (Chen et al., 2007; Roychowdhury et al., 2019) refers to the ability of managers to learn from the trades of informed traders (Ferracutti and Stubben, 2019; Roychowdhury et al., 2019). Managers might disclose less about their firm's earnings through less frequent management forecasts to allow more room for informed investors to trade on their own independent information, which may allow improved managerial learning from investor trading. Thus, a lower frequency of management earnings forecasts may proxy for managerial learning (Chen et al., 2021). However, we do not find evidence that when managers make fewer forecasts the association between enhanced firm information environment and firm-level investment efficiency is affected in a significant way. A second alternative channel relates to a lower cost of equity capital. Past research has shown that higher options trading volumes reduce the implied cost of equity capital (Naiker et al., 2013). Thus, a lower cost of capital stemming from more options trading activity could help improve the profitability of firm investment projects, benefiting firm-level investment efficiency. Again, we do not find any significant evidence that options trading mitigates inefficient investment via reducing the firm's cost of equity (Naiker et al., 2013).

Finally, we perform several supplementary analyses to corroborate our main results. Our main findings regarding a positive association hold more strongly when unexpected investment (a signal of poor performance, see Chen et al., 2017b) is higher, suggesting that trading volume predominantly improves the information environment for poorly performing firms. Further, our results hold mostly for firms with fewer business segments, suggesting that options trading volume plays an information-enriching role especially when the degree of firm complexity is low. By contrast, the information-enriching effect of options trading volume is less significant for high levels of firm complexity. Our baseline result also becomes weaker for firms with larger boards, indicating that stronger internal corporate governance makes the beneficial effect of higher option volumes on efficient investment weaker, effectively working in a substitutive way. Finally, in light of recent evidence on direct interactions between different types of derivatives on the same firm (Cao et al., 2021), we find that our results are driven mainly by firms which do not trade in other derivatives such as the CDS market. This has repercussions on the substituting role that trading in multiple derivative markets can play in enhancing a firm's informational efficiency. Overall, our evidence provides support for the prediction that an enhanced firm information environment stemming from higher trading activity in options markets is positively associated with more efficient firm-level investment decisions, and that this effect is more pronounced when other mechanisms that also enhance the firm's information environment are weak.

Our study follows a recent stream of research investigating whether financial market operations and a firm's information environment affect corporate investment decision-making (Cao et al., 2022; Roychowdhury et al., 2019; Shroff et al. 2014, 2017). Part of this stream highlights the interaction effects between information production or price informativeness and corporate investment decision-making (Blanco and Wehrheim, 2017). Price informativeness helps to discipline managers providing incentives for enhancing firm value (Holmström and Tirole, 1993; Faure-Grimaud and Gromb, 2004). At the same time, information that is more efficiently incorporated in stock prices can help guide better firm investment decisions (Dow and Gorton, 1997). Concerning the firm's external information environment, Shroff et al. (2014) find that it helps mitigate the agency problems that arise when firms expand their operations across borders thus helping MNCs mitigate information frictions within the firm. The external information environment generally refers to the quality and quantity of information provided by other parties, such as analysts, traders and the business press, supply chain partners and even competitors. We show that an enhanced firm information environment associated with more active options trading is positively related to attaining more efficient levels of firm investment as it helps alleviate concerns related to information asymmetry and moral hazard (an agency channel). Our findings provide insight into the positive association between enhanced informational efficiency and more efficient firm-level investment outcomes.

Our findings go beyond the work of Blanco and Wehrheim (2017) that focuses on the effect of options trading on corporate innovation. These authors find that firms with more options trading generate more patents and citations per dollar invested in R&D. Our work takes a more comprehensive approach in measuring the impact of options trading activity on different types of investment, showing that the beneficial effect on improved investment efficiency extends to acquisition outlays as well as R&D expenses, besides Capex.

Our study specifically relates to research concerning the effect of information production and the information environment on corporate investment decisions with a focus on the efficiency of firm-level investment decisions. Efficient investment represents a corporate outcome which is supported by reductions in information asymmetry and moral hazard concerns between firm insiders and outsiders (Biddle et al., 2009; Cheng et al., 2013; Chen et al., 2017b). Firm performance can be manifested in a number of ways and measured through a range of proxies and outcomes, such as profitability, ease in recruiting new employees, corporate governance effectiveness, sustainability performance etc. However, investment efficiency is triggered by factors which should be mitigated by options trading activity and its effect on the informational efficiency of firms. Thus, we associate information production achieved through more active options trading with this particular corporate performance outcome stemming from the quality and efficacy of firms' information environments, rather than focusing on much broader corporate investment outcomes which might be driven by a multitude of factors. Such factors may not necessarily relate directly to the quality of firms' informational environments (e.g., in the case of value increases). However, firms' informational efficiency should affect whether (increased) realized value deviates from the optimal (theoretical) level.

The rest of the article is organized as follows. Section 2 provides a brief review of the related literature and develops our main research hypotheses. Section 3 describes sample selection and the methodology used for measuring efficient investment. Section 4 discusses our main findings, endogeneity tests, and the effect of external monitoring. Section 5 reports supplementary analyses identifying specific contexts where our results are more pronounced and various robustness controls. Section 6 concludes.

2. Literature review and development of hypotheses

2.1 Literature review

2.1.1 Firm-level investment efficiency

Neoclassical theory posits that firms achieve their optimal levels of investment when the marginal benefit equals marginal cost (Hayashi, 1982; Biddle et al., 2009; Ward et al., 2020). Firms deviate from optimal investment levels due to various market frictions and inefficiencies. Previous literature has identified two main frictions: information asymmetry and agency problems (Biddle and Hilary, 2006; Biddle et al., 2009; Cheng et al., 2013; Chen et al., 2017b; Benlemlih and Bitar, 2018; Cook et al., 2019). Managers possess superior (private) information about the firm's prospects and may time the market issuing capital when the firm stock is overpriced (Biddle et al., 2009; Chen et al., 2017b; Cook et al., 2019). This can result in over-investment if managers make excess capital investments or in under-investment if they refuse to raise capital at discounted prices (Myers, 1984; Myers and Majluf, 1984; Biddle et al., 2009; Chen et al., 201b7; Gao and Sidhu, 2018). According to agency theory and moral hazard, misalignment between managerial incentives and shareholders' interests may also result in deviations from optimal investment (Biddle et al., 2009; Chen et al., 2017b). With plentiful resources, managers may over-invest because of their own private objectives (Jensen, 1986; Blanchard et al., 1994; Chen et al., 2017b), due to hubris if they overestimate their abilities (Chen et al., 2017b), or because of differing risk preferences (Holmström, 1999). Countering this, managers may under-invest if they choose not to dedicate the time and effort to efficiently pursue positive net present value projects, preferring to live the "quiet life" (Hart, 1983; Bertrand and Mullainathan, 2003). If capital providers recognize this ex-ante, they may constrain the supply of capital leading to ex-post under-investment (Lambert et al., 2007; Biddle et al., 2009).

2.1.2 Enhancement in the firm's information environment via options trading activity

Although past research on the effects of option trading activity has mainly focused on stock market outcomes (e.g., Chen et al., 2021), recent work provides new insights into its effect on corporate decision-making (Gao, 2010; Blanco and Wehrheim, 2017; Chen et al., 2021; Cao et al., 2022). This work suggests that options trading activity facilitates the transfer of information from the options to the stock market, enhancing price discovery and informational efficiency as well as the firm's overall information environment (Chakravarty et al., 2004; Pan and Poteshman, 2006; Ge et al., 2016; Blanco and Wehrheim, 2017; Ali et al., 2020; Chen et al., 2021).

Options trading contributes to the production of information useful for managers endeavoring to make better corporate decisions (Cao et al., 2022). Options improve efficiency by expanding investors' opportunity sets (Ross, 1976; Hakansson, 1978). As options trading became more prevalent (Du, 2019), the options market has become the preferred market for informed market participants. Options inherently involve low cost and high leverage; thus, trading options is preferred by informed investors with private information (Black, 1975). Options trading may also stimulate the very production of information (Cao, 1999; Du, 2019) as investors are more likely to access information privy to managers (Cao et al., 2022). If investors search and acquire more information when options trading activity increases, managers are also more likely to release more information (Chen et al., 2021). Options listing further improves stock price liquidity and reduces firms' implied cost of capital (Naiker et al., 2013). Blanco and Wehrheim (2017) further examine the effect of options trading activity on corporate investment decisions by focusing on 'innovation efficiency', as measured by patents and citations per R&D capital. This, however, represents a specialized measure that may not be applicable to a general setting across industries (by contrast to a more general notion of 'investment efficiency'). Finally, Roll et al. (2009) find that options trading activity increases firm market value when the latter is associated with a lower cost of capital or conditional risk of investing in firm assets due to a potentially mechanical relation between higher options trading and market valuation.

2.2 Hypotheses development

According to Roll et al. (2009), if prices reveal more information this can lead to more efficient allocation of corporate resources (Khanna et al., 1994; Subrahmanyam and Titman, 1999). At the same time, more informed trading brought about by options market investors can make stock prices more informative, leading to a decrease in the risk of investing in the underlying asset (Cao, 1999; Roll et al., 2009). When stock prices incorporate and reveal information about the profitability of future investment opportunities, managers can learn from informative stock prices, supporting more efficient corporate investment decision-making (Chen et al., 2007; Bond et al., 2012; Hsu et al., 2021).

Importantly, the informational benefit of options trading depends positively on the options trading volume. According to Blanco and Wehrheim (2017), 'liquidity should attract liquidity' (Pagano, 1989). Informed agents will be more willing to trade on private information in markets with higher trading volumes given that these markets provide traders with opportunities to carry out less costly trades and to camouflage their trades (Kyle, 1985; Glosten and Milgrom, 1985). Conversely, informed traders abstain from trading in low liquidity markets. Therefore, the information benefits from options trading depend on whether the market for options has sufficient trading volume to attract more informed traders (Admati and Pfleiderer, 1988; Chowdhry and Nanda, 1991; Pagano, 1989; Blanco and Wehrheim, 2017). Thus, the informational benefits of options trading are positively associated with the volume of traded options reflecting the degree of activity of market participants in relevant markets.

According to Ferracuti and Stubben (2019), uncertainty about firms' fundamentals stems both from underlying economic factors and from information uncertainty. The first cannot be resolved via information gathering, while the second can be reduced through the accumulation of information. If uncertainty arises as a result of incomplete information, the existence of factors that mitigate uncertainty about investment outcomes, such as trading activity in the options market, should promote more efficient investment decision-making by reducing the negative consequences of uncertainty (Lambert et al., 2007; Ferracuti and Stubben, 2019). We expect that as stock prices become more informative and more efficient price discovery reduces information asymmetries between firm insiders and outside investors with higher options trading volumes, adverse selection and moral hazard problems that typically exacerbate investment inefficiency would be mitigated. We thus anticipate that higher options trading activity, manifested through higher trading volumes, should help enhance investment efficiency as it improves the overall informational efficiency of firms. As options trading activity also facilitates more effective monitoring exerted by firm outsiders, it should further mitigate managerial opportunistic exploitation of superior information that these agents possess, providing them with incentives to raise capital when the firm is overvalued. In this case, adverse selection should also be mitigated. Active options trading may also enhance firms' information environment by attracting more informed investors, thus helping reduce information asymmetries and facilitating financing (Blanco and García, 2021). At the same time, increased informational efficiency should improve the ability of capital providers to formulate more accurate predictions about the firm's value, thus facilitating external monitoring and reducing agency conflicts. Resolution of such concerns should help reduce over-investment tendencies attributed to ineffective monitoring as well as under-investment incentives related to the unwillingness of capital providers to supply capital at low cost due to moral hazard concerns.

The above leads to our first research hypothesis:

H1: Enhancement of the firm's information environment brought about by more active options trading, manifested through higher trading volumes, is positively associated with the efficiency of firm-level investment and a lower deviation from optimal investment levels.

Moreover, the posited effects should be relatively more pronounced for more uncertain and intangible or growth-option type investments. This is because of the limited degree of reliability with which the anticipated profitability from such investments can be forecasted. The anticipated outcomes can vary significantly, given that most growth options are staged and provide opportunities for contraction, exit, or abandonment (Trigeorgis and Lambertides, 2014). The posited effects should therefore manifest themselves differently in the two components of total investment, i.e., Capex and NonCapex investments. NonCapex investments consisting of R&D and acquisition-related outlays are more related to the creation and exercise of growth options, whereas tangible Capex investments mainly expand firm assets-in-place. NonCapex investments are more inherently uncertain in terms of the difficulty in predicting their future outcomes, compared to the more concrete and tangible Capex investments. Information asymmetry between managers and capital providers should be larger for those investments that are more uncertain in terms of potential success, with associated positive repercussions for efficient investment. Capital providers are also more prone to constrain the supply of capital for investments they consider to be particularly uncertain with less predictable outcomes, thus triggering under-investment for these more uncertain, growth-option type investments.

We thus expect that the options trading volume should be relatively more informative and important for advancing investment efficiency for investments that are less tangible and more uncertain, namely for NonCapex as opposed to Capex investments. We anticipate that benefits arising from improvements in firms' information environments associated with more options trading volumes —with positive repercussions for efficient investment— should be relatively stronger for investments in the form of NonCapex, compared to Capex. This leads to:

H2: The positive association between the enhancement in a firm's information environment proxied by more active options trading and the efficiency of firm-level investment (posited in H1) is stronger when the latter takes the form of NonCapex compared to Capex investment.

We further consider how the strength and efficiency of external monitoring moderates the association between the enhancement in the firms' information environment via options trading and firm investment efficiency. On one hand, more active options trading may better enable investors to uncover private information held by managers, as there may be repercussions in terms of reputation loss and managerial career concerns in keeping information from investors (Cao et al., 2022). For example, the presence of over-investment may reflect investment inefficiencies associated with poorly monitored entrenched managers (Chen et al., 2015; Choi et al., 2020). Thus, an improved information environment due to active options trading could enhance the efficiency of governance mechanisms already in place that involve better monitoring, mitigate managerial entrenchment and induce managerial decisions that support the interests of investors. This could make the anticipated increase in investment efficiency due to options trading activity more pronounced for firms with a stronger information environment attributable to more effective external monitoring. However, if the strength and effectiveness of external monitoring help reduce investment inefficiencies by enhancing firms' information environments, the positive association between option trading volumes and investment efficiency may actually be *less* strong when the quality of such monitoring is better. This is because stronger external monitoring should provide managerial discipline and thus could work as a substitutive mechanism for information advantages offered by more options trading activity. In this case, the increase in investment efficiency from options trading should be less pronounced for firms with a more efficient information environment.

In effect, the existence of alternative mechanisms enhancing firms' information environments should make the anticipated mitigating effect of options trading volume on inefficient investment less strong.

There are two reasons for this. First, effective external monitoring represents an important mechanism exerting a positive impact on firms' informational efficiency. Second, more efficient investment is supported by enhanced firm informational efficiency and therefore any mechanism that supports this enhanced efficiency should reduce the impact of active options trading on promoting investment efficiency, as it would work as a substitutive mechanism. This leads to hypothesis *H3*:

H3: The enhancement in a firm's information environment brought about by more active options trading is less strongly associated with the efficiency of firm-level investment when substitutive mechanisms of external monitoring are stronger.

3. Sample Selection and Methodology

3.1 Sample selection

Our initial sample consists of all Compustat firms matched to IvyDB Optionmetrics US during the period 1996-2019. There are 274,593 unique firm-year observations in our sample during this period, of which 69,503 have data available on options trading volumes on Optionmetrics. Financial firms are included in our sample, in accordance with previous studies on the value-relevance of options markets trading information (e.g., Du, 2019; Chen et al., 2021). We apply the Fama and French (1997) 48 industry breakdown (hereafter FF48) to classify firms into industries. The measurement of investment efficiency in our baseline specification is made at the level of the population before any matching of data from Compustat to Optionmetrics. The number of firms and of usable firm-year observations is reduced due to data availability constraints. We obtain a maximum of 43,374 firm-year observations for our baseline model during our sample period; this corresponds to 5,514 unique sample firms in the baseline model. We rely on the Center for Research in Security Prices (CRSP) for return data, Institutional Shareholder Services (ISS) for corporate governance data, Thomson Reuters for institutional holdings, and I/B/E/S for analyst data. All continuous variables are winsorized annually at the 1 and 99 percentiles at the Compustat population level.

3.2 Research methodology - baseline model specification

We measure investment inefficiency as deviation from predicted levels of investment reflected in the error terms of a normative model that predicts optimal levels of investment based on growth opportunities. In our baseline specification of eq. (1) below, the optimal (normal) level of investment is based on sales growth in line with Biddle et al. (2009) (see also Chen et al., 2011; Benlemlih and Bitar, 2018; Gao and Sidhu, 2018):

$$INV_{i,t} = \alpha_0 + \alpha_1 Sales\ Growth_{i,t-1} + \varepsilon_{i,t} \tag{1}$$

Thus, deviations from the predicted optimal (normal) level of investment capture investment inefficiency in the form of the residuals in the model of eq. (1). These deviations are captured via the error terms of regressions as per eq. (1) estimated cross sectionally each year (at the level of the population) using ordinary least squares for each Fama and French (FF48) industry separately (with a requirement of at least 20 observations in an industry-year). Our dependent variable capturing investment efficiency, denoted *INV_EFF,* is the absolute value of the residuals from eq. (1) times minus one, so a higher value means higher efficiency, following Rajkovic (2020) and Gomariz and Ballesta (2014). We measure over-investment by the positive residuals of eq. (1) and under-investment by negative residuals (Rajkovic, 2020).

Investment (*INV*) is defined as the sum of research and development (R&D) expenditures, acquisition expenditures (Acq) and capital expenditures (Capex), less cash receipts from sale of property, plant, and equipment (PPE), multiplied by 100, scaled by lagged total assets as in Biddle et al. (2009). Following Biddle et al. (2009), investment *INV* is decomposed into capital expenditures (Capex) and non-capital expenditures (NonCapex), the latter consisting of R&D and acquisition expenditures, both multiplied by 100, and scaled by lagged total assets. We also measure Capex (respectively NonCapex, namely R&D and Acq) investment efficiency, denoted *Capex_EFF* (respectively *NonCapex_EFF*, namely *R&D_EFF* and *Acq_EFF*), by using the firm-specific residuals from the above regression model when the dependent variable takes only the form of Capex (respectively NonCapex, i.e., R&D and acquisitions-related outlays). In this way, NonCapex is decomposed into its components by making separate estimations for R&D and acquisitions-related investment efficiency measures. Details on the estimation equations for the measurement of *INV_EFF*, *Capex_EFF*, *NonCapex_EFF*, *R&D_EFF, Acq_EFF*, and related variable definitions are given in Appendix A.

The different approaches used in the literature to measure investment efficiency (e.g., based on investment-cash flow sensitivity or deviations from expected levels of investment) come with method-specific advantages but also with criticism regarding the theory underpinning them or their empirical operationalization (Gao and Yu, 2018). Roychowdhury et al. (2019) note that investment efficiency is not actually observable so researchers often use imperfect proxies, each with their own limitations. They refer to the economics and finance literature which discusses the various challenges that arise due to measurement error in using imperfect proxies for growth opportunities, the conflicting evidence regarding the validity of proxies for financing constraints, and misspecification issues in empirical investment models based on q theory. Proxies for growth opportunities can be measured with error which may systematically vary with the external information environment; however, relevant concerns may be mitigated by including a set of control variables in respective models (Shroff et al., 2014).

The measure of investment efficiency in eq. (1) based on estimating deviations from expected levels of investment is founded on accelerator theory. This theory assumes that the level of capital is proportional to the level of output and models net investment as a function of past output growth (Gao and Yu, 2010). Such models often have low explanatory power because output growth relates weakly to optimal investment, while other factors related to future growth opportunities are not taken into consideration. In this context, recognizing that the "true" financial performance of a firm is integrally linked to its investment opportunities both at present and in the future (Roychowdhury et al., 2019), we extend the baseline model of eq. (1) by considering an additional specification aimed at better capturing firms' future growth opportunities. Our approach here is based on the measure of growth opportunities inferred from the market, *GO*, as proposed by Cao et al. (2008) and Trigeorgis and Lambertides (2014). Deviations from the predicted level of investment reflected in the error terms in the model below signify investment inefficiency:

$$INV_{i,t} = \beta_0 + \beta_1 Sales\ Growth_{i,t-1} + \beta_2 GO_{i,t-1} + u_{i,t} \tag{2}$$

$GO_{i,t-1}$ represents the percentage of a firm's market value arising from future growth opportunities, estimated by subtracting from the current market value of the firm the perpetual discounted stream of firm operating cash flows under a no-growth policy. Detailed definitions for all variables are provided in Appendix A. We take the absolute value of the residuals from eq. (2), multiplied by minus one, to construct our investment efficiency proxy that better captures growth opportunities (denoted INV_EFF^{GO}).

Further, we estimate a second variation to the extant investment efficiency measure by using Tobin's *Q* instead of *GO* as a measure of future growth opportunities in eq. (2), this time predicting the level of investment using sales growth and Tobin's *Q*. The use of Tobin's *Q* as a variable to capture corporate growth opportunities is based on standard macroeconomics theory used to infer the right level of investment (Hayashi, 1982). In this case, deviations from the predicted level of investment, as reflected in the error terms of the model, signify investment inefficiency based on the following specification:

$$INV_{i,t} = \gamma_0 + \gamma_1 Sales\ Growth_{i,t-1} + \gamma_2 Q_{i,t-1} + u_{i,t} \tag{3}$$

$Q_{i,t-1}$ represents Tobin's *Q* ratio for firm i in year $t-1$. Again, we take the absolute value of the residuals from eq. (3), multiplied by minus one, to construct our investment efficiency proxy (we denote this measure as INV_EFF^{Q}).

A natural concern is whether the above investment efficiency measures are valid constructs for capturing efficient firm investment. A way to assess this is to test whether higher investment efficiency measured in this way is associated with better firm performance in the future. Presumably, more efficient investment should lead to superior future firm performance. To assess this, we regress one-year-ahead return on equity ($ROE_{i,t+1}$) on our three investment efficiency proxies and control variables, and summarize the estimation results in Table OA.1 of the Online Appendix (to conserve space). All three proxies of investment efficiency positively and significantly (at 1%) associate with future profitability ($ROE_{i,t+1}$), indicating that our measures of efficient investment lead to better firm performance in the future. This provides support for the validity of the construction of these measures for investment efficiency.[2]

[2] We are grateful to the anonymous reviewer of the paper for suggesting this assessment.

To estimate the association between enhancement in firms' information environments proxied by higher options trading volume in year *t* and investment efficiency in year *t+1*, based on the baseline model of eq. (1), we estimate the following specification for the full sample period:

$$INV\_EFF_{i,t+1}\ (or\ Capex\_EFF_{i,t+1}\ or\ NonCapex\_EFF_{i,t+1}\ , or\ R\&D\_EFF_{i,t+1}, or\ Acq\_EFF_{i,t+1})$$

$$= \delta_0 + \delta_1 LnOptVol_{i,t} + \sum_p \xi_p Controls_{p,i,t} + \sum_m \varphi_m Fixed\ Effects_m + v_{i,t} \qquad (4)$$

where $v_{i,t}$ is the error term. The dependent variable is total investment efficiency $INV\_EFF_{i,t+1}$ (or investment efficiency in terms of Capex or NonCapex investment components separately). In the extended versions based on eqs. (2) and (3), the alternative measures $INV\_EFF_{i,t+1}^{GO}$ and $INV\_EFF_{i,t+1}^{Q}$ (and their components) are used instead.[3] The independent variable of interest in eq. (4) is $LnOptVol_{i,t}$, the natural logarithm of one plus the total annual dollar options volume (in $000) for firm *i* in fiscal year *t*. We calculate total annual dollar options volume based on Roll et al. (2009): for each stock *i*, we multiply the daily trading volume by the midpoint of the end-of-day bid-ask spread for each options contract on the stock and then aggregate all listed options contracts on the particular stock across all trading days during fiscal year *t*. The coefficient for $LnOptVol_{i,t}$ should be positive and significant if the volume of options trading enhances future investment efficiency.

The control variables used in eq. (4) capture standard determinants of investment as employed by Biddle et al. (2009) and other related literature (e.g., García Lara et al., 2016; Benlemlih and Bitar, 2018). These controls include firm size ($Size_{i,t}$); market-to-book value of equity ($MB_{i,t}$); controls for the standard deviations of cash flow from operations ($\sigma(CFO)_{i,t}$), sales ($\sigma(Sales)_{i,t}$) and investment ($\sigma(I)_{i,t}$); a proxy for bankruptcy risk based on Altman (1968) ($ZScore_{i,t}$); tangibility based on net PPE over assets ($Tangibility_{i,t}$); financial leverage ($Lev_{i,t}$); cash flow to sales ($CFOSales_{i,t}$); an indicator for financial slack based on the intensity of cash over net PPE ($Slack_{i,t}$); and an indicator variable of whether the firm distributes dividends or not ($Dividend_{i,t}$). We also include firm age ($LogAge_{i,t}$); the length of the operating cycle ($OperCycle_{i,t}$); and a negative profit indicator ($Loss_{i,t}$). As in prior research, eq. (4) is estimated with firm and year fixed effects. Detailed variable definitions are provided in Appendix A.

3.3 *Research methodology - alternative model specifications*

Measuring investment efficiency in this way does not come without challenges as it is inherently not observable (Roychowdhury et al., 2019). These challenges relate to measurement errors when using proxies to capture growth opportunities, the effect of financing constraints, and misspecification in empirical investment models. Biddle et al. (2009) type models are criticized for their assumption that

[3] We also estimate for these alternative measures Capex (and NonCapex, R&D and Acq) investment efficiency, denoted $Capex\_EFF^{GO}$ and $Capex\_EFF^{Q}$ (respectively $NonCapex\_EFF^{GO}$; $R\&D\_EFF^{GO}$, and Acq_EFF^{GO}, and $NonCapex\_EFF^{Q}$; $R\&D\_EFF^{Q}$, and Acq_EFF^{Q}) by using the firm-specific residuals from the regression model of eq. (2) and (3), respectively, when investment takes the form of Capex (NonCapex; R&D, Acq).

firms can adjust their capital fully within one period whereas capital investment typically requires substantial planning, installation and delivery time (Gao and Yu, 2018). For robustness, we use two alternative specifications for measuring investment efficiency as per eq. (1), $INV\_EFF^{GO}_{i,t+1}$ and $INV\_EFF^{Q}_{i,t}$.

Further, we estimate investment efficiency using firm-specific levels of cash and leverage as ex ante firm-specific characteristics may affect the likelihood of a firm over- or under-investing, as in Biddle et al. (2009), Cheng et al. (2013) and Chen et al. (2017b). For this estimation, we calculate the ranked variable $OverFirm_{i,t}$, which represents the average of ranked decile measures of cash and leverage according to year and Fama-French FF48 industry sectors (Chen et al., 2017b), rescaled from 0 to 1. The underlying premise of Biddle et al. (2009) in following this approach is that firms without cash are more likely to be financially constrained and thus prone to under-invest, while firms with high cash balances are more vulnerable to agency temptations (Jensen, 1986) and more prone to over-invest. Relatedly, firms with high leverage are more likely to under-invest when they are more financially constrained and are more vulnerable to debt overhang problems (Biddle et al. 2009). Hence, a firm's likelihood of over (under)-investing increases (decreases) with high cash balances and decreases (increases) with leverage. For over-investment ($OverFirm_{i,t}$), leverage is multiplied by minus one so that it increases with the likelihood of over-investment, while a high (low) value of $OverFirm_{i,t}$ is indicative of a firm prone to over(under)-investment.

In this alternative model specification examining the association of enhancement in firms' information environment proxied by options trading volume in year *t* with investment efficiency in year *t+1*, we follow the methodology of Chen et al. (2017b) based on Biddle et al. (2009) (also employed in Cheng et al., 2013 and García Lara et al., 2016) to estimate

$$INV_{i,t+1}\ (or\ Capex_{i,t+1}, or\ NonCapex_{i,t+1}, or\ R\&D_{i,t+1}, or\ Acq_{i,t+1}) = \zeta_0 + \zeta_1 LnOptVol_{i,t} + \zeta_2 OverFirm_{i,t} + \zeta_3 LnOptVol_{i,t} \times OverFirm_{i,t} + \sum_n \theta_n Controls_{n,i,t} + \sum_m \psi_m Fixed\ Effects_m + e_{i,t} \quad (5)$$

Our independent variables of interest here are $LnOptVol_{i,t}$ and its multiplicative term with $OverFirm_{i,t}$. If options trading volume is negatively associated with under-investment, then coefficient ζ_1 should be positive and significant. As in Biddle et al. (2009), coefficient ζ_1 measures the relation between options trading volume and investment when under-investment is most likely. As ζ_3 measures the incremental relation between options trading volume and investment as over-investment becomes more likely, $\zeta_1 + \zeta_3$ measures the relation between options trading volume and investment when over-investment is likely (Biddle et al., 2009). If options trading volume is negatively associated with over-investment, $\zeta_1 + \zeta_3$ should be negative.

Control variables used in eq. (5) include proxies for monitoring and governance mechanisms and standard determinants of investment (Biddle et al. 2009; Cheng et al., 2013; García Lara et al., 2016;

Chen et al., 2017b). Controls for monitoring/governance include institutional holdings ($INST_{i,t}$) and coverage by financial analysts ($LogAnalysts_{i,t}$). We also include a proxy for accounting quality ($AQ_{i,t}$) as in Chen et al. (2017b). These variables are also interacted with $OverFirm_{i,t}$ to control for their association with over- and under-investment. Controls for investment drivers include leverage at the industry level ($Ind\ K - structure_{i,t}$) and other standard controls.[4] Eq. (5) is estimated with firm and year fixed effects. Variable definitions are provided in Appendix A.

4. Empirical findings

4.1 Descriptive Statistics

Table 1 reports descriptive statistics for all sample firm-year observations used in our baseline model of eq. (4) during 1996-2019 for variables related to investment (in)efficiency, options trading volume, and those used as controls or employed in supplementary analyses and tests for endogeneity. All main variables reported in Table 1 are defined in Appendix A. The average (median) investment (as a % of total assets) for our sample is 14.17% (8.95%) and relevant values fall to 5.74 (3.59) for Capex and 8.69% (2.18%) for NonCapex investment, with values of 4.26% (0%) and 4.44% (0%) for R&D and acquisition expenditures, respectively. Values for the alternative measures of investment efficiency based on the extended models of eqs. (2) and (3), $INV\_EFF_{i,t}^{GO}$ and $INV\_EFF_{i,t}^{Q}$, are generally very close to the ones reported for baseline INV_EFF for total investment (and also for Capex and NonCapex, as well as R&D and Acq separately). $OverFirm_{i,t}$ has an average and median value of 0.50. The average (natural logarithm of one plus) options dollar volume $LnOptVol_{i,t}$ has a mean (median) value of 0.36 (0.07), being highly skewed as noted in Cao et al. (2021). This is also observed in dollar volumes from call and put options separately. The average age of our sample firms is 22 years, and typical firms appear to rely mainly on equity rather than on debt financing (the average leverage ratio is about 20%). On average, 27% of firm-year observations involve losses and about half distribute dividends. About 40% have a credit rating for their long-term debt, while roughly 16% are also traded in CDS markets. Regarding the other control variables, the average (median) Z-Score is 0.934 (1.024), while on average net PP&E is 27.4% of total assets as reflected in the tangibility indicator. The post Option Penny Pilot program inclusion affects 5% of total observations. The summary statistics for the rest of the variables are generally consistent with prior studies (e.g., Chen et al., 2017b; Choi et al., 2020). Untabulated results on Pearson correlations for the main variables indicate that our investment inefficiency measures are not significantly correlated with options trading volume (these are available upon request).

Insert Table 1 about here.

4.2 Main empirical findings

[4] We use the same control variables as previously; we do not include leverage as a separate regressor as this variable was used in the calculation of $OverFirm_{i,t}$ (Biddle et al., 2009; Chen et al., 2017b).

Table 2 reports OLS results for our baseline eq. (4) model for the entire sample, as well as for the over-investment and under-investment subsamples separately; over-investment is measured by positive residuals and under-investment by negative residuals based on eqs. (1), (2), and (3) in Panels A, B, and C, respectively. The table also reports results when the dependent variable takes the form of $Capex\_EFF_{i,t}$ ($NonCapex\_EFF_{i,t}$, $R\&D\_EFF_{i,t}$, $Acq\_EFF_{i,t}$), reflecting Capex (NonCapex, R&D and acquisitions-related) investment efficiency. Panels A, B and C of Table 2 report results when estimating investment efficiency based on eqs. (1), (2) and (3) as $INV\_EFF_{i,t+1}$, $INV\_EFF^{GO}_{i,t+1}$, and $INV\_EFF^{Q}_{i,t+1}$, respectively. Results from the baseline model of Panel A of Table 2 show that $LnOptVol_{i,t}$ proxying for enhancement in firms' information environments is positively and significantly associated (at the 1% level) with investment efficiency, confirming *H1*. This result is separately confirmed for both the under-investment and the over-investment subsamples. Recall that we measure over-investment by the positive residuals of eq. (1) and under-investment by negative residuals (Rajkovic, 2020). $LnOptVol_{i,t}$ negatively and significantly associates with positive residuals indicating over-investment (since a higher positive value of these residuals indicates higher over-investment), while it negatively and significantly associates with negative residuals indicating under-investment (as under-investment becomes more pronounced for more negative values of these residuals). Regarding the two main components of investment, $LnOptVol_{i,t}$ is a positive and significant determinant for both NonCapex and Capex investment efficiency; this result is further confirmed for both individual components of NonCapex, R&D and Acq separately. However, the statistical significance of $LnOptVol_{i,t}$ is higher for NonCapex (and its components) than for Capex. A standard Z-test (as in Clogg et al., 1995) for the equality of the estimated coefficients of $LnOptVol_{i,t}$ in the two different regressions (for Capex and NonCapex) yields a value of $Z = -2.6335$, indicating that the estimated coefficient in the NonCapex equation is statistically higher than that estimated in the Capex equation (at the 1% significance level). The same holds in Panels B and C that are based on the extended models of eqs. (2) and (3), $INV\_EFF^{GO}_{i,t+1}$ and $INV\_EFF^{Q}_{i,t+1}$.

We find modest evidence that enhancement in firms' information environments proxied by options trading volume is more strongly associated with investment efficiency when firm investment is inherently more uncertain, that is for NonCapex expenditures involving R&D and acquisition-related investments rather than for Capex, providing modest support for *H2*. This is in line with higher options trading volumes being positively linked to the firm's information environment when it is most needed, as is the case when investment is less certain.

Insert Table 2 about here.

Regarding the other independent variables, market-to-book is significantly associated with investment efficiency, with the exception of under-investment. Firms with higher market-to-book ratios are associated with higher levels of investment growth and over- (but not under)-investment, in line with Benlemlih and Bitar (2018). Firm size is negatively associated with investment efficiency as large firms have fewer growth opportunities and tend to reduce investment activities. Growth firms indicated by high market-to-book tend to invest more, and hence are more prone to over-investment and higher investment inefficiency (Benlemlih and Bitar, 2018). The result on firm size reverses in the case of under-investment as smaller firms may face a limited supply of capital from investors. Analogously, firm age appears to work as an enhancing factor for overall investment efficiency and a protection from under-investment, but not from over-investment.

Leverage appears positively and significantly associated with investment efficiency as higher levels of debt require firms to pay more interest and limits their ability to raise additional external financing. Both of these factors constrain levered firms' ability to invest, with debt holders playing a monitoring role in avoiding inefficient investment (see Benlemlih and Bitar, 2018). This also holds for firms incurring losses and firms with more financial slack. The latter has a disciplining effect and is negatively associated with over-investment.

Tangibility has positive and significant coefficients for the full sample, the under-investment and the Capex subsamples, but not for the over-investment and NonCapex subsamples. This indicates that a high level of tangible assets already in place is associated with more efficient investment, particularly involving Capex, and provides protection from under-investment. This is in line with mitigating managerial hubris motives and growing the firm beyond an optimal size via excessive investment in tangible assets. The volatilities of investment, cash flows and sales overall have limited significance across the different model specifications, with the exception of the volatility of cash flows which aggravates investment efficiency. The length of the operating cycle seems to protect from over-investment (while it encourages under-investment), while the risk of bankruptcy measured by Altman's Z-Score seems to mitigate over-investment but it does not significantly associate with under-investment. The length of the operating cycle indicates a firm needs more time to collect cash and has a limited ability to undertake long-term investments when the cycle is long. The risk of bankruptcy further tightens financial constraints faced by the firm, producing a similar effect on inefficient investment. Finally, the availability of cash measured by cash flow generation ability, $CFOSales_{i,t}$, does not significantly associate with investment efficiency but does aggravate under-investment as expected.[5]

Table 3 reports OLS results for the alternative model specification of eq. (5). The coefficient for $LnOptVol_{i,t}$ is significantly positive at the 1% level with a value of 2.431 (respectively 2.509, 2.901, 3.189) when the dependent variable is next year's total investment (respectively, NonCapex, R&D, Acq

[5] We further report in Table OA.2 of the Online Appendix that accompanies our paper, essentially an extra Panel (Panel D) of Table 2 in the manuscript. It reports the estimation results of eq. (3), only this time the dependent variable is $INV\_EFF_{i,t+1}^{Q\ only}$, an investment efficiency proxy estimated using the residuals from regressing investment of Tobin's Q only, rather than sales growth together with Tobin's Q. Results remain qualitatively similar.

investment). This is not statistically significant when the dependent variable is Capex. For firms that are more likely to under-invest (*OverFirm* = 0), a higher options trading volume is associated with higher total and NonCapex investment and its components (but not Capex). The coefficient for the interaction term $LnOptVol_{i,t} \times OverFirm_{i,t}$ is negative and significant at the 1% level for the total investment specification (and also for NonCapex, R&D, Acq). It is again non-significant in the Capex estimation. The overall effect of options trading volume on investment for firms that are more prone to over-invest, measured by the sum of the coefficient estimates of $LnOptVol_{i,t}$ and $LnOptVol_{i,t} \times OverFirm_{i,t}$, is -0.5666. This is significantly negative, indicating that the volume of options trading protects from over-investment as the latter is more likely. The *p-value* for the Wald test on the sum of the coefficients of $LnOptVol_{i,t}$ and $LnOptVol_{i,t} \times OverFirm_{i,t}$ is essentially zero, strongly rejecting (at the 1% level) the null hypothesis that the sum of the two coefficients is zero for the total investment and NonCapex model specifications. This indicates that options trading volume is negatively associated with over-investment. This finding also holds for acquisitions (Acq) and for the R&D component of NonCapex. Thus, findings from Table 3 confirm previous evidence (Table 2) suggesting that enhancement in firms' information environments proxied by options trading volumes is positively associated with more efficient investing. These findings are stronger for NonCapex type investments, which include acquisitions as well as R&D, both of which embed more growth options, as opposed to Capex investments which mostly expand tangible assets-in-place.

Insert Table 3 about here.

Regarding the rest of the independent variables, $OverFirm_{i,t}$ is generally positively associated with total investment, and the same applies for analyst following, $LogAnalysts_{i,t}$. Institutional ownership and accounting quality do not appear as related to the levels of future investment. Capital structure at the industry level, firm size, and the loss and dividend payment indicators are all negatively associated with the level of investment, in line with smaller, leveraged, loss-making, and dividend-paying firms investing less in line with past research (e.g., Chen et al., 2017b). The opposite is observed for firms with high market-to-book ratios and asset tangibility, suggesting that higher growth and tangible assets in place are associated with higher levels of investment. For NonCapex (and its R&D and Acq components), higher asset tangibility is negatively associated with investment. Financial slack, measured as cash per dollar of net tangible assets, seems negatively associated with investment levels.

The firm's cash flow generation ability, the length of the operating cycle and bankruptcy risk are all negatively associated with total and NonCapex investments, and positively associated with Capex. The similarity in coefficient signs and significance levels between total and NonCapex specifications (but not for Capex) is in line with the more tangible nature of Capex and the prediction that the association of options trading volume with investment efficiency is driven more by NonCapex investment involving more growth options than by tangible assets-in-place. The volatilities of investment and cash flow positively and significantly relate to future total, Capex, and NonCapex investment.

We conclude this sub-section by discussing estimation results analogous to Table 3 of Biddle et al. (2009) based on multinomial logit pooled regressions. Biddle et al. (2009) employ a multinomial dependent variable equal to zero if the firm invests efficiently, equal to 1 if the firm over-invests and equal to -1 if the firm under-invests (relative to normal investment). We replicate this estimation for our three investment efficiency measures ($INV\_EFF_{i,t+1}$, $INV\_EFF^{GO}_{i,t+1}$ and $INV\_EFF^{Q}_{i,t+1}$) and their components and summarize the results in Table OA.3 of the Online Appendix. In Panels A and B of Table OA.3, the residuals from the sales growth model of Biddle et al. (2009) measure unexplained (inefficient) investment (eq. (1) in the text). Panels C and D contain the results from our augmented model that more fully accounts for growth options based on the *GO* measure (eq. (2) in the text). Panels E and F contain the results from the augmented model that includes Tobin's *Q* to measure unexplained investment (eq. (3) in the text). In all panels, firm-year observations in the bottom quartile of unpredicted investment are classified as under-investing ('Low'), observations in the top quartile are classified as over-investing ('High') and observations in the middle two quartiles are used as the benchmark or normal group ('Mid'). Panels A, C and E show the results for the model predicting the likelihood that a firm will be in the 'Low' (under-invest) group. Panels B, D and F show the results for the model predicting the likelihood that a firm will be in the 'High' (over-invest) group. Our main results remain qualitatively the same when using this multinomial logit model for our baseline analysis. Higher option volumes, proxying for enhancement in firms' information environment, are positively and significantly associated with investment efficiency across all examined measures.

4.3 Controlling for endogeneity

The above results are consistent with our main hypothesis that enhancement in firms' information environments proxied by options trading volume activity is positively associated with firm-level investment efficiency. However, potential endogeneity concerns could muddy this association. This could be the case if options trading volume and firm-level investment efficiency are jointly affected by factors unobservable to the empirical researcher but observable to traders (Blanco and Wehrheim, 2017), for example, if traders adjust their trading patterns in light of anticipated efficient investing by firms. If such factors correlate positively with the level of options trading, model inferences could be biased. In a similar vein, options trading volume could be endogenously determined by the efficiency of firm investment, or efficient investment and options trading volumes might be simultaneously determined by the informational efficiency of the firm's environment. We use three main approaches to mitigate potential endogeneity concerns.

As a first step, we include firm fixed effects when estimating eqs. (4) and (5), in addition to year fixed effects. Second, and more importantly, following Blanco and García (2021) and Cao et al. (2022), we use a semi-natural experiment in the context of the Option Penny Pilot Program as an exogenous positive shock to options trading volumes and the firms' information environments. This program, which was introduced in early 2007, reduced tick sizes for selected options classes and thus trading costs, while increasing trading volumes, liquidity and informational efficiency. The program initially included 13 option classes and reduced minimum tick increments to $0.01 for all option series below $3, and to $0.05 for option series of $3 and above for a select group of pilot firms, leading to a reduction in transaction costs and anticipated improvements in liquidity, options trading volumes and informational efficiency (Cao et al., 2022). Inclusion in the program is decided by the exchange. Furthermore, firms are added gradually to the Penny Pilot program over time, which helps alleviate concerns regarding omitted variables that might arise in the case of one-time shocks. On June 30, 2020 the Penny Pilot program was replaced by the Penny Program with similar provisions.[6]

We obtain information on option class additions to the CBOE Penny Pilot program from CBOE announcements published on a periodic basis for each calendar year.[7] We match firms added to the program according to the Ticker symbol, followed by manual cross checking. Firms not added to the program are treated as non-pilot firms. A total of 291 pilot firms are matched and used in our baseline analysis. Following Cao et al. (2022), we use instrumental variable (IV) analysis to examine the effect of the Penny pilot program inclusion on firms' information environments via options trading volumes and its subsequent impact on the efficiency of corporate investment. We instrument $LnOptVol_{i,t}$ by a binary variable denoted as *PilotPost*, equal to one for the years following the Penny Pilot program inclusion for affected firms and zero otherwise. Table 4 reports the results from re-estimating eq. (4) using a GMM instrumental variable approach, with $PilotPost$ as the excluded IV for identification purposes. Panels A, B, and C of Table 4 report the results based on $INV\_EFF_{i,t+1}$,$INV\_EFF^{GO}_{i,t+1}$, and $INV\_EFF^{Q}_{i,t+1}$, respectively. For brevity, detailed estimation results for the control variables are omitted.[8]

Insert Table 4 about here.

Panels A, B and C of Table 4 confirm that the coefficient signs and the statistical significance of our independent variable of interest, $LnOptVol_{i,t}$, remain unchanged in the GMM estimation in comparison to our baseline model of eq. (4) reported in Table 2, with the exception of the under-investment sample. Options trading volume is again positively and significantly associated with firm-level investment efficiency. This is found primarily in the case of investment efficiency taking the form of over- but not under-investment, suggesting that option trading volumes may have a stronger effect in mitigating agency concerns which induce over-investment but not as much in alleviating relevant concerns from the side of capital providers which trigger under-investment. This result for investment efficiency is

[6] Source: https://www.sec.gov/rules/sro/mrx/2020/34-89163.pdf. For a more detailed description of the Penny Pilot program, see Blanco and García (2021) and Cao et al. (2022).

[7] Data was downloaded from: https://www.cboe.com/us/options/market_statistics/historical_data/penny_class/ and https://www.cboe.com/us/options/notices/product_update/.

[8] We further report Table OA.4 in the Online Appendix, essentially representing (Panel D) of Table 4 in the manuscript. It reports the estimation results of eq.(3), using a two-step, generalized method of moments instrumental variable approach (excluded instrumental variable: $PilotPost_{i,t}$), only this time the dependent variable is $INV\_EFF^{Q\ only}_{i,t+1}$, an investment efficiency proxy estimated using the residuals from regressing investment of Tobin's Q only, rather than sales growth together with Tobin's Q. Results remain qualitatively similar.

also observed in terms of acquisition outlays and R&D investment efficiency.[9] In sum, our baseline results hold under the GMM IV estimation using firm participation in the Option Penny Pilot program as an instrument for the intensity of option volumes trading.

Finally, as a third approach, we apply propensity score matching (PSM) among firms with high vs. low options trading activity to test whether otherwise-similar matched firms that differ only in the volume of their traded option contracts exhibit different levels of investment efficiency. High (low) options trading activity firms are those with options trading volume above (below) their industry-year median based on FF48 industry sectors. The "high" options trading group represents our treatment firms, while firms with "low" options trading are the control firms. We perform PSM between our treatment and control firms based on one-to-one, nearest-neighbor matching with replacement where all the control variables used in eq. (4) are used to produce the propensity scores, as in Ali et al. (2020). Table 5 Panel A reports the average treatment effects from PSM. Panel B reports the results of the PSM estimation of eq. (4) for the treatment and control firms, estimated for the total investment and for the over-investment (or under-investment) subsamples separately. Investment efficiency is estimated again both in terms of Capex and NonCapex. For brevity, detailed estimation results for the control variables are omitted from this table.[10, 11] According to Panel A of Table 5, the average treatment effects between high and low options trading volume firms show significantly higher investment efficiency for the treatment group of 'high' options trading volume firms. This applies to investment efficiency in terms of total investment, as well as separately for Capex and NonCapex. Treatment effects for all other control variables used in our baseline eq. (4) indicate statistical insignificance between the two groups.

For robustness, we also estimate eq. (4) for firms with high options trading volumes and their PS-matched low volume counterparts. Panel B of Table 5 confirms that the full set of our main analyses reported in Table 2 remains qualitatively similar, with results actually becoming stronger as manifested by the magnitude of relevant coefficients for $LnOptVol_{i,t}$, with higher statistical significance. We interpret the results reported in Tables 4 and 5 as being supportive of our main finding that enhancement in firms' information environments proxied by higher options trading volumes is positively associated with investment efficiency and is not likely to be driven by endogenous characteristics of firms listed in the options market or by factors that simultaneously induce more options trading and more efficiency in firm-level investment.

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[9] Regarding Hansen's J statistics in Table 4, in our estimations there is only one excluded IV and hence the equation is exactly identified.

[10] It should be noted that we do not apply PSM for firms before vs. after their option listing given that our research hypotheses are explicitly associated with the *volume* or *intensity* of options trading rather than having options traded on their stock or not.

[11] For brevity, from Table 5 onwards, we only report results for one of our investment efficiency measures, baseline INV_EFF^{Q} based on eq. (3) and not for the basic measure based on eq. (1) INV_INEFF , or measure INV_EFF^{GO} based on eq. (2). This is because the former proxy is more comprehensive in the way it accounts for growth opportunities, compared to the *INV_EFF* measure based on eq. (1), at the same time when it measures growth opportunities in a more mainstream way based on macroeconomics. We make the unreported and qualitatively similar results available from the authors upon request.

Insert Table 5 about here.

4.4 Channel analysis

To examine whether the enhancement in the firm's information environment via higher volume of options trading relates to investment efficiency through an external monitoring channel, as predicted by *H3*, we re-estimate eq. (4), this time interacting our independent variable of interest $LnOptVol_{i,t}$ with measures of the strength of external monitoring. Table 6 summarizes our estimation results of eq. (4) when interacting $LnOptVol_{i,t}$ with a variable indicating takeover susceptibility (using the takeover index by Cain et al., 2017), the magnitude of institutional blockholder ownership, and whether a firm does not have a Standard and Poor's (S&P) credit rating for its long-term debt. The external threat of takeover index by Cain (2017) indicates how vulnerable a firm is to takeovers. Higher hostile takeover susceptibility limits the ability of a firm to defend itself in the market for corporate control. The institutional blockholder ownership variable indicates the % of institutional blockholder ownership (>= 5%, as percentage of fiscal year-end market capitalization) using data from Thomson Reuters 13F. Larger blockholder institutional ownership should increase the strength of external monitoring on the firm, while the absence or presence of an S&P credit rating provides evidence of an independent external assessment (or lack of it) of the firm's long-term survivability prospects.

Insert Table 6 about here.

Table 6 shows that the intensity of institutional blockholder ownership positively and significantly associates with firm-level investment efficiency. This indicates that stronger external monitoring associated with institutional ownership helps mitigate inefficient investment. The relevant result for the hostile takeover susceptibility index is not statistically significant. Importantly though, the coefficient of the interaction term between options trading volume, the threat of hostile takeover, and the institutional blockholder intensity is negative and significant (at 5% and 1%, respectively), indicating that stronger external monitoring countervails the beneficial effect of options trading activity on efficient investment, supporting the prediction of *H3*. The same result is confirmed from the interaction term between options trading volume and the without vs. with long-term S&P credit rating, which is positive and significant at the 10% level. The finding of a positive relation between options trading volume and firm investment efficiency thus seems concentrated in firms without an S&P credit rating and firms operating in a poorer information environment compared to firms with such rating. The no S&P credit rating indicator is negatively associated with investment efficiency itself, consistent with firms without a credit rating facing more overall difficulty in investing efficiently.

Findings from Table 6 show that as the strength of monitoring and information-enriching mechanisms improve, the beneficial role of options trading on enhancing investment efficiency gets weaker. In effect, options trading activity works in the same direction as (and acts as a substitute for) the strength of external monitoring mechanisms in helping promote firm investment efficiency. Presumably both options trading activity and external monitoring help enrich the firm's information environment, enabling a more accurate assessment of the firm's investment opportunities.

We additionally test two alternative explanations that have been put forth in the literature which potentially could also explain our results. First, options trading activity has been associated with improvements in managerial learning from option market traders, proxied with the existence and frequency of management earnings forecasts (Chen et al., 2021). Managers wishing to learn from price movements resulting from informed options market traders can reduce their own managerial forecasts and market disclosures to avoid crowding out informed traders. In this case, they would disclose less and try to learn more from options market traders so that they themselves can make better investment decisions about their firm. This leads to a negative predicted association between options trading volumes and managerial earnings forecasts, as suggested by Chen et al. (2021). The authors further provide evidence on options trading having a stronger positive effect on corporate investment efficiency with lower levels of managerial disclosure (or more managerial learning).

If options trading helps managers learn more about their own firms from prices driven in options markets by informed traders and this aids managers make improved investment decisions about their own firms, higher options trading volumes should improve corporate investment efficiency via this managerial learning channel. This is in line with prices guiding managerial investment decisions (Dow and Gordon, 1997) assuming more efficient prices are associated with more efficient resource allocation when managers learn more from market prices. If options market trading helps managers more effectively process useful information in their firms' investment decisions through a learning channel, then options trading should positively associate with a reduced frequency of managerial forecasts.

A second alternative explanation concerns potential reduction in the cost of capital. Naiker et al. (2013) provide evidence on higher options trading volumes reducing the implied cost of equity capital, consistent with the notion that options trading improves information precision and reduces information asymmetry. If options trading reduces information asymmetry and improves firms' informational environments, lower levels of cost of capital could enhance the profitability of firm investment projects and improve firm-level investment efficiency. In this way, options trading could also positively associate with corporate investment efficiency via a cost of equity capital channel.

To examine whether options trading volume associates with investment efficiency through the managerial learning or the cost of equity channel, we re-estimate eq. (4) by interacting $LnOptVol_{i,t}$ with (i) a measure of the frequency of management earnings forecasts during a fiscal year, and (ii) the firm's cost of equity following Gode and Mohanram (2003). In the first case, the frequency of managerial forecasts should be a decreasing proxy for managerial learning since when managers disclose less they leave more room to informed traders to trade on private, independently acquired information (Chen et al., 2021). Table 6 shows that the coefficient for the managerial learning variable is not statistically significant. Thus, we are not able to provide significant evidence that options trading has a stronger effect on mitigating investment inefficiency when managers disclose less to learn more from informed traders.

When $LnOptVol_{i,t}$ is interacted with the cost of equity capital, we again find no significant evidence about relevant associations. Options trading volume does not seem to promote investment efficiency via reducing the firm's cost of equity. In sum, we do not find support for a cost of capital explanation or for a potential managerial learning mechanism that higher options trading might help managers learn more about their firms' prospects and thus promote improved firm-level investment efficiency.

5. Supplementary Analyses and Robustness Tests

5.1 Supplementary Analyses

In this section we report a number of supplementary analyses and robustness tests to better understand the contexts in which the identified effects are more or less pronounced. Table 7 reports the results of estimating eq. (4) by interacting $LnOptVol_{i,t}$ with (i) unexpected investment,[12] (ii) the number of business segments where a firm operates, (iii) the size of the board of directors, and (iv) estimating eq. (4) separately for firms with and without CDS trading. Unexpected investment is an indicator of poor firm performance (Chen et al., 2017b). Firms with high levels of unexpected investment should be in greater need of an enhancing factor on efficient investing due to their poorer-than-average performance compared to firms with low unexpected investment. Unexpected investment is measured as the deviation of a firm's investment from expected (normal) levels by estimating a regression of total investment on growth opportunities based on lagged market-to-book (assets), a variant of Tobin's Q, and considering firm-specific residuals from this equation (Biddle et al., 2009; Chen et al., 2017b).

Second, we estimate eq. (4) by interacting options trading volume with an indicator of business diversity and complexity, proxied by the number of business segments in which a firm operates (Duchin et al., 2010). Competing in multiple industry segments indicates that a firm confronts more complex operational and informational environments (Bushman et al., 2004). Operating in a more complex business context enables a firm to benefit more from the information environment effects associated with options trading that enhance the efficiency of the firm's investment. For more informationally obscure firms, more private information is likely to be discovered by option market participants so options market activity can play a more important role in information asymmetry mitigation. However, as multi-segment operations have also been associated with capital allocation inefficiency and lower firm value (Anagnostopoulou et al., 2021; Stein, 1997; Lamont and Polk, 2002; Denis et al., 2002), they may moderate negatively the association between options trading and efficient investment. Third, we

[12] Chen et al. (2017b; 228) expect that firms characterized by high levels of unexpected investment, which is considered as an indicator of poor performance, should be more influenced by analyst forecast quality on investment efficiency than firms with low levels of unexpected investment. The underlying assumption behind this conjecture is that poor firm performance goes hand in hand with important deviations from expected investment levels. Therefore, high levels of unexpected investment imply that firms deviate from relevant optimal levels because of poor performance, so any factor that can mitigate investment inefficiency should be more important in doing so for this sample of firms.

interact options trading volume with the natural logarithm of board size, based on data from Boardex. The size of the board has been associated with increased protection of shareholders' interests (Jizi et al., 2014) and might thus indicate more efficient internal corporate governance.

Finally, we re-estimate eq. (4) separately for firms with traded options which also have (or have not) traded CDS. Recent research has shown the existence of direct interactions between different types of derivatives of the same firm (Cao et al., 2021) as end-user demand for one derivative can affect the pricing of other derivatives with correlated unhedgeable risks (Gârleanu et al., 2009; Chen et al. 2019). Firms with both traded options and CDSs have more enhanced informational efficiency, making the relation of options trading volumes and firm investment efficiency less consequential.

Insert Table 7 about here.

Table 7 shows that the positive association between improved firm information environment via options trading volumes and investment efficiency is more pronounced when unexpected investment is high, as seen by the positive sign of the interaction term between options trading volume and unexpected investment. We interpret this finding as indicative of trading volumes improving the information environment for those firms most in need due to their low prior performance. Concerning the second test, our baseline result gets weaker when the number of business segments in which the firm operates is higher. This suggests that the positive association of options trading activity with investment efficiency is weaker when firm operating complexity increases, consistent with multi-segment operations associating with capital allocation inefficiencies that cannot be resolved by the information-enriching role of options trading volumes. Our baseline result also becomes weaker for firms with larger boards, indicating that stronger rather than weaker internal corporate governance makes the effect of option volumes on efficient investment weaker, in line with findings obtained in Table 6 for external monitoring. Finally, Table 7 shows that our main results are driven by firms which do not trade in the CDS market. This is in line with a substitutive role of trading in multiple markets with respect to the firm's information environment. A Chow test on the significance of the difference in the coefficients for options trading volume has an *F-stat* of 14.41 with a p-value of 0.0001 (untabulated results), indicating that the magnitude of the coefficients for $LnOptVol_{i,t}$ is significantly different (at the 1% level) for firms with CDS trading vs. those with no such trading. There is little evidence on options trading activity explaining investment efficiency when firms trade in CDS. Overall, the above findings are in line with trading in options markets being positively related to firms' optimal investment with the association being stronger when other information environment-enhancing mechanisms are weak.

5.2 Robustness Tests

We perform a number of robustness tests that are reported in detail in the Online Appendix, First, we test whether option trading volumes are simply picking up lower variation in investments, as opposed to improved investment efficiency. To test this, we regress absolute values of demeaned investment (and its demeaned components) on option volume and control variables, and report estimation results in Table OA.5 of the Online Appendix. The coefficients of our independent variable of interest, $LnOptVol_{i,t}$ are not significant in every single case, suggesting that trading volumes are not simply predicting lower variation in investments but rather improved investment efficiency.[13]

Additionally, we report in Table OA.6 of the Online Appendix estimation results for baseline eq. (4) when options trading activity is measured differently. Specifically, we use the total number of option contracts rather than their dollar value (Ali et al., 2020), and also employ call and put option volumes separately (Cao et al., 2022). We also estimate results when using the absolute delta-weighted option volume as in Lakonishok et al. (2007). This is because the majority of trading takes place in at-the-money options, yet trading in- or out-of-the money options might convey different information. Thus, trading activity measured using all options might be an imperfect proxy for trading activity incentivizing information gathering by investors (Cao et al., 2022). Results from the Online Appendix confirm that alternative ways of measuring options trading activity do not produce any qualitative change in our results. The coefficient of options trading volumes, regardless of how it is defined, remains positive and significant at 1%. Overall, our results are robust to alternative definitions for the intensity of options trading.

We also perform a robustness test with respect to the econometric methodology used. Chen et al. (2018) highlight potential econometric issues in using OLS regressions to decompose a dependent variable into its predicted and residual components and subsequently using the OLS residuals as the dependent variable in a second-stage regression. This potentially affects the way investment inefficiency, in the form of deviations from optimal or normal levels of investment, is measured in Biddle et al. (2009) and in our baseline model specifications. Chen et al. (2018) argue that this procedure may generate biased coefficients and standard errors leading to incorrect inferences and offer remedies for this problem. In line with the suggestions of Chen et al. (2018), we repeat the estimation of our baseline model (eq. (4), with results reported in Table OA.7 of the Online Appendix) but now we include as additional independent variables the first-stage OLS regressors used for investment decomposition into the predicted and excess components. Specifically, we include $SalesGrowth_{i,t}$ (in Panel A), $SalesGrowth_{i,t}$ and $GO_{i,t}$ (in Panel B) and $SalesGrowth_{i,t}$ and Tobin's $Q_{i,t}$ (in Panel C) which are added as extra independent variables. These results show no qualitative differences in the direction of our main results reported in Table 3. This supports that our main results are not driven by the potential bias reported in Chen et al. (2018).

Furthermore, to make sure that the reported effect of options trading volume is not dominated by any eventual direct effect from stock trading volume on investment efficiency, we report in Online Appendix Table OA.8 estimation results for eq. (4) by explicitly including annual stock volume ($LnStockVol_{i,t}$) as an additional regressor. Our results remain unchanged to this addition for all definitions of investment efficiency.

[13] We are grateful to the anonymous reviewer for suggesting this test.

We hypothesized that options trading volume should mitigate investment inefficiency thanks to enhancement in firms' information environments when inefficient investment is driven by relevant environment asymmetric information and moral hazard concerns. Nevertheless, one could argue that concurrent positive or negative information revelation by the stock market might convey further information concerning the motives and effect of trading volumes in the options market. Of course our argument is about options trading activity associating with efficient investing rather than firm stock market performance (which might be driven by a multitude of systematic and fundamental firm factors going beyond information environment efficiency). However, to consider the above possibility, we impose further explicit controls for stock market performance in our empirical testing. Table OA.9 of the Online Appendix reports baseline eq. (4) results for subsamples depending on the firm's stock return performance (positive or negative) in the previous year, while Table OA.10 reports baseline results from interacting $LnOptVol_{i,t}$ with a dummy variable that takes the value of one if the stock return of firm i in year t is positive ($PositiveStockReturn_{i,t}$) or negative ($NegativeStockReturn_{i,t}$). The two tables present results when investment efficiency is measured as either $INV\_EFF_{i,t+1}$, $INV\_EFF^{GO}_{i,t+1}$ or $INV\_EFF^{Q}_{i,t+1}$. Results from Table OA.9 indicate that the effect of options trading activity on investment efficiency holds regardless of whether the stock market performance of a firm is positive or negative, and findings from Table OA.10 corroborate this result.[14] The above evidence provides additional assurances that what we capture through our main tests is the information effect of options trading activity on investment efficiency rather than any stock performance-related effects on investment.

Finally, we conduct sub-sample analysis to assess whether option trading activity and its effect on investment efficiency vary over the sample years. One might be concerned that option trading activity might have increased steadily over time with a similar time-pattern effect on investment efficiency. This is not the case: average options trading volume has increased for many years but has declined for most years in the latter half of the sample period while average investment efficiency shows several ups and downs over the sample period. To further examine how the effect of options trading activity on investment efficiency has varied over the years, we divide our sample period (1996-2019) into four six-year sub-periods (1996-2001, 2002-2007, 2008-2013 and 2014-2019) and estimate eq. (4) for each sub-period separately. The estimated coefficients of $LnOptVol_{i,t}$ on investment efficiency are (standard errors in parentheses) 2.5437 (0.7269), -0.9789 (0.8198), 0.7386 (0.3587) and 1.4484 (0.5782) respectively, indicating that the positive and significant effect of option trading volume on investment efficiency is present in most sub-periods in our sample time frame (especially in the latter period) and

[14] Interestingly, we observe from results from Table OA.10 that positive (negative) stock returns negatively (positively) associate with investment efficiency, while the combined effect of $LnOptVol_{i,t}$ with positive (negative) returns is negative (positive) and significant. This finding is consistent with a disciplining effect of negative stock market performance by making firms invest more efficiently, which is not found to be the case when firms perform well in the stock market.

that there was no monotonic increase in options trading volume and investment efficiency with the passage of time.

6. Conclusions

The study examines the association between enhancement in firms' information environments via more options trading activity and firm-level investment efficiency, measured as deviation from optimal (normal) investment levels. We examine whether options trading volume, a factor that reduces information asymmetries and improves access to firms' information for investors, is associated positively with improved firm-level investment efficiency.

We test this for US firms with options trading activity during the period 1996-2019 and find that options trading volumes associate positively with firm-level investment efficiency. Our main findings are moderately stronger for NonCapex than for Capex-type investments. This also applies to the individual components of NonCapex —R&D and acquisition outlays— separately. Options trading activity is thus more positively associated with firm investment efficiency when the outcome of investment is more uncertain and entails NonCapex involving more growth options, compared to more tangible Capex that mostly adds to a firm's assets-in-place. Our findings also hold regardless of differences in stock market performance and stock trading volumes among sample firms.

Our results are robust under alternative model specifications and different measures of investment efficiency and options trading activity. Our evidence also holds up after various endogeneity controls. To help alleviate endogeneity concerns, we use firm fixed effects and further employ GMM estimation in a quasi-natural experiment involving firms' inclusion in CBOE's Option Penny Pilot Program, representing a positive exogenous shock in liquidity and option trading volumes. Using first-time Pilot Program inclusion as an instrument, our main results are unaffected and even become stronger. We also employ PSM between sample firms with high and matched firms with low options trading volumes. Results again support our main findings of a positive association between options trading volume and firm investment efficiency.

We find further support for an external monitoring/agency channel as a main mechanism through which options trading activity associates positively with investment efficiency, given that firms' information environments can be shaped by strong external monitoring that limits managerial entrenchment and alleviates adverse selection and moral hazard problems. When the strength of external monitoring and information-enriching mechanisms are stronger, proxied by susceptibility to takeovers, the size of institutional block holdings, and the existence of long-term S&P debt rating, the association between the volume of options trading and investment efficiency significantly weakens. This suggests options trading volumes and the strength of external monitoring might work as substitutes supporting more efficient levels of investment through alleviating information asymmetry and moral hazard concerns.

We find little support for two alternative channels examined, namely managerial learning and a cost of capital channel. In supplementary analyses to better understand the context of the effect we identify, we show that the positive association between options trading and improved investment efficiency holds mostly for firms with high unexpected investment or poor performance, smaller board size, and for firms with no CDS traded. This suggests that the positive association of options trading with enhanced firm investment efficiency is stronger when firms' informational efficiency environment is weaker.

Our broader evidence is thus consistent with more active options trading helping alleviate information asymmetry and moral hazard concerns associated with deviations from optimal levels of corporate investment. Our findings provide new evidence on firm-level investment (in)efficiency and its association with firms' information environments via options trading activity. Overall, our findings suggest that informational improvements associated with trading in options markets also benefit firms' investment-level activities through enhancing the optimal allocation of corporate resources.

References

Admati, A., and Pfleiderer, P. (1988). A theory of intraday patterns: volume and price variability. *Review of Financial Studies*, 1(1): 3-40.

Ali, M.J., Balachandran, B., Duong, H.N., Puwanenthiren, P., and Theobald, M. (2020). Does option trading affect audit pricing? SSRN working paper.

Altman, E.I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, 23(4): 589-609.

Anagnostopoulou, S.C., Gounopoulos, D., Malikov, K., and Pham, H. (2021). Earnings management by classification shifting and IPO survival. *Journal of Corporate Finance*, 66, Article 101796.

Benlemlih, M., and Bitar. M. (2018). Corporate social responsibility and investment efficiency. *Journal of Business Ethics*, 48(3): 647-671.

Bertrand, M., and Mullainathan, S. (2003). Enjoying the quiet life? Corporate governance and managerial preferences. *Journal of Political Economy*, 111(5): 1043-1075.

Bhattacharya, N., Ecker, F., Olsson, P.M., and Schipper, K. (2011). Direct and mediated associations among earnings quality, information asymmetry, and cost of equity. *Accounting Review*, 87: 449-482.

Biddle G.C., and Hilary, G. (2006). Accounting quality and firm-level capital investment. *The Accounting Review*, 81(5): 963-982.

Biddle G.C., Hilary, G., and Verdi, R.S (2009). How does financial reporting quality relate to investment efficiency? *Journal of Accounting and Economics*, 48(2-3): 112-131.

Black, F. (1975). Fact and fantasy in the use of options. *Financial Analysts Journal*, 31, 36-72.

Blanchard, O.J., Lopez-de-Silanes, F., and Shleifer, A. (1994). What do firms do with cash windfalls? *Journal of Financial Economics*, 36(3): 337–360.

Blanco, I., and Wehrheim, D. (2017). The bright side of financial derivatives: Options trading and firm innovation. *Journal of Financial Economics*, 125(1): 99–119.

Blanco, I., and García, S.J. (2021). Options trading and the cost of debt. *Journal of Corporate Finance*, 69, Article 102005.

Bond, P., Edmans, A., and Goldstein, I. (2012). The real effects of financial markets. *Annual Review of Financial Economics*, 4(): 339-360.

Bushman, R., Q. Chen, E. Engel, and Smith, A. (2004). Financial accounting information, organizational complexity and corporate governance systems. *Journal of Accounting and Economics*, 37(2): 167-201.

Cain, M.H., McKeon, S., and Davidoff Solomon, S. (2017). Do takeover laws matter? *Journal of Financial Economics*, 124(3): 464-485.

Cao, C., Simin, T., and Zhao, J. (2008). Can growth options explain the trend in idiosyncratic risk? *Review of Financial Studies*, 21 2599-2633.

Cao, H. (1999). The effect of derivative assets on information acquisition and price behavior in a rational expectations equilibrium. *Review of Financial Studies*, 12(1): 131-163.

Cao, J., Goyal, A., Ke, S., and Zhan, X. (2022). Options trading and stock price informativeness. Swiss Finance Institute Research Paper Series N°19-74, available on SSRN.

Cao, J., Hertzel, M., Xu, J., and Zhan, X. (2022) Options trading and corporate debt structure, SSRN working paper.

Cao, J., Jin, Y., Pearson, N.D. and Tang, D.Y. (2021). Does the introduction of one derivative affect another derivative? SSRN working paper.

Chakravarty, S., Gulen, H., and Mayhew, S. (2004). Informed trading in stock and option markets. *The Journal of Finance*, 59(3): 1235–1257.

Chen, Q., Goldstein, I., and Jiang, W. (2007). Price informativeness and investment sensitivity to stock price. *Review of Financial Studies*, 20(3): 619-650

Chen, R., El Ghoul, S., Guedhami, O., and Wang, H. (2017a). Do state and foreign ownership affect investment efficiency? *Journal of Corporate Finance*, 42: 408-421.

Chen, T., Xie, L., and Zhang, Y. (2017b). How does analysts' forecast quality relate to corporate investment efficiency? *Journal of Corporate Finance*, 43: 217-240.

Chen, T., Harford, J., and Lin, C. (2015). Do analysts matter for governance? Evidence from natural experiments. *Journal of Financial Economics*, 115(2): 383–410.

Chen, W., Hribar, P., and Melessa, S. (2018). Incorrect Inferences when using residuals as dependent variables. *Journal of Accounting Research*, 56(3): 751-796.

Chen, Y., Ng, J., and Yang, X. (2021). Talk less, learn more: Strategic disclosure in response to managerial learning from the options market. *Journal of Accounting Research*, 59(5): 1609-1649.

Cheng, M., Dhaliwal, D., and Zhang, Y. (2013). Does investment efficiency improve after the disclosure of material weaknesses in internal control over financial reporting? *Journal of Accounting and Economics*, 56(1): 1-18.

Choi, J.K., Hann, R.N., Subasi, M., and Zheng, Y. (2020). An empirical analysis of analysts' capital expenditure forecasts. *Contemporary Accounting Research*, in press.

Chowdhry, B., and Nanda, V. (1991). Multimarket trading and market liquidity. *Review of Financial Studies*, 4(3): 483-511.

Clogg, C. C., Petkova, E., and Haritou, A. (1995). Statistical methods for comparing regression coefficients between models. *American Journal of Sociology*, 100(5): 1261-1293

Cook, A.C., Romi, A.M., Sánchez, D., and Sánchez, J.M. (2019). The influence of corporate social responsibility on investment efficiency and innovation. *Journal of Business Finance and Accounting*, 46(3-4): 494-537.

Cremers, M., and Weinbaum, D. (2010). Deviations from put-call parity and stock return predictability. *Journal of Financial and Quantitative Analysis*, 45(2): 335-367.

Denis, D.J., Denis, D.K., and Yost, K. (2002). Global diversification, industrial diversification, and firm value. *The Journal of Finance*, 57(5): 1951-1979.

Diamond D.W., and Verrecchia, R.E. (1987). Constraints on short-selling and asset price adjustment to private information. *Journal of Financial Economics*, 18(2): 277-311.

Dow, J., and Gorton, G. (1997). Stock market efficiency and economic efficiency: Is there a connection? *The Journal of Finance*, 52(3): 1087-1129.

Du, B. (2019). Relative option liquidity and price efficiency. *Review of Quantitative Finance and Accounting*, 52: 1119-1135.

Duchin, R., Matsusaka, J.G., and Ozbas. O. (2010). When are outside directors effective? *Journal of Financial Economics,* 96(2): 195-214.

Fama, E. F. and French, K. R. (1997). Industry costs of equity. *Journal of Financial Economics*, 43(2): 153-193.

Farre-Mensa, J., and Ljungqvist, A. (2016). Do measures of financial constraints measure financial constraints? *Review of Financial Studies*, 29(2), 271-308.

Faure-Grimaud, A., and Gromb, D. (2004). Public trading and private incentives. *Review of Financial Studies*, 17(4): 985-1014.

Ferracuti, E., and Stubben, S.R. (2019). The role of financial reporting in resolving uncertainty about corporate investment opportunities. *Journal of Accounting and Economics*, 68(2-3): Article 101248.

Gao, H.S. (2010). Optimal compensation contracts when managers can hedge. *Journal of Financial Economics,* 97(2): 218-238.

Gao, R., and Sidhu, N.K. (2018). The impact of mandatory IFRS adoption on investment efficiency: Standards, enforcement and reporting incentives. *Abacus,* 54(3): 277-318.

Gao, R., and Yu, X. (2018). How to measure capital investment efficiency: A literature synthesis. *Accounting and Finance*, 60(1): 299-334.

García Lara, J.M., García Osma, B., and Penalva, F. (2016). Accounting conservatism and firm investment efficiency. *Journal* of *Accounting and Economics*, 61(1): 221-238.

Gârleanu, N., Pedersen, L., and Poteshman, A.M. (2009). Demand-based option pricing. *Review of Financial Studies*, 22(10): 4259-4299.

Ge, L., Lin, T.-C., and Pearson, N.D. (2016). Why does the option to stock volume ratio predict stock returns? *Journal of Financial Economics,* 120(3): 601-622.

Glosten, L., and Milgrom, P. (1985). Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics*, 14(1): 71-100.

Gode, D., and Mohanram, P. (2003). Inferring the cost of capital using the Ohlson–Juettner model. *Review of Accounting Studies*, 8: 399-431.

Gomariz, M.F., and Ballesta, J.P. (2014). Financial reporting quality, debt maturity and investment efficiency. *Journal of Banking and Finance,* 40: 494–506

Hakansson, N. (1978). Welfare aspects of options and supershares, *Journal of Finance*, 33(3): 759-776.

Hart, O. D. (1983). The market mechanism as an incentive scheme. *The Bell Journal of Economics,* 14(2): 366–382.

Hayashi, F. (1982). Tobin's marginal q and average q. *Econometrica,* 50(1): 213-224.

Holmström, B., (1989). Agency costs and innovation. *Journal of Economic Behavior and Organization*, 12(3): 305-327.

Hsu, P.-H., Li, F., and Nozawa, Y. (2021). Option trading, managerial risk-taking, and brand development. SSRN working paper.

Hu, J. (2018). Option listing and information asymmetry, *Review of Finance*, 22: 1153-1194.

Jensen, M. (1986). Agency costs of free cash flow, corporate finance, and takeovers. *American Economic Review*, 76(2): 323–329.

Jensen, M, and Meckling. W.H. (1976). Theory of the firm: managerial behavior, agency costs, and ownership structure. *Journal of Financial Economics*, 3(4): 305–360.

Jin, W., Livnat, J., and Zhang, Y. (2012). Option prices leading equity prices: Do option traders have an information advantage? *Journal of Accounting Research*, 5(2): 401-432.

Jizi, M., Salama, A., Dixon, R., and Stratling, R. (2014). Corporate governance and corporate social responsibility disclosure: Evidence from the US banking sector. *Journal of Business Ethics*, 125(4): 601-615.Johnson, T. L., and So, E.C. (2012). The option to stock volume ratio and future returns. *Journal of Financial Economics*, 106(2): 262–286.

Jung, B., Lee, W.J., and Weber, D. (2014). Financial reporting quality and labor investment efficiency. *Contemporary Accounting Research*, 31(4): 1047-1076.

Khanna, N., Slezak, S.L., and Bradley, M. (1994). Insider trading, outside search, and resource allocation. *Review of Financial Studies*, 7(3): 575-608.

Kim, J.B., Kim, Shroff, P., Vyas, D., and Wittenberg-Moerman, R. (2018). Credit Default Swaps and managers' voluntary disclosure. *Journal of Accounting Research*, 56(3): 953-988.

Kumar, R., Sarin, S., and Shastri, K. (1998). The impact of options trading on the market quality of the underlying security: An empirical analysis. *Journal of Finance,* 53(2): 717-732.

Kyle, A. (1985). Continuous auctions and insider trading. *Econometrica*, 53(6): 1315-1335.

Lakonishok, J., Lee, I., Pearson, N.D., and Poteshman, A.M. (2007). Option market activity. *Review of Financial Studies*, 20(3): 813–857.

Lambert, R.A., Leuz, C., and Verrecchia, R.E. (2007). Accounting information, disclosure, and the cost of capital. *Journal of Accounting Research*, 45(2): 385-420.

Lambert, R.A., Leuz, C., and Verrecchia, R.E. (2012). Information asymmetry, information precision, and the cost of capital. *Review of Finance,* 16(1): 1-29.

Lamont, O.A., and Polk, C. (2002). Does diversification destroy value? Evidence from the industry shocks. *Journal of Financial Economics*, 63(1): 51-77.

Lamont, O.A., Polk, C., and Saa-Requejo, J. (2001). Financial constraints and stock returns. *Review of Financial Studies*, 14(2), 529-554.

Modigliani, F., and Miller, M.H. (1958). The cost of capital, corporate finance and the theory of investment. *American Economic Review*, 48(3): 261-297.

Muravyev, D., Pearson,N.D, and Broussard, J.P. (2013). Is there price discovery in equity options? *Journal of Financial Economics*, 107(2): 259-283.

Myers, S.C. (1984). The capital structure puzzle. *The Journal of Finance,* 29(3): 574-592.

Myers, S.C., and Majluf, N.S. (1984). Corporate financing and investment decisions when firms have information investors do not have. *Journal of Financial Economics*, 13: 187-221.

Naiker, V., Navissi, F., and Truong, C. (2013). Options trading and cost of equity capital. *The Accounting Review,* 88(1): 261-295.

Pagano, M. (1989). Trading volume and asset liquidity. *Quarterly Journal of Economics*, 104: 255-274.

Pan, J., and Poteshman, A.M. (2006). The information in option volume for future stock prices. *Review of Financial Studies,* 19(3): 871-908.

Rajkovic, T. (2020). Lead independent directors and investment efficiency. *Journal of Corporate Finance*, 64, Article 101690.

Roll, R., Schwartz, E., and Subrahmanyam, A. (2009). Options trading activity and firm valuation. *Journal of Financial Economics*, 94(3): 345-360.

Ross, S.A. (1976). Options and efficiency. *Quarterly Journal of Economics,* 90(1): 75-89.

Roychowdhury, S., N. Shroff, and R.S. Verdi (2019). The effects of financial reporting and disclosure on corporate investment. *Journal of Accounting and Economics*, 68. Article 101246.

Shroff, N., Verdi, R., and Yost, B.P. (2017). When does the peer information environment matter? *Journal of Accounting and Economics*. 64(203): 184-214.

Shroff, N., Verdi, R., and Yu, G. (2014). Information environment and the investment decisions of multinationals corporations. *The Accounting Review*, 89(2): 759-790.

Stein, J.C. (1997). Internal capital markets and the competition for corporate resources. *The Journal of Finance*, 52(1): 111-133.

Subrahmanyam, A., and Titman, S. (1999). The going-public decision and the development of financial markets. *The Journal of Finance*, 54(3): 1045-1082.

Trigeorgis, L., and Lambertides, N. (2014). The role of growth options in explaining stock returns. *Journal of Financial and Quantitative Analysis*, 49(3): 749-771.

Ward, C., Yin, C., and Zeng, Y. (2020). Motivated monitoring by institutional investors and firm investment efficiency. *European Financial Management*, 26(2): 348-385.

Appendix A. Variable Definitions

Investment efficiency-related variables (Source: Compustat)

INV	The sum of research and development expenditure, capital expenditure, and acquisition expenditure, less cash receipts from sale of property, plant, and equipment (PPE), multiplied by 100, and scaled by lagged total assets.
Capex	Capital expenditure, multiplied by 100, and scaled by lagged total assets.
NonCapex	the sum of research and development expenditure and acquisition expenditure, multiplied by 100, and scaled by lagged total assets.
R&D	Research and development expenditure (zero when missing), multiplied by 100, and scaled by lagged total assets.
Acq	Acquisition expenditure (zero when missing), multiplied by 100, and scaled by lagged total assets.
INV_EFF	Investment efficiency measure, calculated as in Biddle et al. (2009), by using firm-specific residuals from an investment model predicting the level of investment based on growth opportunities, as measured by sales growth. Deviations from the predicted level of investment, as reflected in the error terms of the model signify investment inefficiency: $INV_{i,t} = a_0 + a_1 Sales\ Growth_{i,t-1} + \varepsilon_{i,t}$ where *INV* is as previously defined, and $Sales\ Growth_{i,t-1}$ is the change in sales from year t - 2 to year t – 1. The investment model is estimated cross-sectionally for each year and FF48 industry with at least 20 observations in a year. *INV_EFF* is the absolute value of the residuals from this equation, multiplied by minus one, so a higher value means higher efficiency (Rajkovic, 2020; Gomariz and Ballesta, 2014). We further measure over-investment by positive residuals, and under-investment by negative residuals (Rajkovic, 2020).
INV_EFF^{GO}	Investment efficiency measure, calculated via an extension of the model in Biddle et al. (2009), by using firm-specific residuals from an investment model predicting the level of investment based on growth opportunities, as measured by sales growth and the growth option variable (GO market) in Trigeorgis and Lambertides (2014). Deviations from the predicted level of investment, as reflected in the error terms of the model signify investment inefficiency: $INV_{i,t} = \beta_0 + \beta_1 Sales\ Growth_{i,t-1} + \beta_2 GO(M)_{i,t-1} + u_{i,t}$ where *INV* and $Sales\ Growth_{i,t-1}$ are as previously defined and $GO(M)_{i,t-1}$ is the growth options (market) variable in Trigeorgis and Lambertides (2014), capturing the percentage of a firm's value arising from future growth opportunities (PVGO/V). It can be estimated by subtracting from the current market value of the firm the perpetual discounted stream of firm operating cash flows under a no-growth policy $V_{i,t} = \frac{CF_{i,t}}{WACC_i} + PVGO_{i,t}$ where $V_{i,t}$ is the market value of firm i at time t, $CF_{i,t}$ is the (perpetual) operating cash flow of firm i at time t (measured as net cash flow from operating activities), and $WACC_i$ is the firm's weighted average cost of capital. See Trigeorgis and Lambertides (2014, p. 755) for details of the *GO(M)* variable calculation. The investment model is estimated cross-sectionally for each year and FF48 industry with at least 20 observations in a year. INV_EFF^{GO} is the absolute value of the residuals from this equation, multiplied by minus one, so a higher value means higher efficiency (Rajkovic, 2020; Gomariz and Ballesta, 2014). We further measure over-investment ($OVER\_INV^{GO}$) by positive residuals, and under-investment ($UNDER\_INV^{GO}$) by negative residuals (Rajkovic, 2020).
INV_EFF^{Q}	Investment efficiency measure, calculated via an extension of the model in Biddle et al. (2009), by using firm-specific residuals from an investment model predicting the level of investment based on growth opportunities, as measured by sales growth and Tobin's Q. Deviations from the predicted level of investment, as reflected in the error terms of the model signify investment inefficiency: $INV_{i,t} = \gamma_0 + \gamma_1 Sales\ Growth_{i,t-1} + \gamma_2 Q_{i,t-1} + u_{i,t}$ where *INV* is as previously defined, $Sales\ Growth_{i,t-1}$ is the change in sales from year t - 2 to year t – 1 and Q is Tobin's Q ratio. The investment model is estimated cross-sectionally for each year and FF48 industry with at least 20 observations in a year. INV_EFF^{Q} is the absolute value of the residuals from this equation, multiplied by minus one, so a higher value means higher efficiency (Rajkovic, 2020; Gomariz and Ballesta, 2014). We further measure over-investment by positive residuals, and under-investment by negative residuals (Rajkovic, 2020).
Capex_EFF	Capex investment inefficiency measure, calculated as *INV_EFF* above, when defining investment as *Capex*. Deviations from the predicted level of investment, as reflected in the error terms of the model signify Capex investment inefficiency. *Capex_EFF* is the absolute value of the residuals from the estimation equation, multiplied by minus one, so a higher value means higher efficiency.

Capex_EFF^{GO}	Capex investment inefficiency measure, calculated as *INV_EFF^{GO}* above, when defining investment as *Capex*. Deviations from the predicted level of investment, as reflected in the error terms of the model signify Capex investment inefficiency. *Capex_EFF^{GO}* is the absolute value of the residuals from the estimation equation, multiplied by minus one, so a higher value means higher efficiency.
Capex_EFF^{Q}	Capex investment inefficiency measure, calculated as *INV_EFF^{Q}* above, when defining investment as *Capex*. Deviations from the predicted level of investment, as reflected in the error terms of the model signify Capex investment inefficiency. *Capex_EFF^{Q}* is the absolute value of the residuals from the estimation equation, multiplied by minus one, so a higher value means higher efficiency.
NonCapex_EFF	NonCapex investment inefficiency measure, calculated as *INV_EFF* above, when defining investment as *NonCapex*. Deviations from the predicted level of investment, as reflected in the error terms of the model signify NonCapex investment inefficiency. *NonCapex_EFF* is the absolute value of the residuals from the estimation equation, multiplied by minus one, so a higher value means higher efficiency.
NonCapex_EFF^{GO}	NonCapex investment inefficiency measure, calculated as *INV_EFF^{GO}* above, when defining investment as *NonCapex*. Deviations from the predicted level of investment, as reflected in the error terms of the model signify NonCapex investment inefficiency. *NonCapex_EFF^{GO}* is the absolute value of the residuals from the estimation equation, multiplied by minus one, so a higher value means higher efficiency.
NonCapex_EFF^{Q}	NonCapex investment inefficiency measure, calculated as *INV_EF^{Q}* above, when defining investment as *NonCapex*. Deviations from the predicted level of investment, as reflected in the error terms of the model signify NonCapex investment inefficiency. *NonCapex_EFF^{Q}* is the absolute value of the residuals from the estimation equation, multiplied by minus one, so a higher value means higher efficiency.
R&D_EFF	R&D investment inefficiency measure, calculated as *INV_EFF* above, when defining investment as *R&D*. Deviations from the predicted level of investment, as reflected in the error terms of the model signify R&D investment inefficiency. *R&D_EFF* is the absolute value of the residuals from the estimation equation, multiplied by minus one, so a higher value means higher efficiency.
R&D_EFF^{GO}	R&D investment inefficiency measure, calculated as *INV_IFF^{GO}* above, when defining investment as *R&D*. Deviations from the predicted level of investment, as reflected in the error terms of the model signify R&D investment inefficiency. *R&D_EFF^{GO}* is the absolute value of the residuals from the estimation equation, multiplied by minus one, so a higher value means higher efficiency.
R&D_EFF^{Q}	R&D investment inefficiency measure, calculated as *INV_IFF^{Q}* above, when defining investment as *R&D*. Deviations from the predicted level of investment, as reflected in the error terms of the model signify R&D investment inefficiency. *R&D_EFF^{Q}* is the absolute value of the residuals from the estimation equation, multiplied by minus one, so a higher value means higher efficiency.
Acq_EFF	Acquisitions investment inefficiency measure, calculated as *INV_EFF* above, when defining investment as *Acq*. Deviations from the predicted level of investment, as reflected in the error terms of the model signify Acquisitions investment inefficiency. *Acq_EFF* is the absolute value of the residuals from the estimation equation, multiplied by minus one, so a higher value means higher efficiency.
Acq_EFF^{GO}	Acquisitions investment inefficiency measure, calculated as *INV_EFF^{GO}* above, when defining investment as *Acq*. Deviations from the predicted level of investment, as reflected in the error terms of the model signify Acquisitions investment inefficiency. *Acq_EFF^{GO}* is the absolute value of the residuals from the estimation equation, multiplied by minus one, so a higher value means higher efficiency.
Acq_EFF^{Q}	Acquisitions investment inefficiency measure, calculated as *INV_EFF^{Q}* above, when defining investment as *Acq*. Deviations from the predicted level of investment, as reflected in the error terms of the model signify Acquisitions investment inefficiency. *Acq_EFF^{Q}* is the absolute value of the residuals from the estimation equation, multiplied by minus one, so a higher value means higher efficiency.
OverFirm	A ranked variable calculated as the average of a ranked decile measure of cash and leverage. Cash and leverage deciles are calculated according to year and Fama and French 48 (FF48) industries and are rescaled from 0 to 1. Leverage is multiplied by minus one before rank calculation; so that both the cash and leverage variables increase with the likelihood of over-investment.
Options-related variable variables (Source: IvyDB Optionmetrics)	
LnOptVol	Natural logarithm of one plus the total annual dollar options volume (in $000) in a fiscal year.
LnOptNon$Vol	Natural logarithm of one plus the total annual number of options contracts in a fiscal year.

LnVolCalls	Natural logarithm of one plus the total annual dollar call options volume (in $000) in a fiscal year.
LnVolPuts	Natural logarithm of one plus the total annual dollar put options volume (in $000) in a fiscal year.
LnOptVolDelta	Natural logarithm of the absolute delta-weighted option volume, based on Lakonishok et al. (2007) and Cao et al. (2020).
Control variables for baseline model specification (Source: Compustat, CRSP)	
Lev	An indicator for financial leverage, or long-term debt divided by the sum of long-term debt and the market value of equity (calculated by multiplying the number of shares outstanding by the stock price at fiscal year-end).
Size	Natural logarithm of market value of equity.
MB	Market value of equity at fiscal year-end to the book value of equity ratio.
σ(CFO)	Standard deviation of the cash flow from operations divided by average total assets from years *t-5* to *t-1*.
σ(Sales)	Standard deviation of sales divided by average total assets from years *t-5* to *t-1*.
σ(I)	Standard deviation of annual investment (*INV*) from years *t-5* to *t-1*.
Tangibility	Ratio of net PPE to total assets.
OperCycle	A firm's operating cycle, defined as the logarithm receivables to sales plus inventory to COGS multiplied by 360.
Loss	A binary indicator taking the value of one if income before extraordinary items is negative, and zero otherwise.
CFOSales	Cash flow from operations to sales ratio.
Dividend	An indicator variable equal to 1 if the firm paid a dividend, and zero otherwise (identifying dividend payments as in Biddle *et al.*, 2009).
Slack	An indicator of financial slack, calculated as cash divided by net property, plant and equipment.
ZScore	Altman's Z score for the risk of bankruptcy (Altman, 1968), and calculated as in Biddle et al. (2009).
Age	Natural logarithm of firm age, calculated as the number of years the firm is listed with a non-missing stock price on CRSP.
Additional variables used in alternative investment efficiency model specification (Source: Compustat, Institutional Shareholder Services (ISS), Thomson Reuters, IBES)	
INST	The percentage of firm shares held by institutional investors, using the average value for the four quarters in a fiscal year, from Thomson Reuters 13F.
AQ	Accounting quality, calculated as the standard deviation of the firm-level residuals from the Dechow and Dichev (2002) model during years *t-5* to *t-1* multiplied by minus one, so that the value of the proxy increases with accounting quality. This model is a regression of working capital accruals on lagged, current, and future cash flows, plus the change in revenue and PPE: $Working\ Capital\ Accruals_{i,t} = b_0 + b_1 CFO_{i,t-1} + b_2 CFO_{i,t} + b_3 CFO_{i,t+1} + b_4 \Delta Sales_{i,t} + b_5 PPE_{i,t} + +\varepsilon_{i,t}$ A firm's total working capital accruals are calculated as the change in non-cash current assets minus the change in current non-interest-bearing liabilities. $\Delta Sales_{i,t}$ is change in sales with reference to the previous year, CFO stands for cash flow from operations, and $PPE_{i,t}$ is gross property, plant and equipment. All variables are scaled by average total assets. The model is estimated cross-sectionally for each FF48 industry with at least 20 observations in a year.
LogAnalysts	Natural logarithm of the average number of analysts following the firm and issuing one-year ahead EPS forecasts during a year, from the IBES summary file.
Ind K-structure	The mean *Lev* for firms in the same FF48 industry for the year.
Variables used in controls for endogeneity (Source: CBOE announcements IvyDB Optionmetrics, CRSP)	

PilotPost	A binary variable equal to one for years from and following CBOE Pilot Penny program inclusion for a firm, referring to firms participating in this program, and zero otherwise. Details on the Penny Pilot program and internet sources for CBOE announcement extraction are provided in Section 4.3.
Variables used for the examination of H3 and supplementary analyses (Source: Compustat, Thomson Reuters, IBES, World Bank, Boardex)	
Hostile_Index	Takeover susceptibility index, by making use of the takeover index by Cain et al. (2017). We thank Cain et al. (2017) for making takeover index data available.
InstitOwn.-top five	Institutional blockholder ownership (>=5%), expressed as percentage of market capitalization at fiscal year-end, from Thomson Reuters 13F.
Cost of Capital	Cost of equity, estimated as in Gode and Mohanram (p.403: 2003), when using median analyst forecast values for earnings per share and dividends per share.
Managerial Forecast Frequency	Frequency of management forecasts issued by the firm during a fiscal year, calculated as the natural logarithm of one + the number of annual and quarterly earnings forecasts issued by the firm during a fiscal year (zero if no forecast issued), following Kim et al. (2018).
Rating	A binary indicator taking the value of one if the firm has an S&P rating for its long-term debt in a year, and zero otherwise.
BusSegments	The number of business segments in which the firm operates in a given year, from Compustat..
Unexp_Inv	Firm-year unexpected investment. Unexpected investment is calculated as in Chen et al. (2017b), by estimating a cross-sectional regression of total investment (*INV*) in year *t* on lagged *MVA/BVA* for each year and FF48 industry with at least 20 observations in a year. Deviations from the predicted level of investment, as reflected in the error terms of the model for each firm signify unexpected investment.
LogBoard_Size	Natural logarithm of board size for a firm in a year, from Boardex.
CDS	A binary indicator taking the value of one if a firm has CDS traded in any year during the sample period based on data from Thomson Reuters, and zero otherwise.

Table 1 Descriptive statistics

	Q1	*Mean*	*Median*	*Q3*	*StDev*	*N*
Investment efficiency-related variables						
$INV_{i,t}$	4.279	14.170	8.945	17.366	18.975	43,374
$Capex_{i,t}$	1.637	5.744	3.591	7.086	7.357	43,374
$NonCapex_{i,t}$	0.000	8.687	2.183	10.610	17.274	43,374
$R\&D_{i,t}$	0.000	4.265	0.000	1.119	35.147	43,374
$Acq_{i,t}$	0.000	4.438	0.000	0.203	46.720	43,374
$INV\_EFF_{i,t}$	-12.349	-9.883	-6.439	-2.914	12.678	43,374
$INV\_EFF_{i,t}^{GO}$	-11.715	-9.546	-6.209	-2.857	12.495	43,374
$INV\_EFF_{i,t}^{Q}$	-11.486	-9.395	-5.916	-2.681	12.813	40,667
$Capex\_EFF_{i,t}$	-3.996	-3.555	-2.261	-1.043	4.671	43,374
$Capex\_EFF_{i,t}^{GO}$	-4.010	-3.550	-2.264	-1.057	4.620	43,374
$Capex\_EFF_{i,t}^{Q}$	-3.893	-11.486	-9.395	-5.916	-2.681	40,667
$NonCapex\_EFF_{i,t}$	-9.799	-8.062	-4.411	-2.022	11.697	43,374
$NonCapex\_EFF_{i,t}^{GO}$	-9.128	-7.672	-4.197	-1.918	11.501	43,374
$NonCapex\_EFF_{i,t}^{Q}$	-9.156	-7.749	-4.063	-1.889	11.809	40,667
$R\&D\_EFF_{i,t}$	-22.245	-16.678	-10.807	-3.881	26.007	43,374
$R\&D\_EFF_{i,t}^{GO}$	-19.203	-15.518	-8.416	-2.823	27.850	43,374
$R\&D\_EFF_{i,t}^{Q}$	-19.690	-15.974	-9.705	-3.380	29.687	40,667
$Acq\_EFF_{i,t}$	-22.726	-17.808	-12.358	-4.730	30.230	43,374
$Acq\_EFF_{i,t}^{GO}$	-19.900	-16.653	-9.931	-3.505	33.982	43,374
$Acq\_EFF_{i,t}^{Q}$	-21.623	-17.743	-11.024	-4.213	37.640	40,667
$OverFirm_{i,t}$	0.350	0.505	0.500	0.650	0.201	43,252
Options-related variables						
$LnOptVol_{i,t}$	0.011	0.360	0.066	0.381	0.648	41,699
$LnOptNon\$Vol_{i,t}$	9.090	10.728	10.691	12.455	2.400	41,699
$LnVolCalls_{i,t}$	0.007	0.271	0.041	0.253	0.532	41,627
$LnVolPuts_{i,t}$	0.003	0.191	0.022	0.150	0.415	41,525
$LnOptVolDelta_{i,t}$	7.212	8.792	8.873	10.514	2.445	36,402
Control variables for baseline model specification						
$Lev_{i,t}$	0.013	0.204	0.140	0.316	0.217	43,253
$Size_{i,t}$	6.090	7.322	7.305	8.583	1.876	43,332
$MB_{i,t}$	1.277	2.969	2.129	3.666	7.785	43,318
$\sigma(CFO)_{i,t}$	0.024	0.062	0.043	0.075	0.067	43,374
$\sigma(Sales)_{i,t}$	0.072	0.214	0.145	0.273	0.228	43,374
$\sigma(I)_{i,t}$	0.024	0.122	0.056	0.126	0.271	43,374
$Tangibility_{i,t}$	0.072	0.274	0.183	0.426	0.251	43,355
$OperCycle_{i,t}$	4.198	4.715	4.679	5.144	1.035	43,122
$Loss_{i,t}$	0.000	0.277	0.000	1.000	0.448	43,374
$CFOSales_{i,t}$	0.043	-0.314	0.111	0.206	4.740	43,294
$Dividend_{i,t}$	0.000	0.493	0.000	1.000	0.500	43,374
$Slack_{i,t}$	0.115	9.843	0.601	2.873	282.886	43,335
$ZScore_{i,t}$	0.437	0.934	1.024	1.667	1.771	43,295
$Age_{i,t}$	9.000	21.522	16.000	28.000	18.081	43,032
Variables used in channel analyses and alternative investment efficiency model specification						
$INST_{i,t}$	0.461	0.660	0.705	0.862	1.974	35,485
$AQ_{i,t}$	-0.067	-0.056	-0.041	-0.026	0.055	40,115
$LogAnalysts_{i,t}$	0.602	0.840	0.875	1.132	0.377	40,279

$Ind\ K-structure_{i,t}$	0.086	0.187	0.151	0.258	0.122	43,374
Variables used in channel analyses and robustness controls						
$Hostile\_Index_{i,t}$	0.090	0.158	0.131	0.201	0.090	23,495
$InstitOwn-top\ five_{i,t}$	7.432	34.633	15.600	36.300	50.601	35,532
$Managerial\ Forecast\ Frequency_{i,t}$	0.000	1.419	1.386	2.565	1.258	43,374
$Cost\ of\ Capital_{i,t}$	0.076	0.134	0.098	0.130	0.188	21,171
$Unexp\_Inv_{i,t}$	-8.946	-1.908	-3.672	1.314	16.863	40,680
$BusSegment_{i,t}$	1.000	2.836	3.000	4.000	2.034	42,249
$LogBoard\_Size_{i,t}$	0.845	0.939	0.954	1.000	0.116	31,324
	With	Without				
$Credit\ Rating$	18,244	25,130				43,374
CDS	7,015	36,359				43,374
	Value of one	Value of zero				
$PilotPost$	2,100	41,274				43,374

Note This table reports descriptive statistics for all sample firm-year observations during 1996-2019, with data availability for our baseline model specification (eq. (4)). Detailed variable definitions are provided in Appendix A.

Table 2 Panel A Effect of options trading volume on investment inefficiency, panel OLS estimates

	Dependent variable: $INV\_EFF_{i,t+1}$			Dependent variable:			
Independent variables	Entire sample	Over-investment sample	Under-investment sample	$Capex\_EFF_{i,t+1}$	$NonCapex\_EFF_{i,t+1}$	$R\&D\_EFF_{i,t+1}$	$Acq\_EFF_{i,t+1}$
$\boldsymbol{LnOptVol_{i,t}}$	**1.0366*** **	**-1.9497*** **	**0.5975*** **	**0.3865*** **	**0.8972*** **	**1.6793*** **	**1.6262*** **
	(0.1999)	**(0.5442)**	**(0.1193)**	**(0.0765)**	**(0.1782)**	**(0.4502)**	**(0.3486)**
$Lev_{i,t}$	10.9416***	-31.6377***	-2.8801***	3.3810***	9.9070***	2.9483**	7.4907***
	(0.8399)	(2.6562)	(0.4049)	(0.3203)	(0.7401)	(1.2598)	(1.5764)
$Size_{i,t}$	-0.0243**	-0.7201*	-0.6168***	-0.1070**	0.2385*	0.5514*	1.1543***
	(0.0120)	(0.3991)	(0.0790)	(0.0509)	(0.1242)	(0.3007)	(0.3273)
$MB_{i,t}$	-0.0243**	0.0414*	0.0002	-0.0120***	-0.0213**	-0.0163	-0.0237
	(0.0120)	(0.0230)	(0.0061)	(0.0034)	(0.0101)	(0.0226)	(0.0209)
$\sigma(I)_{i,t}$	1.3598***	-1.4908*	0.3598*	0.0240	1.2145***	-4.5726***	-3.1493***
	(0.4369)	(0.8289)	(0.1903)	(0.0837)	(0.3860)	(1.6973)	(1.1549)
$\sigma(CFO)_{i,t}$	-8.5527***	18.0536***	1.0282	-2.6360***	-7.2692***	-15.1674**	-15.4141**
	(2.8442)	(6.8207)	(1.2058)	(0.6322)	(2.4115)	(6.5146)	(7.1845)
$\sigma(Sales)_{i,t}$	0.0636	0.6783	0.8546***	-0.3579**	-0.0775	3.0372**	0.2511
	(0.5009)	(1.4975)	(0.2454)	(0.1783)	(0.4478)	(1.1778)	(1.5842)
$Tangibility_{i,t}$	2.5641**	-1.8851	6.4507***	1.0361*	-0.5851	-2.9938	-1.5269
	(1.3078)	(3.1769)	(0.7536)	(0.6119)	(1.0614)	(2.2185)	(2.0868)
$OperCycle_{i,t}$	0.0996	-1.1258**	-0.8034***	-0.2070***	0.3934*	0.9519*	-0.2326
	(0.2522)	(0.5559)	(0.1424)	(0.0694)	(0.2232)	(0.5479)	(0.5562)
$Loss_{i,t}$	0.9318***	-2.5945***	-0.1174	0.0435	1.3053***	0.5493	-0.0636
	(0.2089)	(0.6497)	(0.1116)	(0.0716)	(0.1788)	(0.4640)	(0.5421)
$CFOSales_{i,t}$	-0.0081	-0.0451	-0.0823***	-0.0143*	0.0190	0.0826	0.0511
	(0.0398)	(0.0687)	(0.0232)	(0.0080)	(0.0364)	(0.0648)	(0.0935)
$Dividend_{i,t}$	-0.6832***	1.1484	-0.1488	0.3136***	-0.6938***	1.5180***	1.5176**
	(0.2514)	(0.8095)	(0.1360)	(0.1087)	(0.2141)	(0.5046)	(0.6998)
$Slack_{i,t}$	0.0006	-0.0098***	-0.0010***	-0.0001	0.0005	0.0011	0.0019
	(0.0014)	(0.0016)	(0.0002)	(0.0001)	(0.0012)	(0.0007)	(0.0013)
$ZScore_{i,t}$	0.6084***	-1.1565***	0.0836	-0.0479*	0.5309***	1.0470***	0.3971
	(0.1605)	(0.3037)	(0.0796)	(0.0277)	(0.1434)	(0.3152)	(0.4842)
$Age_{i,t}$	0.0176	0.0714*	0.0631***	0.0729***	-0.0321***	0.3462***	0.3720***

	(0.0133)	(0.0431)	(0.0091)	(0.0073)	(0.0115)	(0.0404)	(0.0402)
Intercept	-16.0191***	27.9962***	-2.7664***	-4.1977***	-13.2154***	-33.5953***	-34.0785***
	(1.6338)	(3.8437)	(0.9140)	(0.5093)	(1.4782)	(3.9607)	(3.4656)
Firm and Year FE	YES	YES	YES	YES	YES	YES	YES
N	43,374	13,200	30,174	43,374	43,374	43,374	43,374
R-square	0.0336	0.0404	0.0002	0.0001	0.0339	0.0425	0.0291
No of firms	5,514	3,688	4,944	5,514	5,514	5,514	5,514

Table 2 Panel B Effect of options trading volume on investment inefficiency, panel OLS estimates

	Dependent variable: $INV\_EFF^{GO}_{i,t+1}$			Dependent variable:			
Independent variables	Entire sample	Over-investment sample	Under-investment sample	$Capex\_EFF^{GO}_{i,t+1}$	$NonCapex\_EFF^{GO}_{i,t+1}$	$R\&D\_EFF^{GO}_{i,t+1}$	$Acq\_EFF^{GO}_{i,t+1}$
$\boldsymbol{LnOptVol_{i,t}}$	**0.9677*** **	**-2.0155*** **	**0.4091*** **	**0.3732*** **	**0.8380*** **	**0.8714* **	**1.3640*** **
	(0.1954)	**(0.5037)**	**(0.1187)**	**(0.0777)**	**(0.1752)**	**(0.4583)**	**(0.3856)**
$Lev_{i,t}$	10.9966***	-29.9500***	-2.3736***	3.1915***	9.6652***	1.7971	5.7555***
	(0.8281)	(2.4920)	(0.4213)	(0.3112)	(0.7327)	(1.3873)	(1.8231)
$Size_{i,t}$	0.5481***	-0.5134	-0.1688**	-0.1383***	0.5108***	1.8810***	2.3191***
	(0.1365)	(0.3785)	(0.0817)	(0.0502)	(0.1220)	(0.3162)	(0.3797)
$MB_{i,t}$	-0.0272**	0.0303	-0.0035	-0.0115***	-0.0260**	-0.0131	-0.0080
	(0.0122)	(0.0257)	(0.0061)	(0.0034)	(0.0102)	(0.0218)	(0.0235)
$\sigma(I)_{i,t}$	1.2974***	-1.5136*	0.2865	0.0004	1.2059***	-4.6288***	-3.4494**
	(0.4311)	(0.7761)	(0.2154)	(0.0798)	(0.3860)	(1.6532)	(1.4050)
$\sigma(CFO)_{i,t}$	-8.4814***	16.3414***	1.9846	-2.5488***	-7.6242***	-10.5608	-11.1363
	(2.7595)	(6.2750)	(1.3626)	(0.6385)	(2.4151)	(6.5980)	(7.2520)
$\sigma(Sales)_{i,t}$	0.0914	1.0002	0.9659***	-0.2699	-0.0283	4.3614***	0.6325
	(0.4965)	(1.3788)	(0.2589)	(0.1757)	(0.4445)	(1.2126)	(1.7600)
$Tangibility_{i,t}$	2.3215*	-2.0004	6.0138***	1.1044*	-0.4631	-0.1800	-0.5966
	(1.2840)	(3.0632)	(0.7649)	(0.6019)	(1.0465)	(2.3973)	(2.4909)
$OperCycle_{i,t}$	0.3076	-0.8387	-0.4361***	-0.1621**	0.6045***	1.1784**	-0.3712
	(0.2534)	(0.5622)	(0.1525)	(0.0680)	(0.2251)	(0.5836)	(0.6672)
$Loss_{i,t}$	0.8133***	-2.4610***	-0.2590**	0.1179*	1.1451***	-0.4498	-0.9951
	(0.2066)	(0.6148)	(0.1261)	(0.0701)	(0.1780)	(0.5195)	(0.6470)
$CFOSales_{i,t}$	0.0179	0.0223	-0.0099	-0.0136*	0.0473	0.1834***	0.1861*

	(0.0377)	(0.0754)	(0.0259)	(0.0082)	(0.0336)	(0.0668)	(0.1066)
$Dividend_{i,t}$	-0.6674***	1.2647	-0.1716	0.2884***	-0.7246***	1.9701***	1.3988*
	(0.2536)	(0.7725)	(0.1424)	(0.1064)	(0.2173)	(0.5577)	(0.7933)
$Slack_{i,t}$	0.0004	-0.0091***	-0.0011***	-0.0001	0.0003	0.0016	0.0019
	(0.0014)	(0.0013)	(0.0002)	(0.0001)	(0.0011)	(0.0011)	(0.0017)
$ZScore_{i,t}$	0.5536***	-1.2210***	0.2518**	-0.0521*	0.4723***	1.8105***	1.3957**
	(0.1553)	(0.3084)	(0.1140)	(0.0284)	(0.1413)	(0.3813)	(0.6081)
$Age_{i,t}$	0.0127	0.0662*	0.0603***	0.0739***	-0.0386***	0.2519***	0.2914***
	(0.0133)	(0.0397)	(0.0091)	(0.0073)	(0.0117)	(0.0370)	(0.0422)
Intercept	-18.3742***	25.1306***	-7.3443***	-4.2027***	-15.4962***	-42.8733***	-39.9935***
	(1.6129)	(3.8333)	(0.9686)	(0.5039)	(1.4491)	(4.1252)	(4.2128)
Firm and Year FE	YES	YES	YES	YES	YES	YES	YES
N	43,374	13,842	29,532	43,374	43,374	43,374	43,374
R-square	0.0349	0.0358	0.0031	0.0001	0.0371	0.0667	0.0458
No of firms	5,514	3,817	4,923	5,514	5,514	5,514	5,514

Table 2 Panel C Effect of options trading volume on investment inefficiency, panel OLS estimates

	Dependent variable: $INV\_EFF^{Q}_{i,t+1}$			Dependent variable:			
Independent variables	Entire sample	Over-investment sample	Under-investment sample	$Capex\_EFF^{Q}_{i,t+1}$	$NonCapex\_EFF^{Q}_{i,t+1}$	$R\&D\_EFF^{Q}_{i,t+1}$	$Acq\_EFF^{Q}_{i,t+1}$
$\boldsymbol{LnOptVol_{i,t}}$	**0.9489*** **	**-1.8505*** **	**0.6084*** **	**0.3413*** **	**0.8892*** **	**2.0186*** **	**1.7732*** **
	(0.2149)	**(0.6163)**	**(0.1223)**	**(0.0816)**	**(0.1894)**	**(0.5775)**	**(0.4276)**
$Lev_{i,t}$	12.4891***	-31.7149***	-2.2941***	3.6785***	10.8304***	4.2444***	9.6477***
	(0.8795)	(2.4994)	(0.4224)	(0.3398)	(0.7662)	(1.4581)	(2.1716)
$Size_{i,t}$	0.2790*	-0.9689**	-0.8208***	-0.0819	0.2066	-0.3807	0.4788
	(0.1491)	(0.3977)	(0.0840)	(0.0547)	(0.1333)	(0.3906)	(0.4487)
$MB_{i,t}$	-0.0365***	0.0155	-0.0397***	-0.0112***	-0.0358***	-0.1060***	-0.0770***
	(0.0125)	(0.0252)	(0.0074)	(0.0033)	(0.0111)	(0.0345)	(0.0295)
$\sigma(I)_{i,t}$	1.5385***	-1.5573**	0.3846*	-0.0248	1.4492***	-4.3222**	-2.9741*
	(0.4476)	(0.7059)	(0.1952)	(0.0916)	(0.3883)	(1.7549)	(1.5248)
$\sigma(CFO)_{i,t}$	-8.7230***	11.5003**	-1.8897	-2.4091***	-7.9077***	-25.7686***	-23.9525**
	(2.6824)	(5.2424)	(1.3949)	(0.6285)	(2.3589)	(8.0057)	(9.7398)
$\sigma(Sales)_{i,t}$	-0.2188	2.3282	0.5414**	-0.2316	-0.4380	2.3058*	-1.1073

	(0.5292)	(1.4361)	(0.2631)	(0.1882)	(0.4810)	(1.3969)	(2.2334)
$Tangibility_{i,t}$	1.6229	-0.9160	4.6385***	1.1957*	-1.4770	-6.1970**	-2.5251
	(1.3439)	(3.0630)	(0.7653)	(0.6393)	(1.0993)	(2.8548)	(2.4906)
$OperCycle_{i,t}$	0.4221*	-0.9738*	-0.4398***	-0.1841***	0.6938***	1.4894**	0.2974
	(0.2476)	(0.5341)	(0.1478)	(0.0692)	(0.2210)	(0.7136)	(0.7267)
$Loss_{i,t}$	1.0390***	-2.6087***	-0.2246*	0.0641	1.3184***	0.2433	0.2026
	(0.2176)	(0.6048)	(0.1153)	(0.0768)	(0.1862)	(0.6239)	(0.8375)
$CFOSales_{i,t}$	0.0243	-0.0428	-0.0852***	-0.0131*	0.0504	0.0187	0.0565
	(0.0422)	(0.0647)	(0.0237)	(0.0078)	(0.0379)	(0.0721)	(0.1182)
$Dividend_{i,t}$	-0.6793**	1.5689*	0.0854	0.3403***	-0.6790***	1.5559**	2.1940**
	(0.2680)	(0.8025)	(0.1525)	(0.1149)	(0.2281)	(0.6097)	(1.0214)
$Slack_{i,t}$	0.0004	-0.0062***	-0.0011***	-0.0001	0.0003	0.0018*	0.0019
	(0.0013)	(0.0015)	(0.0003)	(0.0001)	(0.0011)	(0.0011)	(0.0015)
$ZScore_{i,t}$	0.5407***	-1.0456***	-0.0468	-0.0478	0.4824***	1.6988***	1.5508*
	(0.1576)	(0.2636)	(0.0841)	(0.0317)	(0.1398)	(0.6380)	(0.9149)
$Age_{i,t}$	0.0100	0.0999**	0.0669***	0.0700***	-0.0324**	0.4522***	0.4115***
	(0.0141)	(0.0429)	(0.0089)	(0.0077)	(0.0127)	(0.0515)	(0.0518)
Intercept	-16.7615***	27.8897***	-1.6412*	-4.5312***	-13.7917***	-29.6392***	-32.9973***
	(1.6568)	(3.7878)	(0.9723)	(0.5278)	(1.5042)	(4.9736)	(4.7063)
Firm and Year FE	YES	YES	YES	YES	YES	YES	YES
N	40,677	13,231	27,446	40,677	40,677	40,677	40,677
R-square	0.0354	0.0327	0.0014	0.0002	0.0340	0.0376	0.0289
No of firms	5,373	3,728	4,773	5,373	5,373	5,373	5,373

Note: This table reports OLS estimation results of eq. (4) that is shown in the main text. The second column reports results for the entire sample, while the third (respectively fourth) column reports results for the over-investment (respectively under-investment) sub-sample, when we measure over-investment by positive residuals, and under-investment by negative residuals for eq. (1), eq. (2) and eq. (3) reported in text, in Panels A, B and C respectively. The fifth (respectively sixth) column reports results for $Capex\_EFF_{i,t}$ (respectively $NonCapex\_EFF_{i,t}$) as the dependent variable. The seventh (respectively eighth) column reports results for $R\&D\_EFF_{i,t}$ (respectively $Acq\_EFF_{i,t}$) as the dependent variable. Panels A, B and C of the Table report relevant results when defining investment efficiency as $INV\_EFF_{i,t+1}$, $INV\_EFF^{GO}_{i,t+1}$ and $INV\_EFF^{Q}_{i,t+1}$ respectively. The sample selection process is described in Section 3.1. All variables are defined in Appendix A. Standard errors robust to heteroscedasticity and autocorrelation are reported in parentheses. ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively.

Table 3 Effect of options trading volume on over and under-investment, panel OLS estimates					
Independent variables	Dependent variable: $INV_{i,t+1}$	Dependent variable: $Capex_{i,t+1}$	Dependent variable: $NonCapex_{i,t+1}$	Dependent variable: $R\&D_{i,t+1}$	Dependent variable: $Acq_{i,t+1}$
$\boldsymbol{LnOptVol_{i,t}}$	**2.4306*** **	**-0.0846**	**2.5085*** **	**2.9012*** **	**3.3189*** **
	(0.5737)	**(0.2706)**	**(0.5059)**	**(0.7912)**	**(1.0392)**
$\boldsymbol{LnOptVol_{i,t} \times OverFirm_{i,t}}$	**-2.9972** **	**0.8749**	**-3.2573*** **	**-3.6900** **	**-6.4737*** **
	(1.0025)	**(0.6852)**	**(0.8694)**	**(1.6158)**	**(2.0488)**
Joint significance, F-statistic	**10.94**	**1.80**	**20.07**	**2.87**	**9.70**
p-value	**[0.0009]**	**[0.1803]**	**[0.0000]**	**[0.0903]**	**[0.0019]**
$INST_{i,t}$	0.1146	0.1484	-0.1367	-0.1750	1.0976
	(0.3553)	(0.1671)	(0.2658)	(0.4940)	(1.1805)
$LogAnalysts_{i,t}$	2.6108***	0.9597**	1.7529**	1.1483	-1.6588
	(0.9473)	(0.4850)	(0.8179)	(2.1614)	(1.7348)
$AQ_{i,t}$	-4.5155	-1.2967	-3.4432	-0.0158	46.3269
	(8.9080)	(3.3589)	(8.2900)	(15.1599)	(63.6149)
$INST_{i,t} \times OverFirm_{i,t}$	-0.3151	-0.3001	0.1991	0.1483	-2.2422
	(0.7287)	(0.3361)	(0.5536)	(1.0945)	(2.4494)
$LogAnalysts_{i,t} \times OverFirm_{i,t}$	3.6105**	-0.2641	3.6609**	-3.9207	3.3013
	(1.7204)	(0.8414)	(1.5140)	(4.8145)	(3.8984)
$AQ_{i,t} \times OverFirm_{i,t}$	14.8676	2.8483	12.7467	21.1408	-101.605
	(13.7796)	(5.2836)	(12.7037)	(27.7833)	(120.7183)
$OverFirm_{i,t}$	4.4227***	3.3806***	0.8373	9.5000*	-0.8913
	(1.6939)	(0.7840)	(1.4726)	(4.9410)	(5.2142)
$Size_{i,t}$	-1.8210***	-0.2646***	-1.5777***	-1.4570***	-1.4788***
	(0.1335)	(0.0610)	(0.1133)	(0.2835)	(0.2606)
$MB_{i,t}$	0.0939***	0.0209***	0.0706***	-0.0475	-0.0650
	(0.0187)	(0.0062)	(0.0164)	(0.0599)	(0.0618)
$\sigma(CFO)_{i,t}$	37.2586***	7.5110***	29.5135***	11.3944	19.8303
	(3.8455)	(1.2072)	(3.4446)	(8.4886)	(15.4706)
$\sigma(Sales)_{i,t}$	-2.3065***	-0.0404	-2.2867	2.5602	5.3156
	(0.7957)	(0.2140)	(0.7332)	(2.6060)	(4.0955)
$\sigma(I)_{i,t}$	2.4507***	1.0724***	1.4363***	3.1173	-1.4774
	(0.5216)	(0.2839)	(0.4572)	(2.3602)	(1.3236)

$ZScore_{i,t}$	-2.3895***	0.2902***	-2.6343***	-2.7462***	-3.4591
	(0.3087)	(0.0490)	(0.2838)	(0.9649)	(2.8252)
$Tangibility_{i,t}$	5.2383***	18.76434***	-12.6618***	-6.4868***	-4.8593***
	(0.7461)	(0.5835)	(0.5638)	(1.4970)	(1.6936)
$Ind\ K - structure_{i,t}$	-20.6468***	-7.0753***	-13.3366***	-8.9663***	0.0109
	(1.4253)	(0.7840)	(1.1889)	(2.6392)	(2.2954)
$CFOSales_{i,t}$	-0.1188***	0.0408***	-0.1583***	-0.2731	0.2436
	(0.0413)	(0.0101)	(0.0397)	(0.2912)	(0.1724)
$Dividend_{i,t}$	-1.2610***	-0.8914***	-0.4178	0.4774	0.6635
	(0.3140)	(0.1462)	(0.2786)	(0.5684)	(1.0452)
$Age_{i,t}$	-0.0086	-0.0193***	0.0108*	0.0469***	0.0306
	(0.0069)	(0.0034)	(0.0063)	(0.0104)	(0.0219)
$OperCycle_{i,t}$	-0.8510***	0.1701**	-1.0256***	-1.5477**	-0.5333
	(0.2299)	(0.0722)	(0.2139)	(0.6932)	(0.4810)
$Loss_{i,t}$	-2.9769***	-1.0915***	-1.6872***	0.1013	-4.0288
	(0.4220)	(0.1230)	(0.3789)	(1.3452)	(3.1302)
$Slack_{i,t}$	-0.0023***	-0.0005*	-0.0017***	0.0021	-0.0027
	(0.0006)	(0.0003)	(0.0005)	(0.0042)	(0.0025)
Intercept	32.6387***	2.3189***	30.6530***	23.2405***	20.3354***
	(2.0899)	(0.7480)	(1.8898)	(5.4839)	(7.2619)
Industry FE	YES	YES	YES	YES	YES
N	32,078	32,078	32,078	32,078	32,078
R-square	0.1666	0.3656	0.2097	0.0350	0.0167
No of firms	4,310	4,310	4,310	4,310	4,310

Note: This table reports OLS estimation results of eq. (5) that is shown in the main text. Under joint significance, the *F-statistic* of a Wald test on the sum of the coefficients of $LnOptVol_{i,t}$ and $LnVOptol_{i,t} \times OverFirm_{i,t}$, is reported. The null hypothesis of the Wald test is that the sum of the coefficients of $LnVol_{i,t}$ and $LnVol_{i,t} \times OverFirm_{i,t}$ is zero. *P-values* of the Wald test *F-statistic* are reported in square brackets. The sample selection process is described in Section 3.1 All variables are defined in Appendix A. Standard errors robust to heteroscedasticity and autocorrelation are reported in parentheses. ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively.

Table 4 Panel A Effect of options volume on investment efficiency, two-step GMM IV estimates using a quasi-natural experiment on the Penny Pilot Program

Effect on investment inefficiency, two-step GMM IV estimates							
	Dependent variable: $INV\_EFF_{i,t+1}$			Dependent variable:			
Independent variables	Entire sample	Over-investment sample	Under-investment sample	$Capex\_EFF_{i,t+1}$	$NonCapex\_EFF_{i,t+1}$	$R\&D\_EFF_{i,t+1}$	$Acq\_EFF_{i,t+1}$
$\boldsymbol{LnOptVol_{i,t}}$	**0.5021****	**-2.5154*****	**0.2672**	**0.3580*****	**0.3866*****	**2.2784*****	**2.1861*****
	(0.2335)	**(0.6867)**	**(0.2077)**	**(0.0785)**	**(0.1125)**	**(0.3088)**	**(0.3458)**
Controls	YES	YES	YES	YES	YES	YES	YES
Firm and Year FE	YES	YES	YES	YES	YES	YES	YES
Hansen's J statistic	Equation exactly identified	Equation exactly identified	Equation exactly identified	Equation exactly identified	Equation exactly identified	Equation exactly identified	Equation exactly identified
N	43,374	13,200	30,174	43,374	43,374	43,374	43,374
R-square	0.0799	0.0860	0.0679	0.1514	0.0996	0.0825	0.0565
No of firms	5,514	3,688	4,944	5,514	5,514	5,514	5,514

Table 4 Panel B Effect of options volume on investment efficiency, two-step GMM IV estimates using a quasi-natural experiment on the Penny Pilot Program

Effect on investment inefficiency, two-step GMM IV estimates							
	Dependent variable: $INV\_EFF^{GO}_{i,t+1}$			Dependent variable:			
Independent variables	Entire sample	Over-investment sample	Under-investment sample	$Capex\_EFF^{GO}_{i,t+1}$	$NonCapex\_EFF^{GO}_{i,t+1}$	$R\&D\_EFF^{GO}_{i,t+1}$	$Acq\_EFF^{GO}_{i,t+1}$
$\boldsymbol{LnOptVol_{i,t}}$	**0.6178*****	**-2.7818*****	**0.2188**	**0.3524*****	**0.4990****	**0.9244*****	**0.6261**
	(0.2223)	**(0.6640)**	**(0.1734)**	**(0.0793)**	**(0.2004)**	**(0.3303)**	**(0.4048)**
Controls	YES	YES	YES	YES	YES	YES	YES
Firm and Year FE	YES	YES	YES	YES	YES	YES	YES
Hansen's J statistic	Equation exactly Identified	Equation exactly Identified	Equation exactly Identified	Equation exactly Identified	Equation exactly Identified	Equation exactly Identified	Equation exactly Identified
N	43,374	13,842	29,532	43,374	43,374	43,374	43,374
R-square	0.0829	0.0825	0.0849	0.1565	0.1014	0.0925	0.0683
No of firms	5,514	3,817	4,923	5,514	5,514	5,514	5,514

Table 4 Panel C Effect of options volume on investment efficiency, two-step GMM IV estimates using a quasi-natural experiment on the Penny Pilot Program

Effect on investment inefficiency, two-step GMM IV estimates							
	Dependent variable: $INV\_EFF^{Q}_{i,t+1}$			Dependent variable:			
Independent variables	Entire sample	Over-investment sample	Under-investment sample	$Capex\_EFF^{Q}_{i,t+1}$	$NonCapex\_EFF^{Q}_{i,t+1}$	$R\&D\_EFF^{Q}_{i,t+1}$	$Acq\_EFF^{Q}_{i,t+1}$
$\boldsymbol{LnOptVol_{i,t}}$	**0.7471***	**-2.5602***	**0.0224**	**0.3347***	**0.6021***	**3.1973***	**2.7268***
	(0.2291)	**(0.6718)**	**(0.1850)**	**(0.0829)**	**(0.2070)**	**(0.3646)**	**(0.4218)**
Controls	YES	YES	YES	YES	YES	YES	YES
Firm and Year FE	YES	YES	YES	YES	YES	YES	YES
Hansen's J statistic	Equation exactly Identified	Equation exactly Identified	Equation exactly Identified	Equation exactly Identified	Equation exactly Identified	Equation exactly Identified	Equation exactly Identified
N	40,677	13,231	27,446	40,677	40,677	40,677	40,677
R-square	0.0816	0.0834	0.0754	0.1590	0.1030	0.0794	0.0517
No of firms	5,373	3,728	4,773	5,373	5,373	5,373	5,373

Note: This Table reports the results of re-estimating eq. (4) reported in text using a two-step, generalized method of moments instrumental variable approach. To achieve identification, the following excluded instrumental variable (IV) is employed: $PilotPost_{i,t}$. Under *Hansen's J statistic* we report a heteroskedasticity-consistent test of overidentifying restrictions in GMM estimation; its joint null hypothesis is that the instruments are valid, and the excluded instruments are correctly excluded from the estimated equation. Panels A, B and C of the Table report relevant results when defining investment inefficiency as $INV\_EFF_{i,t+1}$, $INV\_EFF^{GO}_{i,t+1}$ and $INV\_EFF^{Q}_{i,t+1}$ respectively. The sample selection process is described in Section 3.1. All variables are defined in Appendix A. Standard errors robust to heteroscedasticity and autocorrelation are reported in parentheses. For brevity, detailed estimation results for the control variables are omitted. ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively.

Table 5 Effect of options trading volume, propensity score matching analysis

Panel A Propensity score matching (PSM)

Variables	Treatment (Firms with high options volume)	Control (Firms with low options volume)	*t-test*
$\boldsymbol{INV\_EFF^{Q}_{i,t}}$	**-9.6490**	**-10.6782**	**8.28*** **
$\boldsymbol{Capex\_EFF^{Q}_{i,t}}$	**-3.5513**	**-4.2913**	**14.80*** **
$\boldsymbol{NonCapex\_EFF^{Q}_{i,t}}$	**-8.00942**	**-8.5188**	**4.61*** **
$Lev_{i,t}$	0.1948	0.2014	-0.35
$Size_{i,t}$	8.1410	8.1620	-0.03
$MB_{i,t}$	3.6760	3.5967	1.12
$\sigma(I)_{i,t}$	0.1342	0.1359	-0.57
$\sigma(CFO)_{i,t}$	0.0642	0.0641	0.23
$\sigma(Sales)_{i,t}$	0.2326	0.2407	-1.40
$Tangibility_{i,t}$	0.2858	0.2892	-1.57
$OperCycle_{i,t}$	4.6642	4.6799	-0.69
$CFOSales_{i,t}$	-0.2996	-0.3625	1.45
$ZScore_{i,t}$	1.0619	1.0873	-1.33
$Age_{i,t}$	22.2047	21.4601	1.09

Panel B Propensity score matching panel OLS

	Dependent variable: $INV\_EFF^{Q}_{i,t+1}$			Dependent variable:			
Independent variables	Entire sample	Over-investment sample	Under-investment sample	$Capex\_EFF^{Q}_{i,t}$	$NonCapex\_EFF^{Q}_{i,t}$	$R\&D\_EFF^{Q}_{i,t}$	$Acq\_EFF^{Q}_{i,t}$
$\boldsymbol{LnOptVol_{i,t}}$	**0.9608***** **(0.1935)**	**-1.9058***** **(0.6192)**	**0.6304***** **(0.1258)**	**0.3236***** **(0.0832)**	**0.9162***** **(0.1852)**	**1.6926**** **(0.5032)**	**1.6638***** **(0.4114)**
Controls	YES	YES	YES	YES	YES	YES	YES
Firm and Year FE	YES	YES	YES	YES	YES	YES	YES
N	30,203	9,865	20,338	30,203	30,203	30,203	30,203
R-square	0.0284	0.0262	0.0033	0.0000	0.0337	0.0453	0.0223
No of firms	4,725	3,153	4,085	4,725	4,725	4,725	4,725

Note: Panel A reports average treatment effects obtained from propensity score matching (PSM -Section 4.3), between firms with high options trading activity (above FF48 sector-year median), representing our treatment firms, and firms with low options trading activity, or our control firms. Panel B of the Table reports the results of the PSM estimation of eq. (4) that is shown in the main text. The second column reports results for the entire sample, while the third (respectively fourth) column reports results for the over-investment (respectively under-investment) subsample, when we measure over-investment by positive residuals, and under-investment by negative residuals for eq. (3) reported in text. The fifth (respectively sixth) column reports results for $Capex\_EFF^{Q}_{i,t}$ (respectively $NonCapex\_EFF^{Q}_{i,t}$) as the dependent variable. The seventh (respectively eighth) column reports results for $R\&D\_EFF^{Q}_{i,t}$ (respectively $Acq\_EFF^{Q}_{i,t}$) as the dependent variable. The sample selection process is described in Section 3.1 All variables are defined in Appendix A. Standard errors robust to heteroscedasticity and autocorrelation are reported in parentheses. ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively.

Table 6 Effect of options trading volume on investment efficiency, channel analysis

	Dependent variable: $INV\_EFF^{Q}_{i,t+1}$				
Independent variables	(1)	(2)	(3)	(4)	(5)
$\boldsymbol{LnOptVol_{i,t}}$	**1.7608*****	**1.2629*****	**0.7845*****	**0.2547***	**0.9758*****
	(0.5299)	**(0.3501)**	**(0.2265)**	**(0.1340)**	**(0.3098)**
$\boldsymbol{Hostile\_Index_{i,t}}$	**-4.6440**				
	(3.3625)				
$\boldsymbol{LnOptVol_{i,t} \times Hostile\_Index_{i,t}}$	**-3.8908****				
	(1.9384)				
$\boldsymbol{InstitOwn.-top\ five_{i,t}}$		**2.33 X 10^{-8}*****			
		(4.82 X 10^{-9})			
$\boldsymbol{LnOptVol_{i,t} \times InstitOwn.-top\ five_{i,t}}$		**-6.83 X 10^{-9}*****			
		(2.47 X 10^{-9})			
$\boldsymbol{NoCreditRating_{i,t}}$			**-1.1266*****		
			(0.3669)		
$\boldsymbol{LnOptVol_{i,t} \times NoCreditRating_{i,t}}$			**0.5234***		
			(0.3012)		
$\boldsymbol{Managerial\ Forecast\ Frequency_{i,t}}$				**0.0808**	
				(0.1033)	
$\boldsymbol{LnVol_{i,t} \times Managerial\ Forecast\ Frequency_{i,t}}$				**0.4755**	
				(0.3634)	
$\boldsymbol{Cost\ of\ Capital_{i,t}}$					**0.7089**
					(0.7071)
$\boldsymbol{LnVol_{i,t} \times Cost\ of\ Capital_{i,t}}$					**0.7669**
					(0.8876)
Controls	YES	YES	YES	YES	YES
Firm and Year FE	YES	YES	YES	YES	YES
N	23,241	34,053	40,677	40,677	21,688
R-square	0.0232	0.0169	0.0356	0.0348	0.0039
No of firms	3,352	4,859	5,373	5,373	3,335

Note: This table reports OLS estimation results of eq. (4) that is shown in the main text, when interacting our independent variable of interest $LnOptVol_{i,t}$ with (1) $Hostile\_Index_{i,t}$ that stands for the high takeover susceptibility index, (2) $InstitOwn.-top\ five_{i,t}$ that stands for institutional blockholder ownership, (3) $NoCreditRating_{i,t}$, an indicator variable taking the value of one if firm's i debt has no credit rating in year t, (4) $Managerial\ Forecast\ Frequency_{i,t}$ that stands for the firm's managerial guidance frequency and (5).$Cost\ of\ Capital_{i,t}$ that stands for a firm's cost of capital. The sample selection process is described in Section 3.1. All variables are defined in Appendix A. Standard errors robust to heteroscedasticity and autocorrelation are reported in parentheses. ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively.

Table 7 Effect of options trading volume on investment efficiency, supplementary analysis

	Dependent variable: $INV\_EFF^{Q}_{i,t+1}$				
Independent variables	(1) Unexpected investment	(2) Business segments	(3) Board size	(4a) Firms with CDS trading	(4b) Firms without CDS trading
$\boldsymbol{LnOptVol_{i,t}}$	**1.0988*** (0.2326)**	**1.1589*** (0.3919)**	**5.7487*** (1.4963)**	**0.3524 (0.3261)**	**1.1302*** (0.2977)**
$\boldsymbol{Unexpected\_INV_{i,t}}$	**0.0252*** (0.0068)**				
$\boldsymbol{LnOptVol_{i,t} \times Unexpected\_INV_{i,t}}$	**0.0298*** (0.0083)**				
$\boldsymbol{No\_of\_Business\_Segments_{i,t}}$		**0.2945*** (0.0710)**			
$\boldsymbol{LnOptVol_{i,t} \times No\_of\_Business\_Segments_{i,t}}$		**-0.2671*** (0.0724)**			
$\boldsymbol{LogBoard\_Size_{i,t}}$			**6.2943*** (1.6351)**		
$\boldsymbol{LnOptVol_{i,t} \times LogBoard\_Size_{i,t}}$			**-4.7933*** (1.4829)**		
Controls	YES	YES	YES	YES	YES
Firm and Year FE	YES	YES	YES	YES	YES
N	40,098	42,315	28,908	6,412	34,265
R-square	0.0345	0.0353	0.0284	0.0076	0.0352
No of firms	5,350	5,293	3,855	426	4,947

Note: This table reports panel OLS estimation results of eq. (4) that is shown in the main text, when interacting our independent variable of interest $LnVol_{i,t}$ with (1) $Unexpected\_INV_{i,t}$ that stands for unexpected investment, (2) $No\_of\_Business\_Segments_{i,t}$ that stands for the number of firm business segments and (3) $LogBoard\_Size_{i,t}$ that stands for the natural logarithm of the size of the board of directors. Under (4a) and (4b), the main equation is estimated separately for firms with and without CDS trading. The sample selection process is described in Section 3.1. All variables are defined in Appendix A. Standard errors robust to heteroscedasticity and autocorrelation are reported in parentheses. ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively.