Option listing and information asymmetry *

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Abstract

Option listing significantly increases both informed and uninformed trading in a sample of 1517 common stocks in the US between 2001 and 2010. Although the average increase of informed trading reaches 12.4%, uninformed trading increases even more by 23.9%, reducing relative information risk. The causal effects of option listing are established using a control sample of stocks with similar propensities of listing, are robust in subsamples of stocks, and are confirmed by a quasi-natural experiment using option listing standards. A placebo test shows that options on exchange-traded-funds increase only uninformed trading. The benefits are more prominent for stocks with active options trading and opaque stocks. We also find that the reduction of information risk is larger for good news than bad news, and that the stock price response to earnings surprise weakens after listing. The results suggest that options improve the overall market information environment beyond substitutional effects to stock trading.

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1. Introduction

Derivative assets, such as options, are redundant assets in a frictionless market under geometric Brownian motions as stock price dynamics, documented in Black and Scholes (1973) and Merton (1973). However, in the real market, introducing options can have significant impact on the underlying asset. On the one hand, Ross (1976b) and Hakansson (1982) show that options complete the market, implying that investors' trading demand can increase because of hedging purposes. In the presence of information asymmetry, increased hedging transactions can reduce the probability of trading against informed traders for uninformed traders. On the other hand, Black (1975) notes that options can also increase the amount of informed trading because options provide higher leverage to financially constrained informed traders. Similarly, Cao (1999) shows that investors become more motivated to acquire private signals if options are available. Figlewski and Webb (1993) and Johnson and So (2012) argue that options facilitate informed trading by relaxing the short-sale constraint on stocks. All of these studies suggest that option listing leads to more informed trading, and hence higher information risk for uninformed traders. Finally, Biais and Hillion (1994) show that the option listing effects condition on exogenous parameters. The key result in their model is that introducing options can potentially solve the market breakdown problem due to information asymmetry if uninformed traders value the benefit of hedging more than the risk of trading against informed traders. As a result, both informed and uninformed trading become more active after options are introduced. If the incomplete market does not break down at the first place, the benefit from expanded trading opportunities is less meaningful for uninformed traders. Biais and Hillion (1994) show that under certain parameters, uninformed traders trade less because they can hedge more precisely using options, thus making the liquidity orders less attractive to informed traders. In this case, option introductions can reduce the incentive of informed traders and the stock price becomes less efficient.

Given contradicting predictions of option listing effects on trading incentives and the level of information asymmetry, it is better to examine this question empirically. A large body of the literature examines the lead-lag relation between the stock and options prices and volumes, and finds mixed evidence regarding options' contribution to price discovery.[1] However, those studies do not answer the question whether the same amount of information extracted from the two markets can be revealed without options. If options only cause traders to migrate across markets, there may be no impact on the *overall* information environment that an uninformed investor faces because options reduce informativeness of the underlying market. In this case, even if options trading conveys information not in the stock market, that is insufficient to show that options increase the total amount of private information revealed to the market. To understand whether options affect the market information environment beyond substitutional effects, this paper instead focuses on option listing events.

To gauge overall information asymmetry before and after option listing, we examine the aggregate stock market order flow assuming that options market makers perform full delta hedging. Under this assumption, the total stock order flow nests the liquidity and information in the options order flow because options market makers transfer options order flow to the stock market. Therefore, the dynamic of the stock order flow around option listing suffices to describe the overall trading environment. Admittedly, because of transactions cost and liquidity constraints, full delta hedging is a strong assumption unlikely to hold in practice despite the fact that delta hedging is now a standard practice by all options market makers. Nevertheless, the inherent connection between the options order flow and the stock order flow through delta hedging makes the order flow a better choice to assess the overall market condition than other variables such as the bid-ask spread and price volatility. To quantify the level of information asymmetry using order flows, we estimate the sequence trade model of Duarte and Young (2009) (DY hereafter), which extends the famous Easley and O'Hara (1992) (EO hereafter) model. The order arrival rates from informed (μ) and uninformed traders (ε) are two main parameters of the EO model. The other two parameters are the probability of information events (α) and the probability of an information event being good news (β). Based on empirical observations that the EO model overlooks simultaneous shocks to buy and sell orders, DY propose to include a symmetric increase (δ) in both uninformed buy and

[1] For example, Manaster and Rendleman (1982), Anthony (1988), Easley, O'Hara, and Srinivas (1998), Pan and Poteshman (2006), Bali and Hovakimian (2009), Cremers and Weinbaum (2010), Xing, Zhang, and Zhao (2010), and Hu (2014) find that the options market leads the stock market in price discovery. Studies showing the opposite result include, for example, Bhattacharya (1987), Stephan and Whaley (1990), Chan, Chung, and Fong (2002), and Muravyev, Pearson, and Broussard (2013).

sell orders in a liquidity shock event with a probability of θ, and achieve better data fits. Moreover, DY show that the original probability of informed trading (PIN) of EO can be decomposed into an asymmetry component ($APIN$) and a symmetric liquidity shock component ($PSOS$). This paper examines the DY model constructs as well as the model parameters to identify the levels and sources of the listing effects.[2]

Because options exchanges do not randomly select stocks to list, we follow Mayhew and Mihov (2004) and use the propensity score matching (PSM) method to examine the listing effects in a sample of 1517 common stocks experiencing option listing in the US between February 11, 2001 and February 28, 2010. Consistent with previous findings by Mayhew and Mihov (2004) and Danielsen, van Ness, and Warr (2007), we find that options exchanges select stocks based on the firm size, trading volume, return standard deviation, bid-ask spread, and industry category. Moreover, the analysis shows that the selected stocks on average have higher institutional ownership, greater buying pressure, and more balanced order flows, consistent with the notion that options exchanges prefer stocks with large hedging demand, high short selling costs, and low market-making costs. Each listing stock is then matched to an eligible but non-listing stock with the closest propensity score of option listing at the same time to construct a control sample.

In the matched sample, the average treatment effect of option listing on the daily volume of informed trades (μ) is an increase of 12.4% with a t-statistic of 3.07 in the first year after option listing. The treatment effects on the daily volume of uninformed trades (ε) and symmetric shock to uninformed order flow (δ) average at 23.9% and 14% with t-statistics of 10.01 and 3.51, respectively. There is no significant change in the probabilities of information events (α) or liquidity shocks (θ) although the average impact is negative for both types of events. Due to the disproportional increases in informed and uninformed trading, the probability of informed trading ($APIN$) is reduced by 8.8% with a t-statistic of -6.71. The probability of a trade from a symmetric liquidity shock ($PSOS$) is also reduced by 7.2% with a t-statistic of -4.56. We verify the listing effects using alternative stock order flows, which considers understated options market activity due to

[2] Using the EO model instead generates largely the same results regarding the option listing effects on informed and uninformed trading and the level of information asymmetry. We report these results in Section D of the internet appendix to the paper.

discrete delta hedging. Therefore, our results hold even if the full delta hedging assumption is violated. The listing effects are robust to different measures of order flow using the number of trades or number of shares traded, and are consistent across stock and options exchanges involved in the listing event. Regression analysis of the treatment effects on an option listing dummy and control variables shows that option listing effects on the market information environment cannot be explained by firm characteristics related to the probability of informed trading as suggested by Aslan, Easley, Hvidkjaer, and O'Hara (2008).

We perform three additional tests to make sure that the findings are indeed driven by option listing events. Firstly, concerning that the structural breaks may not occur around the listing date, we investigate the dynamics of the DY model parameters and the estimated *APIN* at the quarterly frequency. The results show that the most significant treatment effects on both informed and uninformed trading occur in the first quarter after option listing. Secondly, the baseline analysis is repeated in a sample of 56 listing stocks with prices just above the minimum price required for option listing. The control stocks are the non-listing stocks that have prices just below the minimum price, but share similar characteristics to the listing stocks. This test is based on the notion that the mandated minimum stock price splits otherwise identical firms into the treatment and control groups and creates a quasi-natural experiment to identify the listing effects. All results from the baseline analysis hold qualitatively the same in this alternative sample, except that the option listing effect on *PSOS* loses statistical significance. Finally, we conduct a placebo test on exchange-traded-fund (ETF) options. Like common stocks, ETFs can also be listed on options exchanges subject to the same regulatory requirement. However, private information is less important for ETFs because such information is usually about specific firms and should not have significant price impact on diversified stock portfolios such as ETFs. Therefore, the option listing impact on ETFs can be different from that on common stocks. Indeed, we find that in a sample of 85 ETFs that experience option listing during the same period, there is no significant change in informed trading, but only in uninformed trading.

The option listing effects exhibit significant cross-sectional heterogeneity. In particular, the reduction of *APIN* is larger for stocks with high options volumes and large options-to-stock volume ratios, consistent with the notion that an active options market reveals more private information. The reduction of *APIN* is also greater for stocks with large bid-ask spreads, low market capitalization, large earnings surprise, little voluntary disclosure, low institutional holding, and low accrual quality. Since these stocks are associated with weak information environment, the option listing effect is stronger when other information channels are less effective.

We also find that the listing effect is asymmetric to the probability of informed trading based on good news (*APIN_Good*) and the probability of informed trading based on bad news (*APIN_Bad*). Although both probabilities are reduced by option listing, the reduction in *APIN_Good* is much larger and statistically more significant than *APIN_Bad*. This is true because getting around short-sale constraints can be an important motivation of options trading for informed traders. As a result, the increase in informed selling exceeds the increase in informed buying, and the excess increase of informed selling curtails the reduction in *APIN_Bad*. Analysis on the probability of information being good (β) shows that β becomes significantly lower after option listing, suggesting that options make it easier for informed traders to take advantage of bad news.

The decrease in the overall level of information asymmetry may cause an inference problem for uninformed traders and reduce price efficiency (Stein (1987)). Although more private information is revealed, the information is clouded by increased noise trading, hence more difficult to learn. For price efficiency to improve in this case, uninformed investors must be sophisticated enough to filter out the increased noise. We find that the price response to earnings surprise becomes weaker after option listing, suggesting that uninformed investors are able to learn more private information from the capital markets even though the information is diluted by noise trading. Therefore, introduction of options also improves price efficiency. Finally, to avoid relying exclusively on the DY model, we examine alternative asymmetry measures including the bid-ask spread, order imbalance, return standard deviation, realized volatility, and *VPIN* of Easley, Lopez de Prado, and O'Hara (2012). Our results indicate that option listing significantly reduces these alternative asymmetry measures as well except the return standard deviation.

This paper's contribution to the literature is mainly four folds. First, our analysis of order flow is able to capture the trading activity on both stock and options markets through the link of delta hedging. Therefore, the inference about information asymmetry pertains to the *overall* market. Such conclusion cannot be obtained by existing studies that focus only on the stock market. Second, more importantly, we identify the underlying mechanism of this risk reduction by examining different types of traders' activities estimated from the DY model. Although there is much less attention on these model parameters than the probability of informed trading, these parameter estimates have important economic meanings to study the dynamics around the listing event. Kumar, Sarin, and Shastri (1998) show that information risk measured by the adverse selection component of the stock bid-ask spread reduces after option listing. However, they could not pinpoint the source of the effect by examining the spread, a reduced-form efficiency measure. Our analysis shows that both informed and uninformed traders become significantly more active after option listing but the increase of uninformed trading dominates the increase of informed trading. Meanwhile, option listing does not significantly change the probability of information events. Therefore, uninformed traders are less likely to trade against informed traders as a result of imbalanced growth in trading demands. This result is consistent with the theoretical prediction in Biais and Hillion (1994). To the best of our knowledge, the direct empirical evidence of increased informed trading intensity after option listing is not documented in the literature. Third, our cross-sectional analysis on heterogenous option listing effects is new to the literature. We find both options market liquidity and firm information environment significantly affect the role of options in reducing information asymmetry. Finally, our results can be used to address an empirical puzzle regarding information asymmetry and price efficiency after option listing. Despite lower information risk after listing documented by Kumar, Sarin, and Shastri (1998), price efficiency improves as shown by Skinner (1990), Ho (1993), and Kumar, Sarin, and Shastri (1998). This is puzzling because less informed trading should make the price less efficient. We show that the amount of private information revealed to the market is actually higher after option listing through more active informed trading, leading to greater efficiency. But an even larger increase in uninformed trading dilutes the informed trades and makes information risk lower. Therefore, lower information risk can be reconciled with improved efficiency. In addition, the analysis identifies institutional ownership and investor order imbalance as important determinants of option listing decisions. These findings are helpful for empirical investigation into other option listing effects not considered in this paper and more generally the introduction effects of other derivative securities such as the credit default swap (CDS) and single stock futures (SSF). Finally, the numerical methodology proposed in Section B of the internet appendix can be used to address the data overflow problem in model estimation in other applications.

The remainder of the paper is organized as follows. Section 2 discusses the related literature and develops testable hypotheses. Section 3 describes the sample selection and matching procedure. Section 4 reports the empirical results of option listing effects on the information environment. And Section 5 concludes.

2. Related literature and hypothesis development

The investigation of option listing effects has a long history in the finance literature. The modern derivative pricing models starting from Black and Scholes (1973) and Merton (1973) typically assume a frictionless market and geometric Brownian motions as stock price dynamics. In this framework, options can be perfectly replicated by the underlying asset and a cash bond. Therefore, introducing options has no effect on the underlying asset prices or trading volumes. However, these two assumptions imply market completeness, which does not hold in practice. If the market is incomplete, it is possible that introducing options can make the market more complete and increase investors' welfare as shown by Ross (1976b) and Hakansson (1982). The improved opportunity set also implies more trading for hedging purposes. Since the optimizers' hedging trades do not dependent on private information, they can be viewed as liquidity or uninformed trades. Therefore, we have the following hypothesis.

Hypothesis 1: Options increase the hedging demand by completing the market. The treatment effect of option listing on the intensity of uninformed trading is positive.

If options only increase uninformed trading, the information risk will become lower after option listing. However, options can also become informed traders' target. The informational role of options is first noted by Black (1975) as he argues that informed traders can use options to achieve higher leverage. Figlewski and Webb (1993) find an increase in the short interest after option listing. Since short selling is more likely to be information based (Diamond and Verrecchia (1987)), relaxing shot-sale constraints can lead to more informed trading. Options can also increase traders' incentive to collect costly information, resulting in more informed trading as in the partially rational expectation framework of Cao (1999). Therefore, we have the second hypothesis below.

Hypothesis 2: Options benefit informed traders by relaxing capital requirement or short-sale constraint. The treatment effect of option listing on the intensity of informed trading is positive.

Given possible option listing effects on both informed and uninformed trading, the equilibrium effect on the level of information asymmetry becomes ambiguous. Conceptually, the option listing effect on the overall level of asymmetry will depend on the magnitude of listing effects on both types of trades. This problem becomes even more complicated when liquidity and informed trades are interdependent and the informed traders mimic the liquidity traders as in Biais and Hillion (1994). In addition to the classic no trade problem under information asymmetry as in Milgrom and Stokey (1982), Biais and Hillion (1994) show that in an incomplete market with a single tradable security of stock, the market can break down even without the presence of information asymmetry. If the benefit of increased hedging opportunity by using options exceeds the potential loss of trading against informed traders, introducing options solves the no trade problem. As a result of more liquidity trading, the informed traders also trade more, and more private information is revealed to the market. However, if there is no breakdown in the incomplete market, option introduction can reduce the incentive and the profit of the informed traders because the liquidity traders structure less extreme trades using options to hedge their endowment shocks, making the liquidity orders less attractive to the informed traders. In line with the argument of Stein (1987) about information externality, Huang and Wang (1997) reach similar conclusions on information efficiency by noting that option introduction increases the informational trades but also changes the information content of the existing allocational trades. Given the contradicting predictions, we have the following hypothesis.

Hypothesis 3: If option listing affects both informed and uninformed trading, the treatment *effect on the level of information asymmetry depends on the dominating effect between informed and uninformed trading.*

The empirical test strategy for the above hypotheses is nontrivial because neither informed nor uninformed trading is observable in the market and the information risk is hard to quantify. We rely on the sequence trade models developed by EO and DY to measure the trading intensity and information asymmetry. The order arrival rates from informed and uninformed traders are the two main model parameters that can be estimated using daily order flow data.[3] One important result of this model is that the probability of informed trading (PIN) can be calculated from estimated model parameters. Unlike price-based measures of information asymmetry such as the bid-ask spread, PIN focuses on information in order flow and is a quantity-based measure of information asymmetry. Compared to the price-based measures, PIN has two distinguished advantages. First, the stock market PIN is able to nest the information in options order flow if options market makers perform full delta hedging. Delta hedging eventually transmits all stock exposure and stock price information in the options market to the stock market. Therefore, the total stock order flow suffices to represent the activities in the two markets under this assumption. This feature is particularly important when studying the option listing effect on the overall market conditions without utilizing the options transaction data. Second, the EO model estimates enable empirical tests on all of the three hypotheses discussed earlier while the reduced-form information measures are silent on the trading intensity of different types of traders. While there is a long list of studies that examine PIN as a measure of information asymmetry, investigation into the model parameters is largely absent.[4] The empirical evidence regarding the performance of PIN is mixed. While supporting evidence of PIN as an asymmetry measure is provided by many studies, e.g., Brown, Hillegeistb, and Lo (2004), Vega (2006), Ellul and Pagano (2006), Chen, Goldstein, and Jiang (2007), and Ellul and Panayides (2016), several studies raise questions on the effectiveness of PIN before major corporate events, e.g., Benos and Jochec (2007), Aktas, de Bodt, Declerck, and van Oppens (2007), and Collin-Dufresne and Fos (2015). There is also mixed evidence regarding the pricing

[3]Interested readers can refer to the internet appendix for more details about the EO and DY models. The internet appendix also contains a new maximum likelihood estimation method to circumvent the data overflow problem.

[4]One exception is Duarte, Hu, and Young (2015), who compare the estimated probability of information events (α) from several models.

effect of *PIN*, e.g., Easley, Hvidkjaer, and O'Hara (2002), Lambert, Leuz, and Verrecchia (2007), Duarte and Young (2009), Mohanram and Rajgopal (2009), and Lai, Ng, and Zhang (2014). The major weakness of the *PIN* model is pinpointed by DY as that the EO model restricts the buy and sell orders from simultaneous increases. Motivated by the observed positive correlation between buy and sell orders, DY introduce a symmetric liquidity shock to the EO model and decompose the original *PIN* into an adjusted probability of informed trading, *APIN*, and a probability of a trade from symmetric liquidity shocks, *PSOS*. Since the DY model fits the historical data better than the EO model, we adopt the DY model in the paper. Nevertheless, we also use the EO model as an alternative and find consistent results. Those reports are available in Section D of the internet appendix of the paper. One limitation of using the EO and DY models is that informed traders can only use market orders to trade with a market maker in this framework. Theoretically, informed traders can also choose limit orders if the competition among informed traders is not intense as shown by Kaniel and Liu (2006). There is also supporting evidence for the information content of limit orders from laboratory settings (Bloomfield, O'Hara, and Saar (2005) and Bloomfield, O'Hara, and Saar (2015)) and empirical studies (Barclay, Hendershott, and McCormick (2003), Collin-Dufresne and Fos (2015), and Baruch, Panayides, and Venkataraman (2015)). Given the data limitation, we are unable to directly investigate the asymmetry measures based on the limit order book around option listing. To avoid relying exclusively on the trade sequence models, we instead examine additional information asymmetry measures to validate our main result.

Most empirical studies on option introductions focus on the underlying asset price or volatility.[5] In sparse empirical analysis of the option listing effects on stock market quality, Kumar, Sarin, and Shastri (1998) find that the stock market bid-ask spread narrows and the quote depth increases after option listing, indicating that information asymmetry reduces. Danielsen, van Ness, and Warr (2007) show that the bid-ask spread starts decreasing even before option listing. Both studies, however, are subject to a criticism of Mayhew and Mihov (2004), that option listing decisions are endogenous. In a matched sample, Mayhew and Mihov (2004) find that option listing has the same

[5]For example, studies on option listing impact on the underlying price include Branch and Finnerty (1981), Conrad (1989), Detemple and Jorion (1990), Sorescu (2000), and Danielsen and Sorescu (2001). Studies on option listing impact on the underlying volatility include Conrad (1989), Skinner (1989), Fedenia and Grammatikos (1992), Kumar, Sarin, and Shastri (1998), Bollen (1998), and Mayhew and Mihov (2004).

impact on the volatilities of both listing and control stocks and the treatment effect is negligible. One limitation of the existing empirical studies is that the samples often end before 2000 when the options market in the United States was not yet a consolidated national market (Battalio, Hatch, and Jennings (2004)). The option listing effects can be greatly undermined by lack of price competition and illiquidity in the options market at that time. The options market has developed significantly as a result of more stringent regulations and technology innovations since then. Therefore, investigating a recent sample period can provide timely and more relevant information about the underlying effects of option listing. In this paper, we follow Mayhew and Mihov's method to create a matched sample of option listing after 2000. We then investigate the treatment effect of option listing on the DY model parameters as well as the model constructs, *APIN* and *PSOS*. Although predictions about option listing effects on the probability of information events (α), the probability of liquidity events (θ), the liquidity shock order flow (δ), and the probability of liquidity shock trading (*PSOS*) are not contained in the theoretical models discussed in the paper, empirical evidence of additional option listing effects can be important for future research. For example, several recent studies explore liquidity dynamics and the asset pricing implication (see Bali, Peng, Shen, and Tang (2014) and Chordia, Hu, Tong, and Subrahmanyam (2015)). The option listing effect on θ, δ, and *PSOS* may provide insight on the sources of liquidity shocks.

The existing literature lacks discussion on the heterogenous option listing effects in the cross section. From a social planner's standpoint, it is important to understand what kind of stocks benefit more from options listing. We posit that the option listing effects on information asymmetry depend on at least two types of firm characteristics, namely the options market liquidity and firm information environment. Consider options market liquidity first. Admati and Pfleiderer (1988) point out that options are not beneficial to informed traders without sufficient liquidity in the market. Empirically, Holowczak, Simaan, and Wu (2006) and Hu (2014) show that the informational role of options strengthens when the options market is active. Roll, Schwartz, and Subrahmanyam (2009) argue that stocks with high options volumes have more efficient prices and enjoy higher valuation. Roll, Schwartz, and Subrahmanyam (2010) and Johnson and So (2012) find that the options to stock volumes ratio conveys stock price information. All these studies highlight the importance of options volumes in the feedback effect on the underlying market. Therefore, we have the following hypothesis.

Hypothesis 4: The option listing effect on the adjusted probability of informed trading, APIN, is larger for stocks with more liquid options.

Next, we turn to the firm information environment. In addition to security trading, private information can be disseminated through several other channels. For example, the role of stock analysts in mitigating information asymmetry is well documented in the literature (e.g., see Holden and Subrahmanyam (1992), Hong, Lim, and Stein (2000), Barth and Hutton (2004), and Ellul and Panayides (2016)). Firms can also provide voluntary disclosure to reduce information asymmetry. Empirically, Balakrishnan, Billings, Kelly, and Ljungqvist (2014) show that firms use earnings guidance as an substitute to analyst coverage. Institutions with significant holding of the stock can also be motivated to collect more private information as shown by Bushee and Noe (2000), Ajinkya, Bhojraj, and Sengupta (2005), and Amihud and Li (2006). All these information channels can be substitutional to each other regarding a firm's fundamental information. Therefore, we have the following hypothesis.

Hypothesis 5: The option listing effect on the adjusted probability of informed trading, APIN, is stronger for less transparent stocks before listing.

The calculation of *APIN* is not affected by the probability of news being good or bad. However, the option listing effect can be asymmetric for the two types of information due to short-sale constraints. Options relax such constraints but the benefit is relevant only for informed traders to sell before bad news. Therefore, the likelihood of informed selling should increase more than informed buying. *Ceteris paribus*, the reduction in the adjusted probability of informed trading should be larger for good news than for bad news. Following Brennan, Huh, and Subrahmanyam (2015), we decompose *APIN* into a probability of informed trading based on good news ($APIN\_Good = \beta * APIN$) and a probability of informed trading based on bad news ($APIN\_Bad = (1-\beta) * APIN$). And we propose the following testable hypothesis.

Hypothesis 6: The option listing effect on the adjusted probability of informed trading conditioning on good news, APIN_Good, is more negative than the adjusted probability of informed *trading conditioning on bad news, APIN_Bad*.

Finally, we concern the impact of option listing on price efficiency of the underlying stock. The effect is not straight-forward given potential offsetting effects from informed and uninformed trading. On the one hand, more trading activity from informed traders after option listing can bring more information to the market and potentially make the stock price more efficient. On the other hand, increased uninformed trading and expanded trading set of informed traders can make the private information more difficult to learn as argued by Stein (1987), Grossman (1988), and Back (1993). Therefore, the overall effect is ambiguous. In an experimental setting, de Jong, Koedijk, and Schnitzlein (2006) find that the introduction of options leads to more aggressive insider trading and improve price efficiency. The empirical literature typically addresses the issue by examining the price behavior after public information shocks such as earnings announcements. If options trading makes the stock price more efficient by revealing private information before announcements, price reaction to announcement surprise should become less significant. Early studies such as Skinner (1990) and Ho (1993) support this hypothesis. However, Mendenhall and Fehrs (1999) find that after 1986, stocks with options exhibit slightly larger price reaction to earnings surprise than stocks without options. The results in these studies are also clouded by the early sample period examined and lack of matching based on the probability of receiving treatment. Using a listing-probability matched sample from a recent period, we test the following hypothesis.

Hypothesis 7: Options trading improves stock price efficiency. Therefore, the price response to earnings surprise becomes weaker after option listing.

3. Data, sample selection, and matching

3.1. Option listing stocks

Information on option listing events is acquired from the Options Clearing Corporation (OCC) between February 11, 2001 and February 28, 2010. Included in the analysis are only new listing stocks that have no options traded at any options exchange in the US at the time of listing. The main analysis excludes options on indices and ETFs and focuses on single name equity options (CRSP code 10 and 11) because information asymmetry considered in this study is less relevant for diversified portfolios. To construct explanatory variables for listing decisions, a listing firm must have valid price information in the CRSP database and valid transaction data in the NYSE TAQ database for at least 252 trading days prior to the option listing date. To study the treatment effect, the options must continue trading for at least 252 trading days after listing. Options can also be delisted and relisted later. If a stock has more than one qualified listing event during the sample period, only the first record is used. The final sample includes 1517 observations. Table 1 shows the number of new listings every year during the sample period. The number of new listings increases gradually in the first half of the sample period and peaks at 246 in 2004. It decreases slightly afterward and remains 143 in 2009. The sample covers only the first two months in 2010 and there are 27 option listing events in those two months. The time series pattern shows that there are active option listings in the entire sample period.

[Table 1 about here]

3.2. Eligible non-listing stocks

We follow Mayhew and Mihov (2004) and constructs a sample of control stocks that are eligible, but not selected, for option listing. Mayhew and Mihov (2004) document detailed regulation changes in option listing standards imposed by the SEC before 1997. Comparing the current requirements with the requirements at the end of their sample period, several differences are noted: (i) the requirement of minimum trading volume has been removed; (ii) a stock can have options five days after its initial public offering (IPO) now, while previously it had to be traded for at least twelve months after IPO; (iii) the minimum security price is reduced from $7.50 to $3.00. The other three requirements remain unchanged: (1) the stock must be listed on a national exchange; (2) the stock must have at least seven million publicly held shares; (3) there must be at least two thousand shareholders. This paper defines eligible stocks for option listing in the next month as those meeting requirements (1) and (2) at the end of each month with the price above $3.00,[6] but having no options trading history in the previous year, and having at least 252 trading days in the CRSP database. Mayhew and Mihov (2004) argue that it is practically impossible to filter according to requirement (3) because many shareholders hold shares in street names, and this omission is unlikely to misclassify qualified stocks. Therefore, this listing criterion is also deactivated in this study. We adopt more stringent criteria about the trading history due to the needs of constructing explanatory variables for listing decisions. Insider holdings data is extracted from the Thomson Reuter's insider database and daily stock price and volume data from the CRSP. The filtering generates 140,277 eligible firm-month observations during the entire sample period. The annual breakdown is also reported in Table 1. As equity options become more common over time, the pool of eligible stocks for listing shrinks from 18,117 observations in 2001 (1,647 stocks per month) to 9,792 observations in 2009 (816 stocks per month).

3.3. Determinants of the option listing decision

Options exchanges have the incentive of listing stocks that are likely to generate large options volumes. In practice, new listing proposals are initiated by options market makers affiliated with the exchanges. These market makers are typically reputable brokerage houses or hedge funds that are able to collect and process large amounts of data from both public and private sources. Previous studies on determinants of option listings find significant effects of the firm size, trading volume, return standard deviation, industry classification (Mayhew and Mihov (2004)) and the percentage bid-ask spread (Danielsen, van Ness, and Warr (2007)). In addition to these easily observable variables, we investigate the role of three other firm characteristics in the listing decisions:

1. Volume order imbalance (VOI). Stock order imbalance can reflect the difficulty of short selling. Pessimistic investors are less likely to participate in trading in the presence of short-sale constraints and stock order imbalance can become positively biased. As an alternative to short

[6] The minimum price requirement was relaxed at the beginning of the sample period of this study. For example, Hecla Mining Co. (ticker: HL) was traded at $4.27 when its options were listed on January 22, 2003, and Golden Star Resources, Ltd (ticker: GSS) was traded at $3.77 when its options were listed on October 6, 2003. Therefore, setting the minimum price to $3.00 is unlikely to bias the sample toward penny stocks in this recent sample period.

selling, options on such stocks can generate high trading volumes, and options exchanges should prefer to list these stocks to attract short sellers. Therefore, a positive relation is expected between order imbalance and the likelihood of option listing. In this paper, the order imbalance is defined as $(B-S)/(B+S)$, where B and S denote daily buyer-initiated and seller-initiated dollar trading volumes, respectively. The Lee and Ready (1991) algorithm is employed to determine the trade direction. Unlike Lee and Ready, however, we do not apply a five-second delay in matching quotes and trades because this reporting lag is found absent after 1998 as shown by Madhavan, Porter, and Weaver (2005) and Chordia, Roll, and Subrahmanyam (2005). Specifically, if a transaction is executed at a price above (below) the midpoint of the contemporaneous National Best Bid and Offer (NBBO) prices, it is classified as buyer-initiated (seller-initiated). For trades falling on the mid quote price, they are classified as buyer-initiated (seller-initiated) if the last price change is positive (negative).

2. Absolute volume order imbalance (AVOI). Intuitively, this variable measures the magnitude of the unsigned order imbalance that relates to liquidity and market making costs.[7] It is more challenging for options market makers to perform delta hedging in an imbalanced stock market because options market makers usually do not make market for the underlying stock and may need to pay the bid-ask spread when performing delta hedging.[8] When order flow is imbalanced, options market makers need to compete with other liquidity demanders to hedge the options positions, increasing the uncertainty of delta hedging costs. Therefore, options exchanges should prefer to list stocks with small absolute volume order imbalance. Using $AVOI$ as a potential determinant for option listing also mitigates the concern that the option listing decision might be based on the dynamics of information asymmetry. Easley, Engle, O'Hara, and Wu (2008) show that the probability of informed trading (PIN) in the original EO model is approximately equal to the expectation of the absolute order imbalance $E[\frac{|B-S|}{B+S}]$. Therefore, including this variable in the selection model controls for the pre-listing dynamic of the information environment itself.

[7]The absolute imbalance has the same information as the variance of order imbalance in the cross section. Chordia, Hu, Tong, and Subrahmanyam (2015) provide both theoretical reasoning and empirical evidence that the variance of order imbalance captures the liquidity dynamic in the presence of informed traders.

[8]Options market makers can also use limit orders in the stock market, which reduces the trading costs but increases the likelihood of failure in hedging if the limit order is not executed.

3. Institutional ownership. Institutional ownership has contradicting effects on the likelihood of option listing. On the one hand, institutional investors are more likely to trade options if they do not have contractual or legal restrictions from using equity options for hedging purposes.[9] Therefore, options exchanges should prefer stocks with large institutional ownership to cater to their hedging demand. On the other hand, institutional ownership is negatively related to the stock borrowing cost for short sellers because institutional investors provide the most supply in the security lending market. Therefore, options exchanges may select stocks with low institutional ownership to attract short sellers targeting those stocks. The overall effect of institution holdings is thus unclear.

Both Mayhew and Mihov (2004) and Danielsen, van Ness, and Warr (2007) use a long-term average version and a short-term abnormal version of each independent variable to predict option listings. To improve the prediction accuracy, this study considers the innovations in the independent variables as an additional type of determinant. This is achieved by adding further lagged variables to the model. At the end of each month, for each of the explanatory variables except return standard deviation and institutional ownership, we calculate the average daily values in the previous year ($t-1$, $t-12$), the previous month ($t-1$), and twelve months ago ($t-12$). Return standard deviation (STD) is calculated using daily stock returns in the three measurement windows. Institutional ownership is updated at quarterly frequency. Constructing three variables from scarce observations can lead to serious multicollinearity. Therefore, we use only the most recent value ($t-1$) and the one-year lagged value ($t-12$) of institutional ownership. To investigate determinants of option listings, we estimate the following model using logistic regressions in the full sample:

$$\begin{aligned} Listing_t = & \beta_0 + \beta_1 Size_{t-1} + \beta_2 Volume_{t-1,t-12} + \beta_3 Volume_{t-1} + \beta_4 Volume_{t-12} + \beta_5 STD_{t-1,t-12} \\ & + \beta_6 STD_{t-1} + \beta_7 STD_{t-12} + \beta_8 Spread_{t-1,t-12} + \beta_9 Spread_{t-1} + \beta_{10} Spread_{t-12} \\ & + \beta_{11} VOI_{t-1,t-12} + \beta_{12} VOI_{t-1} + \beta_{13} VOI_{t-12} + \beta_{14} AVOI_{t-1,t-12} + \beta_{15} AVOI_{t-1} \\ & + \beta_{16} AVOI_{t-12} + \beta_{17} Institution_{t-1} + \beta_{18} Institution_{t-12} + \omega Industry + \theta Year + \varepsilon, \end{aligned} \tag{1}$$

[9]A recent study of Natter, Rohleder, Schulte, and Wilkens (2014) shows that over 87% of actively managed US equity mutual funds with N-SAR filings are permitted to use equity options.

where the dependent variable, $Listing_t$ is a dummy variable equal to one for listing stock-month observations and zero otherwise, $Size_{t-1}$ is the natural logarithm of the market capitalization at the end of month $t-1$, all *Volume* and *STD* variables are in natural logarithm for standardization, percentage spread (*Spread*) is calculated as 2(ask-bid)/(ask+bid) at the market close, *Industry* is a vector of 71 industry dummy variables based on the two-digit SIC code, and *Year* is a vector of year dummies to control for time fixed effects. Firm subscription is omitted for all variables in the equation for brevity.

The estimation results are reported in Table 2. To establish a benchmark, the first model uses only independent variables that have been used in previous studies. All variables have predictive ability with significant coefficient estimates at the 1% level. Specifically, large stocks and stocks with high volatility and low bid-ask spread are more likely to be listed, consistent with Mayhew and Mihov (2004) and Danielsen, van Ness, and Warr (2007). However, the effect of trading volume is not clear. The long-term trading volume has a negative coefficient estimate, but the short-term volume has a positive one, both significant at the 1% level. The second model includes one-year lagged trading volume, volatility, and spread. All lag variables have significant coefficient estimates while the original predictors retain the predictive ability. The results reveal important information about the dynamics of trading volume, volatility, and spread of the listing stocks. At one year before the listing date, these stocks have lower trading volume, higher volatility, and larger percentage spread than non-listing stocks. Approaching the listing date, however, these stocks experience an increase in trading volume and a decrease in percentage spread, while the volatility remains high. The findings are consistent with the pre-listing spread dynamic as in Danielsen, van Ness, and Warr (2007).

[Table 2 about here]

The last column in Table 2 reports the full specification test results of Equation (1). With additional explanatory variables, firm size becomes an insignificant predictor for option listing decisions. Stock trading volume is still a significant predictor at all lags with similar magnitude of coefficient estimates. The volatility and spread effects slightly weaken. The new variables, namely the volume order imbalance, absolute volume order imbalance, and institutional ownership are important determinants of option listing because all of these variables have statistically significant coefficient estimates. The recent and one-year average buy pressures measured by the volume order imbalances (VOI) positively and significantly predict option listings, while the one-year lagged order imbalance has an insignificant coefficient estimate. This result is consistent with the prediction that options exchanges prefer stocks with higher short-selling costs because short-sale constraints are likely to sideline sellers and make VOI more positive. Introducing options on such stocks can potentially attract high trading volumes from short sellers. Both of the recent and one-year absolute volume order imbalances ($AVOI$) negatively predict option listings and the coefficient estimate is positive for the lagged absolute imbalance, suggesting that the listing stock's order flow becomes more balanced over time and is more balanced than unselected stocks at the time of listing. This result is consistent with the conjecture that options exchanges prefer stocks with low market-making costs. The dynamic of the absolute order imbalance also suggests that information asymmetry can play a role in the option listing decision. Growth in institutional ownership also predicts option listings. At one year before the listing date, the listing stocks have significantly lower institution holdings than unselected stocks. At the time of listing, however, the listing stocks have significantly higher institutional ownership, suggesting that the hedging demand of institutions outweighs the consideration of catering to excess short interests. The full model generates the highest McFadden's pseudo-R squared out of the three models in Table 2 and has the highest accuracy ratio. Therefore, we use the full-model prediction to match stocks later.[10]

As a summary of the logistic regression results, we find that when selecting stocks for listing, options exchanges consider both the concurrent level and the dynamic of several stock characteristics. The probability of option listing is higher for stocks experiencing recent increases in the trading volume, volatility, volume order imbalance, and institutional ownership, and decreases in the bid-ask spread and absolute order imbalance. The uncovered pre-listing dynamics of liquidity-related variables such as the bid-ask spread, trading volume, and order imbalance are particularly important for analysis on listing effects because these trends may continue after listing, and

[10] Matched samples based on the other models in Table 2 generate largely the same results, which are available upon request.

changes in the informational environment might be caused by the same variables that affect options exchanges' decisions (selection effect) rather than the treatment effect of option listing. Therefore, it is critical to use a control group of stocks with similar characteristics including pre-listing dynamics to disentangle the selection effect and the treatment effect.

3.4. Matching listing stocks to eligible non-listing stocks

After obtaining the propensity score of option listing, we match each listing stock to the eligible non-listing stock with the closest propensity score in the same calendar month. The matching is done without replacement and once a non-listing stock is matched, it exits the pool of non-listing stocks for one year before it becomes available for matching again to avoid overlapping observations. The firm characteristics of the listing and the matched stocks are reported in Table 3. The average log size of the listing stocks is 20.23, equivalent to an average market capitalization of 610 million dollars. The matched non-listing stocks have similar size on average but the standard deviation is larger than that of the listing stocks. The rest of the reported characteristics exhibit the same pattern that the means of the two groups are well matched but the standard deviation of the control group is larger than that of the listing group. Unreported t-tests on the mean confirm that there is no systematic difference between the two groups. Finally, the last row in Table 3 presents the mean and standard deviation of the fitted probability of option listing in the two groups. The average predicted probability is 6% for the listing group and 5.3% for the control group.

[Table 3 about here]

4. Option listing effect on the information environment

This section performs empirical tests about the effects of option listings on the overall market information environment. Since the study focuses on the information in investors' order flow, the structural break should occur when options become available to investors but not when the listing decisions are announced. Therefore, the event day (day 0) is defined as the listing date recorded by the OCC. The analysis leaves a one-month window around the listing date[11], and defines the event year before listing as trading days $[-262, -11]$ and the event year after listing as trading days [11, 262].

4.1. Baseline test

We estimate the DY model in the two event windows for all of the listing and control stocks and calculate the paired difference between the two groups as the treatment effect of option listing. The results are reported in Table 4. Panel A presents the cross-sectional averages of the estimated model parameters, *APIN*, and *PSOS* for the two groups. The probability of information events (α) and the probability of liquidity shocks (θ) are almost unaltered in both groups after the listing event. The order arrival rates are reported in natural logarithm for cross-sectional standardization. In both groups, all three of the order arrival rates increase after listing. The average probability of informed trading (*APIN*) of the listing stocks is 15.5% before listing and 13.3% after listing. The average *APIN* of the control stocks is 16% before listing and 14.9% after listing. A similar reduction is observed for the probability of a trade from liquidity shocks (*PSOS*) in both groups.

Panel B reports the average changes in the model parameters and constructs after option listing, and the treatment effects with robust t-statistics. To account for cross-sectional variation in the parameters, the changes are calculated as log differences to approximate percentage changes. On average, the listing stocks experience significant increases in the probability of information events (α), arrival rate of informed orders (μ), symmetric liquidity shock order flow (δ), and arrival rate of uninformed orders (ε), but no significant change in the probability of liquidity shocks (θ). The probability of informed trading (*APIN*) and the probability of a trade from liquidity shocks (*PSOS*) decrease by 15.7% and 16.8%, respectively. As expected, the control stocks exhibit similar changes in all the variables. To identify the treatment effect, the last column in Panel B reports the averages

[11] Not all options become available immediately on the listing date if the appointed market maker is not ready for providing quotes. There can be several days of delay before the options are quoted and traded on the exchange. Moreover, the options market makers usually need to establish a reasonable inventory of the underlying stocks before options trading starts. Their purchase of the underlying stocks can cause uninformative order imbalance before the listing date and potentially contaminate the measure of information asymmetry.

of the paired differences between the listing group and the control group. On the one hand, the listing effects on the probability of information events (α) and probability of liquidity shocks (θ) are both negative but statistically insignificant. On the other hand, the listing effects on all three order flow variables are positive and statistically significant at the 1% level. Specifically, option listing on average increases the informed order flow (μ), symmetric liquidity shock order flow (δ), and uninformed order flow (ε) by 12.4%, 14%, and 23.9%, respectively. The results support both Hypotheses 1 and 2. The average treatment effects on *APIN* and *PSOS* are -8.8% and -7.2%, respectively. Quantifying the selection effect using the results on the control group in the second column, it is found that the treatment effects on *APIN* and *PSOS* are at the same magnitude as the selection effect.

The above analysis shows that the reduction in information asymmetry could be due to imbalanced growth in the three order flow variables. While the percentage analysis might potentially overstate the change due to a small initial value, we explicitly examine the economic significance of option listing by focusing on a relative measure of order flows. Note that in the DY model, *APIN* is defined as

$$APIN = \frac{\alpha\mu}{\alpha\mu + 2\theta\delta + 2\varepsilon} = \frac{\alpha}{\alpha + 2\frac{\theta\delta+\varepsilon}{\mu}}. \tag{2}$$

Given insignificant treatment effect on α, the listing effect on *APIN* is largely determined by the intensity of uninformed trading ($\theta\delta + \varepsilon$) relative to the intensity of informed trading (μ) in the denominator of the above equation. We term this relative order flow variable *ROF* and it is clear that a larger *ROF* leads to a lower *APIN*. We find that the average *ROF* is 0.86 (0.84) for listing (control) stocks before listing, and 1.061 (0.946) after listing. Although both listing and control stocks have higher *ROF* after option listing, the increase is much larger on the listing stocks. The treatment effect on *ROF* reaches 0.094 with a *t*-statistic of 4.76.

The results in this subsection indicate that option listing significantly reduces the probability of informed trading in the market. Moreover, this change is not due to change in the probability of information events but disproportional increases in uninformed and informed trading. Both types of traders become more active when options are available but the increase in uninformed trading outweighs the increase in informed trading, reducing the likelihood of trading against an informed trader.

[Table 4 about here]

4.2. Robustness

This subsection conducts robustness tests on the baseline results documented in the previous subsection to warrant the causal inference regarding option listing effects.

4.2.1. Deviation from full delta hedging assumption

The key assumption in our analysis is full delta hedging. Only under this assumption the stock order flow perfectly represents trading in both stock and options markets. In this subsection, we investigate the effect of discrete delta hedging on our inference of option listing effects. The modern option pricing research is generally motivated by the non-arbitrage argument, which implies full delta hedging by liquidity providers (see, e.g., Merton (1973) and Ross (1976a)). The role of transactions cost in replication and hedging is also studied by Leland (1985), Boyle and Vorst (1992), and Longstaff (1995). However, without detailed information on options market makers' positions in all securities, how frequently delta hedging is performed on option positions remains largely unknown to academics. Indirectly, Easley, O'Hara, and Srinivas (1998), Holowczak, Hu, and Wu (2014), and Hu (2014) find that options delta order flow strongly affects the contemporaneous stock prices, indicating that delta hedging could occur within the test horizon in these studies. While Easley, O'Hara, and Srinivas (1998) and Hu (2014) mainly examine the inter-day dynamics, Holowczak, Hu, and Wu (2014) show clear contemporaneous price impact from options delta imbalance at all frequencies they examine ranging from five seconds to fifteen minutes.

Although the true delta hedging frequency and total hedging volumes cannot be empirically identified, our conversations with options market makers yield a consistent remark that the market makers typically go home "flat". Having little inventory risk overnight is also consistent with the market making practice in other security markets. Therefore, the imbalance in options delta should always be hedged in the underlying stock market at the end of the day regardless of the hedging frequency. If the market maker performs discrete hedging and waits for offsetting trades, some symmetric positions in long and short delta may not lead to delta hedging, resulting in lower trading volumes in the underlying stock than full delta hedging. In this case, the stock order flow underestimates the total trading activities in the two markets. Estimating the DY model with lower buy and sell volumes are likely to lead to spurious inferences about option listing effects. To understand the potential bias due to the unhedged delta volumes, it is important to note that the gap between the observed stock order flow and unobservable total order flow is the same for both the buyer-initiated and seller-initiated volumes because the unhedged volumes should be netted out. To recover the unobserved total order flow, we set the unhedged volume to be 25%, 50%, 75%, and 100% of the total options trading volume of the same stock on a day. After adding half the unhedged volume to both the buy and sell stock volumes on the same day, we estimate the DY model using these alternative order flow numbers and reexamine the listing effects. Note that since there is no options trading on the listing stocks before listing or on the control stocks during the entire event period, we perform this volume adjustment only for the listing stocks after listing. Table 5 reports the results using these alternative volumes. Compared to the main results in Table 4, we find that the volume adjustment does not significantly change the treatment effects of option listing on any of the DY model parameters or the model constructs. The volume adjustment has similar effects to symmetric liquidity shocks in the DY model. Indeed, we find that the listing effect of the liquidity shock order flow (δ) increases as the volume adjuster increases from 25% to 100%. Larger estimates of liquidity trading also lowers *APIN* and increases *PSOS*. Therefore, the listing effects on *APIN* becomes marginally smaller and the effects on *PSOS* becomes marginally larger. Nonetheless, the reduction in *APIN* remains at 7.5% with a t-statistic of -5.48 even when the unhedged options volume reaches 100%. The analysis in this subsection indicates that our conclusions about the option listing effects do not critically depend on the full delta hedging assumption.

[Table 5 about here]

4.2.2. Alternative model estimation and subsample analysis

We first estimate the DY model using number of trades instead of trading volumes and report the difference-in-difference analysis results in Column (1) of Table 6. Comparing the treatment effects in this column to the main results in Table 4, it is clear that the same pattern exists that both informed (μ) and uninformed trading (ε) increase and the effect of the latter dominates, resulting in a lower probability of informed trading. The magnitude of the estimated listing effects and the statistical significance are also close to those in Table 4.

[Table 6 about here]

The second robustness test concerns that the listing stocks of the full sample come from all stock exchanges in the US, but the NASDAQ is traditionally a dealers' market, making the inference of order flow potentially different from that of a specialists' market such as the New York Stock Exchange (NYSE). We then divide the full sample into two subsamples based on the stock exchange of the listing stock and report the listing effects in Column (2) for NASDAQ stocks and in Column (3) for NYSE and American Stock Exchange (AMEX) stocks. The pattern of the parameter dynamics in these two columns is consistent with the main findings. Interestingly, the option listing effects on the order flow variables are greater for NYSE and AMEX stocks but the listing effects on *APIN* and *PSOS* are weaker for the same stocks, suggesting that the imbalanced growth in informed and uninformed trading is more prominent for NASDAQ stocks. NASDAQ stocks, generally with smaller market capitalization, can be less transparent than NYSE and AMEX stocks on average. Therefore, options trading as an additional information channel is possible to have larger effects on NASDAQ stocks in reducing information asymmetry. We formally revisit the impact of firm information environment in Subsection 4.3 when we test Hypothesis 5.

There might be concerns that the baseline results are contaminated by the great financial crisis (GFC) in 2008 because of extreme stock market volatilities. Moreover, the short selling ban during the crisis period can also have significant impact on options trading (see, for example, Grundy, Lim, and Verwijmeren (2012)). To isolate the effect of GFC, Column (4) excludes the option listing events in 2008 and 2009 and replicates the baseline analysis. The estimated listing effects are almost identical to the baseline results in Table 4. In an unreported test using only observations during GFC, no significant results are found on the treatment effects, suggesting that the option listing effects come from the non-GFC period only.

Next, we examine the option listing effects conditioning on which options exchange is involved. In our sample, the Chicago Board of Options Exchange (CBOE) is the most active participant in listing new options.[12] Out of the 1517 events examined in the study, CBOE is involved in 676 listings. Given CBOE's unique industry position and longest history of trading options, Columns (5) and (6) report the listing effects in the subsamples of CBOE listings and non-CBOE listings, respectively. While the parameter dynamics generally show the same pattern in the two columns, it is found that CBOE listings exhibit a smaller increase in informed trading (9.9% versus 14.3%) but a much larger increase in uninformed trading (32.2% versus 17.7%) than non-CBOE listings. As a result, the reductions in *APIN* and *PSOS* for CBOE listings almost double the reductions for non-CBOE listings. Increased informed trading increases the cost of delta hedging for options market makers because the order flow is more likely to be imbalanced. It is possible that as the oldest options exchange, CBOE and its market makers are better at selecting stocks to manage their hedging costs.

4.2.3. Controlling for firm dynamics

Aslan, Easley, Hvidkjaer, and O'Hara (2008) find that several firm characteristics explain the cross-sectional variation in the probability of informed trading (*PIN*). Specifically, they estimate the following model:

$$\begin{aligned} PIN = b_0 + b_1 Size + b_2 Growth + b_3 Age + b_4 Analyst + b_5 Turnover + b_6 Insider \\ + b_7 Institution + b_8 Accrual + b_9 ROA + b_{10} STD + b_{11} TobinQ + \Omega Industry + \eta, \quad (3) \end{aligned}$$

[12] Eight options exchanges operated in the US during the sample period including the American Stock Exchange, Better Alternative Trading System, Boston Options Exchange, Chicago Board Options Exchange, International Securities Exchange, NASDAQ, New York Stock Exchange ARCA, and Philadelphia Stock Exchange.

where $Growth$ is the annual growth rate in sales, Age is the length of history in CRSP, $Analyst$ is the number of analysts following the company, $Turnover$ is the annual stock market trading volume scaled by shares outstanding, $Insider$ is the percentage ownership of company insiders, $Accrual$ is the estimate of the discretionary component of total accruals, ROA is return on asset calculated as net income after depreciation over total asset, $TobinQ$ is the market value of equity plus book value of debt over total asset, and $Size$, STD, and $Industry$ are the same as defined earlier in Equation (1). Those authors find that all variables are significantly related to PIN except $Accrual$. Given the close relation between the EO model and the DY model, it is possible that the same firm characteristics also affect $APIN$ and $PSOS$. Therefore, we estimate the first order difference version of Equation (3) using pooled observations of both the listing and control stocks:

$$\begin{aligned} dY = & b_0 Listing + b_1 dSize + b_2 dGrowth + b_3 dAnalyst + b_4 dTurnover + b_5 dInsider \\ & + b_6 dInstitution + b_7 dROA + b_8 dSTD + b_9 dTobinQ + \eta, \end{aligned} \tag{4}$$

where $Listing$ is a dummy variable equal to one for listing stocks and zero for control stocks, and all the other variables are annual changes after option listing. The dependent variables dY are changes of all the DY model parameters and constructs examined in previous analysis. All of the three order flow variables are calculated as the natural logarithm of the DY model estimates. $Accrual$ is dropped from the model because it is not related to PIN. Also excluded from the model are Age and $Industry$ because the change in the firm age is identical for all stocks and the industry classification is unlikely to change.

The sample size decreases slightly after merging the DY model estimates with firm characteristics extracted from several other databases. The balance sheet items are from the COMPUSTAT database. Analyst coverage is from the I/B/E/S and is assigned zero if no record is found for the firm. Insider holding data are from the Thomson Reuters. There are 1,256 listing stocks and 1,283 control stocks with all firm characteristics available after data merging. Table 7 reports the OLS regression results. Across the columns, the listing dummy has negative but insignificant coefficients for the two probability parameters (α and θ), positive and significant coefficients for all three order flow variables (μ, δ, and ε), and negative and significant coefficients for both *APIN* and *PSOS*, again consistent with the main results. Given the pre-listing averages of 15.5% and 31.7% for listing stocks' *APIN* and *PSOS*, the estimated reductions of 1.4% and 3% in *APIN* and *PSOS* in this table translate to about 10% of the original value. The economic significance in this multivariate test is therefore at the same order of magnitude as the main test on the percentage changes in *APIN* and *PSOS* contained in Table 4.

[Table 7 about here]

4.2.4. Dynamic analysis

Event studies examining long event windows could potentially generate spurious inferences. For example, if the structural break occurs a few months before the option listing date, comparing information in the two annual event windows before and after listing may still generate similar results. To explore the dynamic effects of option listing, we estimate the DY model for four quarters before and after the option listing date. Event quarter -1 is defined as trading days [-73, -11] relative to the option listing date (day 0) and event quarter 1 is defined as trading days [11, 73]. The rest of the event quarters are defined in a similar way so that each event quarter contains 63 trading days.[13] We exclude the estimates with corner solutions and examine the quarterly treatment effects from option listing in Table 8.

The first column shows that the number of paired observations in each event quarter is between 1513 and 1515, indicating that the majority of the sample is free from the corner solution problem in estimation. The second column shows that there is a marginal increase in the probability of information events, α in quarter 2, which then quickly reverses in quarter 3. There is no significant treatment effect on α in the other event quarters. No significant listing effect is observed on the probability of liquidity shocks (θ) in any event quarter in Column (3). Column (4) shows that the treatment effect on the informed order flow, μ, is significant in two event quarters, 1, and 3. Average μ of the listing stocks increases by 12% over the control stocks (t-statistic = 3) in quarter

[13] Further increasing the granularity of the analysis may have insufficient number of observations to reliably estimate the DY model.

1, making it the biggest quarterly change in terms of both magnitude and statistical significance across all quarters. Column (5) shows that the liquidity shock order flow, δ, also receives significant treatment effect in the first quarter after option listing. The increase in δ is 19.7% with a t-statistic of 4.89. A mild reversal in δ is found in quarter 3 (-7.6% with a t-statistic of -1.92). Column (6) shows that the arrival rate of uninformed trading (ε) experiences consistent increase over all event quarters, indicating that the stock liquidity generally improves around option listing. However, the most significant increase in ε occurs in quarter 1. The treatment effect of 12.5% (t-statistic = 6.1) in the first quarter is more than double the effect from any other quarter. Column (7) shows that the probability of informed trading ($APIN$) is significantly reduced by more than 5% (t-statistic = -3.36) in the first quarter after option listing. There is further reduction in $APIN$ in the two following quarters amounting to 3.4% together. However, these changes are no longer statistically significant in individual quarters. Finally, the last column shows that the listing stocks exhibit some changes in the probability of a trade from liquidity shocks (*PSOS*) only before listing but not after. We also calculate the cumulative change relative to the last quarter before listing for all event quarters after listing. Not surprisingly, the cumulative change is always positive and significant for μ, δ, and ε, and always negative and significant for $APIN$. The cumulative change of *PSOS* becomes significantly negative in the second quarter after listing. The dynamic analysis results in this table support the causal effects from option listing on the information environment because the most significant impact occurs in the first quarter after listing.[14]

[Table 8 about here]

4.2.5. A quasi-natural experiment on option listing

Causal effects from option listings are at the center of the analysis. However, the inference from PSM analysis so far can be impeded by missing variables in the selection process if these variables

[14] We also conduct an additional placebo test to confirm the timing of structural breaks using randomized event dates. Specifically, for each pair of listing and control stocks, a pseudo-event date is randomly chosen from last three months before the option listing date. Then we replicate the baseline analysis using one quarter's data before and after the pseudo-event date. The results show no significant treatment effect from these pseudo events. These results are available upon request.

affect the listing decisions and the information environment at the same time. To address this concern, this subsection examines an alternative matched sample in a quasi-natural experiment of option listing. The SEC mandates a minimum stock price requirement for option listing, which creates discontinuity in the probability of option listing. If two stocks share similar characteristics including stock prices but only one stock marginally meets the listing standard, the listing decision is then more likely a result from the exogenous listing standard. Such observations are useful in identifying the causal effect from the treatment, i.e. option listing in this case. To find the listing stocks on the margin, we include only listing stocks with prices above the mandated minimum price by less than one dollar at the time of listing.[15] There are 56 such listing events during the sample period. To find the control sample, we first construct a sample of non-listing common stocks that have prices below the minimum price requirement by less than one dollar, but meet all the other requirements. Then the same logistic regression is estimated for Equation (1), and the non-listing stock with the closest propensity of listing at the same time is matched to a listing stock.

Table 9 replicates the baseline analysis in this alternative sample. Despite relatively small sample size, similar dynamics in the DY model parameters and constructs are found in this table. Focusing on the treatment effect in the last column, it is clear that all of the three order flow variables receive significant and positive treatment effects from option listing, but the two probability variables do not. The magnitude of the increase in the informed order flow (μ) is again dwarfed by those in the liquidity shock order flow (δ) and uninformed order flow (ε). As a result, *APIN* significantly reduces by 14.5% with a t-statistic of -2.36. The treatment effect on liquidity shocks (*PSOS*), however, is not statistically significant in this sample although the estimated average effect is negative and large (-10.7%, t-statistic = -1.18). The results in this quasi-natural experiment support the causal effect from option listing on the information environment and the estimated dynamics are consistent with the main findings.

[Table 9 about here]

[15] The minimum price is set to \$7.5 until end of 2002 and is set to \$3 thereafter because the first low-price listing on GSS occurs in January 2003.

4.2.6. A placebo test on ETF options

The analysis so far excludes ETF options because private information is usually firm-specific and affects the price of common stocks more than diversified stock portfolios such as ETFs. However, the liquidity effect can exist for ETF options because of increased hedging trades. Therefore, the overall information risk can still decrease but the mechanism is different. This subsection examines the option listing effect on ETFs as a placebo test. There are 85 ETFs that experience option introductions and have enough information to compute the selection variables during the same sample period. We also estimate the propensity of option listing for ETFs only in a separate logit regression and construct a control sample of ETFs. The previous difference-in-difference analysis on the DY model parameters is repeated in this matched ETF sample. Table 10 shows that for the DY model parameters, there are significant listing effects on the uninformed order flow (ε), but not on the informed order flow (μ, t-statistic = 0.27). The increase in ε reaches 48% with a t-statistic of 4.76. The probability of informed trading ($APIN$) is also reduced in this sample at an even larger magnitude (-23%) than the effect in the common stock sample (-8.8%) because informed trading does not become more active in the ETFs after option listing. The effect on $PSOS$ is absent. The results of this placebo test suggest that although option listing increases liquidity in general, the effect on informed trading is found only on common stocks, consistent with the notion that informed trading is more relevant for individual stocks than diversified stock portfolios.

[Table 10 about here]

4.3. Heterogenous listing effects

To test the heterogenous listing effects in the cross section of Hypotheses 4 and 5, we merge the main sample with additional databases. To measure options market liquidity, we extract options volume data from the Option Metrics database. The daily options volume is the aggregate trading volume of all option contracts on the same stock. The options to stock volume ratio, O/S, is then the aggregate options volume scaled by the stock trading volume on the same day. Figure 1 plots the average daily O/S in the cross section of listing stocks in the first year after listing. A clear trend of growth in O/S is found. The average O/S is around 2.5% immediately after the listing date and it gradually increases to around 5% at the end of the first year, comparable to the average O/S at 5.78% of all stocks with options between 1996 and 2010 reported by Johnson and So (2012). The growth is rapid in the first three months (before day 63) and large variation in O/S is also found. We calculate the average daily options volume (*OpVol*) and average daily O/S ratio in the first year after listing for each listing stock to measure the options market activeness.

[Figure 1 about here.]

To measure the listing stock's information environment before listing, we calculate the following proxies using stock price data from CRSP, financial statements from COMPUSTAT, analyst, earnings, and voluntary disclosure information from I/B/E/S, and ownership data from Thomson Reuter's 13f filings database.

- *Spread*: Average daily closing bid-ask spread scaled by the midpoint of the bid and ask in the year before listing. Classic market microstructure theories such as Glosten and Milgrom (1985) and Easley and O'Hara (1992) suggest that information risk widens the dealer's bid-ask spread.

- *Size*: Market capitalization in logarithm at the end of the month before listing. Large firms tend to be more transparent because more attention from investors are given to them.

- *Analyst*: Number of analysts following the stock in the year before listing. Greater coverage of analysts generally reduces information asymmetry.

- $|SUE|$: Average absolute earnings surprise of four quarters before listing, where earnings surprise is calculated as the actual earnings minus the median analyst forecast scaled by the stock price at the end of the previous month. It is more difficult to forecast earnings for opaque firms, leading to larger magnitude of earnings surprise. Therefore, firms with weak information environment usually have large $|SUE|$.

- *Guidance*: A dummy variable that equals one for firms that issue any earnings guidance in the year before listing, and zero otherwise. Managers' voluntary disclosure is an important information channel as shown by Balakrishnan, Billings, Kelly, and Ljungqvist (2014). Firms issuing earnings guidance should have more transparent information environment.

- $InstHolding$: Average fraction of shares held by institutional investors in four quarters before listing. Higher institutional holding is likely to reduce information asymmetry because with significant risk exposure from large positions, institutional investors have the incentive to collect private information as argued by Amihud and Li (2006).

- $NumInst$: Number of institutional investors at the time of listing.

- $AccrualQuality$: Standard deviation of residuals from a regression of current accruals on lagged, current, and future cash flows from operations as in Dechow and Dichev (2002). We run the regressions using quarterly data from three years before listing. Dechow and Dichev (2002) argue that a close mapping between accounting accruals and cash is more desirable in terms of accounting quality, leading to a small standard deviation of residuals in the proposed regression. Therefore, $AccrualQuality$ is inversely related to information transparency.

For each conditioning variable, the listing stocks are sorted into quintile portfolios by ascending order except for *Guidance*, which allows us to separate the sample into only two groups that either issue (High) or do not issue (Low) earnings guidance. Table 11 presents the average treatment effect on $APIN$ for each quintile portfolio as well as the difference between the top and bottom quintiles with robust t-statistics.

[Table 11 about here]

We examine the options liquidity effect first. Both Columns (1) and (2) show that the listing effects on $APIN$ are negative in all quintile portfolios except for the lowest options volume and O/S quintile portfolios, suggesting that reduction of information asymmetry is a general phenomenon in the cross section of stocks that experience option listings. Moreover, it is clear that the listing effect becomes stronger (more negative) when options liquidity increases. The difference between the top and bottom quintile groups reaches -0.218 (-0.16) with a t-statistic of -5.27 (-3.72) for sorting based on $OpVol$ (O/S). The evidence is consistent with the notion that an active options market brings more informational benefit to investors, supporting our Hypothesis 4.

Next, we turn to Hypothesis 5, which posits that firms with weaker information environment before option listing benefit more. Our analysis generates the following results. First, regardless of the information proxy we use, the option listing effect on $APIN$ is always negative in all characteristic groups. Second, focusing on the difference between the top and bottom quintile groups, the listing effect is stronger (more negative) for stocks with large bid-ask spread, small market capitalization, low analyst coverage, large absolute earnings surprise, little earnings guidance, low institutional ownership, low number of institutional investors, and low accrual quality. Since such firms are typically less transparent, the evidence is consistent with Hypothesis 5 that opaque firms benefit more from option listings. Finally, the average difference between the top and bottom characteristic groups is statistically significant for all information environment measures except analyst coverage and the t-statistics range between 1.86 and 3.06.

In Table 12, we perform multivariate regression analysis of the option listing effects on $APIN$ using all of the conditioning firm characteristics. Column (1) reports the regression results on options liquidity proxies, $OpVol$ and O/S, only. Although both $OpVol$ and O/S are negatively correlated with the listing effect on $APIN$ in Table 11, only $OpVol$ retains the significant effect in the multivariate regression. Column (2) reports the results using all information environment proxies. Although the signs of the estimated coefficients are largely consistent with the results in Table 11, the only significant coefficient belongs to $|SUE|$. It is possible that the information environment proxies are correlated. When all variables are included in the regression in Column (3), the results are similar. $OpVol$ and $|SUE|$ have significant and negative coefficients, indicating that higher options volume and larger earnings surprises before listing are correlated with stronger (more negative) option listing effects on information asymmetry. This result is robust in Column (4) when a time trend is added to the model.

[Table 12 about here]

4.4. short-sale constraint and option listing effects

Out of the six parameters in the DY model, the analysis so far excludes the probability of information being good, β, because this parameter does not affect the calculation of either *APIN* or *PSOS*. However, β can also be affected by option listing if getting around short-sale constraints is an important motivation of informed traders. In this subsection, we examine the role of short sale constraint in option listing effects on *APIN*. Specifically, following Brennan, Huh, and Subrahmanyam (2015), we decompose *APIN* into a probability of informed trading based on good news ($APIN\_Good = \beta * APIN$) and a probability of informed trading based on bad news ($APIN\_Bad = (1-\beta) * APIN$) and investigate the asymmetric effect from option listing.

In Table 13, we replicate the option listing effect analysis in Table 4 on β, *APIN_Good*, and *APIN_Bad*. Panel A reports the average estimates before and after listing. The listing stocks have an average β of 0.588 before listing and 0.566 after listing. The control stocks have an average β of 0.572 before listing and 0.569 after listing. The fact that β is well above 0.5 in all the periods indicates that the observed information shocks can be asymmetric. This could be due to the short-sale constraints in place because the estimated probability of bad news is lower than the true probability of bad news if informed traders cannot trade ahead of negative news under binding short-sale constraints. A large β also makes *APIN_Good* greater than *APIN_Bad* in the sample. In Panel B, we find β reduces by 5% for the listing stocks (t-statistic = -5.48) but does not have a significant reduction in the sample of control stocks (t-statistic = -0.73). As a result, the treatment effect on β is negative and significant (-2.9%, t-statistic = -3.04). The negative option listing effect on β is consistent with the notion that options help informed traders get around the short-sale constraints on the underlying stocks and the stock has a greater chance of experiencing selling pressure after option listing. Turning to the asymmetric effects on the probability of informed trading, we find that both *APIN_Good* and *APIN_Bad* have negative and significant treatment effects. However, the effect on *APIN_Good* is almost three times that on *APIN_Bad* (-14.9% versus -5.4%) and the t-statistic is also much larger on *APIN_Good* (-5.93 versus -1.68). The results support our Hypothesis 6 that option listing has asymmetric effects on the probability of informed trading and the reduction in *APIN_Good* is larger than the reduction in *APIN_Bad*. In Panels C and D, we replicate the conditional analysis on $APIN\_Good$ and $APIN\_Bad$ in the cross section. The results can be summarized as follows. First, the option listing effects on $APIN\_Good$ and $APIN\_Bad$ have the same sign as the effect on $APIN$ for all the conditioning variables. This means that both options liquidity and listing stock's information environment affect $APIN\_Good$ as well as $APIN\_Bad$. Second, comparing the conditional option listing effect based on options liquidity in the first two columns, it seems that the impact of options liquidity is comparable between $APIN\_Good$ and $APIN\_Bad$ in terms of both the high minus low result and statistical significance. Third, the option listing stock's information environment has a more significant impact on $APIN\_Good$ than $APIN\_Bad$ because significant difference in $APIN\_Good$ between the high and low groups is found for $Spread$, $|SUE|$, and $Guidance$ while such significant difference in $APIN\_Bad$ exists only for $|SUE|$. The results in the last two panels are again consistent with the asymmetric effect of option listing on the probability of informed trading.

[Table 13 about here]

4.5. Option listing and price efficiency

If options trading reveals private information, the information value of earnings announcements will become lower after option listing. Empirically, Skinner (1990), Ho (1993), and Mendenhall and Fehrs (1999) find mixed evidence regarding the role of options in conveying earnings information for option listing stocks. We examine this question in a matched sample based on the option listing probability using a fixed effect regression method because some stocks do not have analyst forecasts in the I/B/E/S database in some quarters. Specifically, we regress the cumulative abnormal return from days $[-1,1]$ on the earnings surprise (SUE), the option listing dummy ($Listing$), a time dummy ($After$) that equals one for observations after listing and zero otherwise, and interactions of these variables. The option listing effect is identified by the three-way interaction variable of SUE, $Listing$, and $After$. We include firm and year fixed effects in the regressions and apply year clustering in calculating the t-statistics. Table 14 reports the results. Column (1) shows that in the univariate model, the stock price response to earnings surprise is positive and significant as the estimated coefficient (0.002) has a t-statistic of 4.31. We add the listing dummy and the interaction of $Listing$ and SUE to the model in Column (2). The coefficient on SUE remains positive and significant and the coefficient of the interaction term $SUE * Listing$ is negative with a t-statistic of -1.89, indicating that on average, the option listing stocks have lower price response to earnings surprise conditioning on the level of surprise. Column (3) includes the time dummy $After$, its interactions with SUE and $Listing$, and the three-way interaction. The variable of interest, the three-way interaction, has a coefficient estimate of -0.008 with a t-statistic of -3.2. The significant negative estimate indicates that the price sensitivity to earnings surprise becomes weaker for option listing stocks after listing, supporting Hypothesis 7.[16]

[Table 14 about here]

4.6. Other option listing effects

Concerning that the $APIN$ model may not well capture the information risk, we examine the option listing effect on five additional stock market metrics in this subsection, including the percentage bid-ask spread ($Spread$), absolute order imbalance ($AVOI$), return standard deviation (STD), realized volatility ($RVol$)) defined as the squared root of the daily sum of five-minute return squares, and $VPIN$ of Easley, Lopez de Prado, and O'Hara (2012). $VPIN$ is proposed as an alternative measure of information asymmetry based on the original PIN model:

$$VPIN = \frac{\sum_{\tau=1}^{n} |V_\tau^S - V_\tau^B|}{nV}, \tag{5}$$

where V_τ^S, V_τ^B, and V are the seller-initiated, buyer-initiated, and total volumes in a bucket, and n is the number of buckets in a measurement window (say, a day). The buckets are divided in volume time so that each bucket contains the same number of shares traded. Compared to the original PIN, $VPIN$ is more flexible and utilizes the volume information. This paper follows Easley, Lopez de Prado, and O'Hara (2012) to use 50 buckets in calculating daily $VPIN$. $Spread$, $AVOI$, STD, and

[16]In Section E of the internet appendix, we test the effect on price efficiency using delayed price response to order imbalance following Chordia and Subrahmanyam (2004). The results also support the hypothesis that price efficiency improves after option listing.

$VPIN$ are calculated on a daily bases and then averaged in the two annual event windows before and after option listings. STD is calculated using all daily observations in the annual event windows. All these variables should be positively correlated with the level of information asymmetry.

Table 15 examines the option listing effects on these variables. We find that the average bid-ask spread decreases by 45.3% in the listing group and by 28.1% in the control group after option listing. The treatment effect of option listing is -17.2% with a t-statistic of -10.12. Analysis on $AVOI$, as an approximation of the expected value of PIN, shows that trading becomes more balanced after option listing. The average annual imbalance decreases by 23.4% for the listing stocks and 13.3% for the control stocks. The difference between the two groups averages at -10.1% and is significant at the 1% level. Similar to Mayhew and Mihov (2004), we do not find option listing significantly reduces the return standard deviation. Although the listing stocks have an average decrease of 2.4% in STD, the control stocks have an average decrease of 1.9%, making the treatment effect of -0.005 statistically insignificant. However, when we turn to the realized volatility (*RVol*), we find a significant reduction after option listing. Table 15 shows that *RVol* reduces by 24% for the listing stocks (t-statistic = -6.32), but no significant change in *RVol* of the control stocks. As a result, the treatment effect is -19.3%, statistically significant at the 1% level (t-statistic = -4.02). Finally, we find that the average $VPIN$ decreases by 19.3% for the listing stocks and 9.5% for the control stocks. The treatment effect is -9.8%, statistically significant at the 1% level (t-statistic = -17.38). Collectively, these results suggest that using alternative measures of information asymmetry, option listing still significantly reduces the level of asymmetry.

[Table 15 about here]

5. Conclusion

This article investigates the impact of option introductions on the information environment of the overall market. Between February 11, 2001 and February 28, 2010, we match each of the 1517 option listing stocks to an eligible, but non-listing, stock in the same month, and study the treatment effects of option listing on several stock market metrics based on the Duarte and Young (2009) model. The results show that option listing significantly reduces the probability of informed trading by 8.8% in the year after listing. Also reduced is the impact of liquidity shocks. Both informed and uninformed trading increase after option listing but the probability of information events does not change compared to the control group. The decline in the risk of trading against an informed trader is due to disproportional increases in the informed and uninformed trading. The results are robust to several alternative empirical methods including relaxing the full delta hedging assumption and using alternative order flow calculations, and exist in subsamples of stocks and after controlling for firm characteristics associated with the probability of informed trading. Dynamic analysis shows that the most significant structural break occurs in the first quarter after option listings. A quasi-natural experiment also confirms the causal effects of option listing by comparing stocks on the margin of the SEC requirement of option listing. A placebo test on ETF options shows that there is no significant change in the level of informed trading in these securities after option listing although the increased uninformed trading also reduces information risk. Consistent with our hypotheses, we also find that the listing effects are stronger for stocks with active otions trading and weak information environment before listing. Short-sale constraints play an important role in the option listing effects as the listing effect is stronger for the probability of informed trading based on good news than bad news. Finally, we find stock price response to earnings surprise weakens after options listing, indicating that the stock price efficiency improves after listing.

The findings suggest that information content in the options market documented by previous studies such as Easley, O'Hara, and Srinivas (1998), Pan and Poteshman (2006), and Hu (2014) does not come only from driving informed traders out of the stock market. Option introductions reduce the overall information risk and improve market liquidity. There is a net gain of information efficiency from options trading on top of substitutional effects to stock trading. The current analysis does not include informed trading on stock return volatilities. It is important to jointly analyze informed trading on both the stock price and the return volatility to uncover a more comprehensive picture of the options trading effects. Private information about volatility is profitable in the options market, but not so in the stock market given mixed empirical relations between the return and volatilities. Grossman (1988) points out that even if options can be synthesized by a dynamic trading strategy, the real trading process transmits volatility information that will not be revealed by the dynamic trading strategy. Back (1993) shows that information asymmetry and option introductions together cause stochastic volatility in the underlying market. Informed trading on volatility in the options market is unlikely to bias the results in this study because it has neutral impact on the stock prices and order imbalance if volatility traders use delta-neutral strategies such as straddles, or if both volatility traders and option market makers dynamically hedge the delta exposure of their option positions. The hedging transactions on the stock market can increase the total trading volume but will not make the stock order flow imbalanced. Therefore, these hedging trades can be viewed as liquidity trades in the stock market. Empirically, it is difficult to study the option listing effect on volatility trading because volatility trading is unobservable without options trading. Moreover, current microstructure theories are unable to produce empirical measures to disentangle informed trading on stock volatilities from that on stock prices. Without a reliable identification strategy of informed volatility trading, we leave the challenge to future studies. It would also be interesting to explore the role of index funds, ETFs, hedge funds, and other institutional investors in the increase of trading demand post option listing.

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Table 1

Number of option listing events over time

The table reports the time series distribution of the number of stocks selected for option listing between February 11, 2001 and February 28, 2010 as well as for the firm-month observations that are qualified for option listing but not selected. The selection criteria include: (1) the underlying must be listed on NYSE, AMEX, NASDAQ, or any other national stock exchange; (2) the stock price is not below \$3.00; (3) there must be at least seven million publicly-held shares; (4) there must be at least 252 trading days prior to this date; (5) the listing stocks must have options trading for at least 252 days after listing.

Year	Listing	Eligible Non-listing
2001	105	18117
2002	105	16660
2003	136	16516
2004	246	17409
2005	136	17372
2006	229	16525
2007	179	15127
2008	211	11931
2009	143	9792
2010	27	828
Total	1517	140277

Table 2
Determinants of option listing: logistic regression results
This table presents the regression results from a logit model for the option listing decisions. The sample includes all firm-month observations that meet the option listing criteria between February 11, 2001 and February 28, 2010. The dependent variable is equal to one for the firm-month observation when an options exchange listed a stock without options traded on it previously, and zero otherwise. The independent variables are log market capitalization ($Size_{t-1}$) in the last month, log average daily trading volume in the past 12 months ($Volume_{t-1,t-12}$), log average daily volume in the last month ($Volume_{t-1}$), log average daily volume in month $t-12$ ($Volume_{t-12}$), log standard deviation of daily returns in the past year ($STD_{t-1,t-12}$), log standard deviation of daily returns in the last month (STD_{t-1}), log standard deviation of daily returns in month $t-12$ (STD_{t-12}), average daily percentage bid-ask spread at market close in the past year ($Spread_{t-1,t-12}$), average daily closing spread in the last month ($Spread_{t-1}$), average daily closing spread in month $t-12$ ($Spread_{t-12}$), average daily volume order imbalance in the past year ($VOI_{t-1,t-12}$), average daily volume order imbalance in the last month (VOI_{t-1}), average daily volume order imbalance in month $t-12$ (VOI_{t-12}), average daily absolute volume order imbalance in the past year ($AVOI_{t-1,t-12}$), average daily absolute volume order imbalance in the last month ($AVOI_{t-1}$), average daily absolute volume order imbalance in month $t-12$ ($AVOI_{t-12}$), institutional ownership last month ($Institution_{t-1}$), institutional ownership one year ago ($Institution_{t-12}$), 71 two-digit SIC industry dummies, and year dummies. Associated t-statistics are in parentheses. *,**,***denote statistical significance at the 10%, 5%, and 1% level, respectively.

Model	(1)	(2)	(3)
Intercept	-19.560	-19.769	-11.143
	(-0.09)	(-0.09)	(-0.07)
$Size_{t-1}$	0.115^{***}	0.139^{***}	0.027
	(3.51)	(4.21)	(0.76)
$Volume_{t-1,t-12}$	-1.137^{***}	-0.769^{***}	-1.217^{***}
	(-18.79)	(-9.48)	(-13.15)
$Volume_{t-1}$	1.389^{***}	1.297^{***}	1.494^{***}
	(24.85)	(22.40)	(23.27)
$Volume_{t-12}$		-0.294^{***}	-0.287^{***}
		(-6.89)	(-5.69)

Table 2 (continued)

Model	(1)	(2)	(3)
$STD_{t-1,t-12}$	0.676***	0.416***	0.335***
	(7.34)	(3.58)	(2.71)
STD_{t-1}	0.240***	0.287***	0.003
	(3.78)	(4.31)	(0.04)
STD_{t-12}		0.242***	0.289***
		(3.46)	(4.00)
$Spread_{t-1,t-12}$	−0.132**	−0.294***	0.077
	(−2.26)	(−4.39)	(1.22)
$Spread_{t-1}$	−1.261***	−1.113***	−0.423***
	(−11.46)	(−9.86)	(−4.24)
$Spread_{t-12}$		0.031**	0.037**
		(2.49)	(2.20)
$VOI_{t-1,t-12}$			2.366***
			(3.66)
VOI_{t-1}			2.256***
			(5.77)
VOI_{t-12}			−0.271
			(−0.96)
$AVOI_{t-1,t-12}$			−7.264***
			(−7.79)
$AVOI_{t-1}$			−5.873***
			(−9.07)
$AVOI_{t-12}$			1.365***
			(2.98)
$Institution_{t-1}$			1.556***
			(7.77)
$Institution_{t-12}$			−0.697***
			(−3.41)
Industry Fixed Effects	yes	yes	yes
Year Fixed Effects	yes	yes	yes
McFadden's R^2	2.08%	2.12%	2.49%
Accuracy Ratio	85.7%	86%	87.6%

Table 3
Matching option listing stocks to eligible but non-listing stocks
This table compares the characteristics of the listing stocks and those of the matched control stocks. For each of 1517 listing stocks between February 11, 2011 and February 28, 2010, the eligible but non-listing stock with the closest propensity score of option listing in the same month is chosen without replacement. Sample statistics are reported for the log market capitalization before listing ($Size_{t-1}$), log average daily trading volume in the past 12 months ($Volume_{t-1,t-12}$), log average daily volume in the last month ($Volume_{t-1}$), log average daily volume in month $t-12$ ($Volume_{t-12}$), log standard deviation of daily returns in the past year ($STD_{t-1,t-12}$), log standard deviation of daily returns in the last month (STD_{t-1}), log standard deviation of daily returns in month $t-12$ (STD_{t-12}), average daily percentage bid-ask spread at market close in the past year ($Spread_{t-1,t-12}$), average daily closing spread in the last month ($Spread_{t-1}$), average daily closing spread in month $t-12$ ($Spread_{t-12}$), average daily volume order imbalance in the past year ($VOI_{t-1,t-12}$), average daily volume order imbalance in the last month (VOI_{t-1}), average daily volume order imbalance in month $t-12$ (VOI_{t-12}), average daily absolute volume order imbalance in the past year ($AVOI_{t-1,t-12}$), average daily absolute volume order imbalance in the last month ($AVOI_{t-1}$), average daily absolute volume order imbalance in month $t-12$ ($AVOI_{t-12}$), current institutional ownership ($Institution_{t-1}$), institutional ownership one year ago ($Institution_{t-12}$), and fitted probability of listing ($Prob_{fit}$) from Model (3) in Table 2.

	Listing		*Matched*	
Variable	Mean	Std. dev.	Mean	Std. dev.
$Size_{t-1}$	20.227	1.038	20.108	1.453
$Volume_{t-1,t-12}$	12.259	0.858	12.062	1.477
$Volume_{t-1}$	12.655	0.944	12.526	1.448
$Volume_{t-12}$	11.761	1.106	11.580	1.708
$STD_{t-1,t-12}$	−0.718	0.503	−0.738	0.546
STD_{t-1}	−0.738	0.591	−0.731	0.667
STD_{t-12}	−0.874	0.609	−0.884	0.626
$Spread_{t-1,t-12}$	0.626	0.779	0.730	1.019
$Spread_{t-1}$	0.385	0.450	0.431	0.421
$Spread_{t-12}$	0.897	1.587	1.043	1.910
$VOI_{t-1,t-12}$	0.022	0.064	0.022	0.062
VOI_{t-1}	0.027	0.085	0.031	0.082
VOI_{t-12}	0.012	0.116	0.012	0.125
$AVOI_{t-1,t-12}$	0.192	0.067	0.206	0.088
$AVOI_{t-1}$	0.157	0.060	0.162	0.067
$AVOI_{t-12}$	0.224	0.104	0.243	0.133
$Institution_{t-1}$	0.355	0.225	0.329	0.251
$Institution_{t-9}$	0.301	0.231	0.277	0.243
$Prob_{fit}$	0.060	0.073	0.053	0.057

Table 4

Option listing effects on market information environment

This table reports the option listing effect on the market information environment estimated using the Duarte and Young (2009) model. For each of 1517 listing stocks between February 11, 2001 and February 28, 2010, a control stock is chosen based on the predicted probability of option listing from Model (3) in Table 2. For both listing and control stocks, Panel A reports the averages of the probability of information events (α); the probability of a symmetry liquidity shock (θ); log daily order arrival rate of informed trades (μ); log additional uninformed order arrival rate on liquidity shock days (δ); log daily order arrival rate of uninformed trades (ε); the adjusted probability of informed trading (*APIN*); and the probability of a liquidity order from symmetric liquidity shocks (*PSOS*) estimated in one year before and after the listing date. Panel B reports the treatment effect of option listing on these variables. For each variable, the percentage change is calculated as the natural logarithm of the post-listing value minus the natural logarithm of the pre-listing value. The cross-sectional mean and associated t-statistics calculated using year-clustered standard errors (in parentheses) are then reported for the listing stocks, the control stocks, and the paired difference between these two groups. *,**,***denote statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: Averages of DY model parameters and constructs

	Listing stocks		Control stocks	
	Before	After	Before	After
α	0.304	0.322	0.300	0.314
θ	0.212	0.208	0.206	0.205
$\log(\mu)$	7.085	7.302	6.954	7.047
$\log(\delta)$	7.463	7.753	7.295	7.446
$\log(\varepsilon)$	6.213	6.805	6.003	6.355
APIN	0.155	0.133	0.160	0.149
PSOS	0.317	0.262	0.307	0.274

Panel B: Option listing effect

	Listing stocks	Control stocks	Listing − Control
α	0.058^{**}	0.096^{***}	−0.038
	(1.97)	(2.99)	(−0.87)
θ	−0.026	0.011	−0.037
	(−0.95)	(0.36)	(−0.90)
μ	0.217^{***}	0.093^{***}	0.124^{***}
	(7.81)	(3.12)	(3.07)
δ	0.290^{***}	0.150^{***}	0.140^{***}
	(10.67)	(5.18)	(3.51)
ε	0.592^{***}	0.353^{***}	0.239^{***}
	(33.74)	(18.62)	(10.01)
APIN	-0.157^{***}	-0.069^{***}	-0.088^{***}
	(−16.78)	(−7.07)	(−6.71)
PSOS	-0.168^{***}	-0.096^{***}	-0.072^{***}
	(−15.55)	(−8.18)	(−4.56)

Table 5

Deviation from full delta hedging

This table relaxes the full delta hedging assumption in the main analysis and reexamines option listing effects on the market information environment estimated using the Duarte and Young (2009) model. For each of 1517 listing stocks between February 11, 2001 and February 28, 2010, a control stock is chosen based on the predicted probability of option listing from Model (3) in Table2. For listing stocks, the model estimation after listing uses adjusted daily buyer- and seller-initiated stock volumes. Specifically, both buy and sell stock volumes are increased by half of the potentially unhedged options volume, equal to 25%, 50%, 75%, and 100% of the total options volume of the same stock on the same day in Columns (1)-(4), respectively. Reported are the treatment effect of option listing on the probability of information events (α); the probability of a symmetry liquidity shock (θ); log daily order arrival rate of informed trades (μ); log additional uninformed order arrival rate on liquidity shock days (δ); log daily order arrival rate of uninformed trades (ε); the adjusted probability of informed trading (*APIN*); and the probability of a liquidity order from symmetric liquidity shocks (*PSOS*). For each variable, the percentage change is calculated as the natural logarithm of the post-listing value minus the natural logarithm of the pre-listing value and the treatment effect is the paired difference between the listing and control stocks. Associated *t*-statistics calculated using year-clustered standard errors are reported in parentheses. *,**,***denote statistical significance at 10%, 5%, and 1% levels, respectively.

	Unhedged options volume			
	25%	50%	75%	100%
α	−0.039	−0.042	−0.038	−0.045
	(−0.93)	(−1.03)	(−0.84)	(−0.95)
θ	−0.037	−0.036	−0.035	−0.033
	(−0.86)	(−0.89)	(−0.88)	(−0.75)
μ	0.121***	0.129***	0.147***	0.141***
	(2.89)	(3.27)	(3.15)	(2.96)
δ	0.147***	0.148***	0.153***	0.155***
	(3.63)	(3.68)	(3.39)	(3.66)
ε	0.247***	0.253***	0.257***	0.252***
	(11.66)	(11.02)	(12.03)	(11.05)
APIN	−0.082***	−0.079***	−0.079***	−0.075***
	(−6.84)	(−6.23)	(−6.10)	(−5.48)
PSOS	−0.074***	−0.077***	−0.080***	−0.084***
	(−4.19)	(−5.58)	(−5.12)	(−5.64)

Table 6
Robustness checks of the option listing effects
For each of 1517 listing stocks between February 11, 2001 and February 28, 2010, a control stock is chosen based on the predicted probability of option listing from Model (3) in Table 2. Using the Duarte and Young (2009) model, this table examines the robustness of option listing effects on the averages of the probability of information events (α); the probability of a symmetry liquidity shock (θ); log daily order arrival rate of informed trades (μ); log additional uninformed order arrival rate on liquidity shock days (δ); log daily order arrival rate of uninformed trades (ε); the adjusted probability of informed trading (*APIN*); and the probability of a liquidity order from symmetric liquidity shocks (*PSOS*) estimated in one year before and after the listing date. For each variable, the percentage change is calculated as the natural logarithm of the post-listing value minus the natural logarithm of the pre-listing value for both listing and control stocks. The cross-sectional mean and associated *t*-statistics calculated using year-clustered standard errors (in parentheses) are then reported for the the paired difference between the two groups. In Column (1), the model parameters are estimated using the number of trades. Columns (2) and (3) report results in the subsamples of NASDAQ stocks, and NYSE and AMEX stocks, respectively. The financial crisis period of 2008 and 2009 is excluded in Column (4). Columns (5) and (6) report the results in subsamples that involve option listing on CBOE and non-CBOE exchanges, respectively. *,**,***denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) Number of trades	(2) NASDAQ	(3) NYSE+AMEX	(4) ex-GFC	(5) CBOE	(6) non-CBOE
α	−0.019	−0.080	0.008	−0.034	−0.001	−0.066
	(−0.65)	(−1.28)	(0.13)	(−0.70)	(−0.02)	(−1.14)
θ	−0.050*	−0.082	0.012	−0.046	−0.035	−0.039
	(−1.70)	(−1.46)	(0.20)	(−0.97)	(−0.54)	(−0.73)
μ	0.175***	0.107*	0.143**	0.121***	0.099*	0.143***
	(5.78)	(1.87)	(2.50)	(2.68)	(1.80)	(2.68)
δ	0.182***	0.112**	0.169***	0.137***	0.149**	0.133**
	(6.00)	(2.00)	(2.99)	(3.04)	(2.46)	(2.51)
ε	0.385***	0.216***	0.265***	0.244***	0.322***	0.177***
	(5.80)	(5.97)	(8.60)	(8.79)	(8.55)	(5.77)
APIN	−0.084***	−0.100***	−0.075***	−0.088***	−0.117***	−0.066***
	(−7.63)	(−5.24)	(−4.19)	(−6.06)	(−5.95)	(−3.77)
PSOS	−0.108***	−0.097***	−0.044*	−0.084***	−0.101***	−0.050**
	(−7.02)	(−4.75)	(−1.83)	(−4.63)	(−3.93)	(−2.54)
N	1517	791	726	1163	648	869

Table 7
Option listing effects controlling for firm characteristics
The table reports the ordinary least squares regression results in the sample of 1256 option listing stocks and 1283 control stocks between February 11, 2001 and February 28, 2010:

$$dY = b_0 Listing + b_1 dSize + b_2 dGrowth + b_3 dAnalyst + b_4 dTurnover + b_5 dInsider \\ + b_6 dInstitution + b_7 dROA + b_8 dSTD + b_9 dTobinQ + \eta,$$

where all variables are the changes from one year before option listing to one year after, except *Listing*, a dummy variable that is equal to one for the listing stocks and zero otherwise. *Size* is the natural logarithm of the market capitalization. *Growth* is the annual growth rate in sales. *Analyst* is the number of analysts following the company. *Turnover* is the annual stock market trading volume scaled by shares outstanding. *Insider* is the percentage ownership of company insiders. *Institution* is the percentage of shares held by institutional investors. *ROA* is the return on asset calculated as net income after depreciation over total asset. *STD* is the standard deviation of the daily returns. *TobinQ* is the market value of equity plus book value of debt over total asset. The dependent variables are annual changes in the estimates of the Duarte and Young (2009) model including the probability of information events (α); the probability of a symmetry liquidity shock (θ); log daily order arrival rate of informed trades (μ); log additional uninformed order arrival rate on liquidity shock days (δ); log daily order arrival rate of uninformed trades (ε); the adjusted probability of informed trading (*APIN*); and the probability of a liquidity order from symmetric liquidity shocks (*PSOS*). The associated t-statistics calculated using year-clustered standard errors are in parentheses. *,**,***denote statistical significance at the 10%, 5%, and 1% level, respectively.

Model Indep.\Dep.	(1) $d\alpha$	(2) $d\theta$	(3) $dlog(\mu)$	(4) $dlog(\delta)$	(5) $dlog(\varepsilon)$	(6) $dAPIN$	(7) $dPSOS$
Listing	−0.004	−0.004	0.153***	0.187***	0.343***	−0.014***	−0.030***
	(−0.56)	(−0.89)	(4.13)	(5.33)	(15.25)	(−8.99)	(−7.73)
dSize	0.065	−0.055	0.322***	0.403***	0.537***	−0.094***	−0.133***
	(0.84)	(−0.77)	(4.64)	(6.11)	(12.76)	(−3.94)	(−4.96)
dGrowth	0.002	−0.001	0.000	0.003**	0.003***	0.000	0.000
	(1.03)	(−0.55)	(0.32)	(2.43)	(2.88)	(−0.82)	(−0.03)
dAnalyst	0.130**	−0.168***	0.065	0.330***	0.260***	−0.019	−0.053**
	(2.10)	(−2.91)	(1.17)	(6.23)	(7.68)	(−1.02)	(−2.46)
dTurnover	0.001	0.003***	0.000	−0.001	0.001*	0.000	0.001
	(0.67)	(2.84)	(0.44)	(−1.03)	(1.67)	(−0.43)	(1.64)
dInsider	−0.004	0.004	0.005	−0.001	0.002	−0.001	0.001
	(−0.77)	(0.84)	(1.11)	(−0.21)	(0.81)	(−0.71)	(0.45)
dInstitution	0.339	−0.073	0.224	0.287	1.717***	−0.426***	−0.774***
	(1.30)	(−0.30)	(0.95)	(1.29)	(12.06)	(−5.30)	(−8.56)
dROA	0.090	−0.040	−0.304***	−0.275***	−0.287***	0.064*	−0.037
	(0.75)	(−0.36)	(−2.84)	(−2.70)	(−4.43)	(1.73)	(−0.91)
dSTD	−0.360***	−0.123	0.773***	0.774***	0.378***	−0.074***	0.164***
	(−4.36)	(−1.60)	(10.39)	(10.95)	(8.37)	(−2.90)	(5.74)
dTobinQ	0.010	0.000	0.054***	0.076***	0.095***	−0.020***	−0.006
	(0.63)	(0.00)	(3.92)	(5.87)	(11.51)	(−4.18)	(−1.23)
Adj R-sq	0.011	0.006	0.063	0.109	0.379	0.097	0.144

Table 8

Quarterly option listing effects

This table reports the quarterly option listing effects on the model parameters and constructs of Duarte and Young (2009) around the option listing date. For each of 1517 listing stocks between February 11, 2001 and February 28, 2010, a control stock is chosen based on the predicted probability of option listing from Model (3) in Table 2. Estimates with corner solutions are excluded and *N* is the number of observations in each event quarter. α is the probability of information events. θ is the probability of a symmetry liquidity shock. μ is the daily order arrival rate from informed trades. δ is the increment in uninformed order arrival rate on liquidity shock days. ε is the daily order arrival rate from uninformed trades. *APIN* is the adjusted probability of informed trading. *PSOS* is the probability of a trade from liquidity shocks. For each variable, the treatment effect is calculated as the difference in the quarterly percentage changes between the listing stocks and the control stocks. The cross-sectional mean and *t*-statistics calculated using year-clustered standard errors (in parentheses) of the treatment effects are then reported in event quarters relative to the option listing date. *,**,***denote statistical significance at the 10%, 5%, and 1% level, respectively.

Event quarter	(1) N	(2) α	(3) θ	(4) μ	(5) δ	(6) ε	(7) *APIN*	(8) *PSOS*
−3	1514	0.021	−0.011	0.053	0.059	0.043**	0.020	−0.007
		(0.54)	(−0.32)	(1.31)	(1.50)	(2.24)	(1.27)	(−0.44)
−2	1513	−0.006	0.049	0.017	0.032	0.037*	−0.025	0.035**
		(−0.15)	(1.36)	(0.45)	(0.86)	(1.95)	(−1.33)	(2.07)
−1	1515	0.038	−0.009	−0.036	−0.041	0.030	0.000	−0.053***
		(0.96)	(−0.26)	(−0.86)	(−1.01)	(1.61)	(−0.02)	(−3.06)
1	1514	−0.033	−0.055	0.120***	0.197***	0.125***	−0.051***	0.014
		(−0.83)	(−1.48)	(3.00)	(4.89)	(6.10)	(−3.36)	(0.78)
2	1515	0.068*	−0.011	−0.049	0.042	0.055***	−0.010	−0.017
		(1.77)	(−0.32)	(−1.28)	(1.06)	(3.33)	(−0.62)	(−0.99)
3	1513	−0.81*	0.051	0.078**	−0.076*	0.020	−0.024	−0.016
		(−1.92)	(1.46)	(2.03)	(−1.92)	(1.21)	(−1.43)	(−0.95)
4	1514	0.009	−0.049	0.003	0.036	0.012	0.005	−0.021
		(0.23)	(−1.40)	(0.07)	(0.90)	(0.73)	(0.28)	(−1.15)

Table 9

A quasi-natural experiment on option listing

This table reports the option listing effects in a quasi-natural experiment. The sample includes 56 listing stocks with prices above the SEC mandated minimum price by less than one dollar between February 11, 2001 and February 28, 2010. Control stocks are the non-listing stocks with prices below the SEC mandated minimum price by less than one dollar. Each listing stock is then matched to a control stock at the same time that has the closest predicted probability of option listing. Reported are the average treatment effects on Duarte and Young (2009) model's parameters and constructs including the probability of information events (α); the probability of a symmetry liquidity shock (θ); log daily order arrival rate of informed trades (μ); log additional uninformed order arrival rate on liquidity shock days (δ); log daily order arrival rate of uninformed trades (ε); the adjusted probability of informed trading (*APIN*); and the probability of a liquidity order from symmetric liquidity shocks (*PSOS*) estimated in one year before and after the listing date. For each variable, the percentage change is calculated as the natural logarithm of the post-listing value minus the natural logarithm of the pre-listing value. The cross-sectional mean and associated t-statistics calculated using year-clustered standard errors (in parentheses) are then reported for the listing stocks, the control stocks, and the paired difference between these two groups. *,**,***denote statistical significance at 10%, 5%, and 1% levels, respectively.

	Listing stocks	Control stocks	Listing − Control
α	−0.064	0.058	−0.121
	(−0.36)	(0.37)	(−0.52)
θ	−0.110	0.091	−0.200
	(−0.70)	(0.65)	(−0.93)
μ	0.309^{***}	0.022	0.287^{**}
	(2.70)	(0.15)	(2.19)
δ	0.309^{**}	−0.095	0.404^{*}
	(2.18)	(−0.69)	(1.82)
ε	0.710^{***}	0.283^{**}	0.427^{**}
	(7.37)	(2.05)	(2.58)
APIN	-0.218^{***}	-0.073^{*}	-0.145^{**}
	(−5.03)	(−1.74)	(−2.36)
PSOS	-0.263^{***}	-0.157^{***}	−0.107
	(−3.61)	(−3.01)	(−1.18)
N	56	56	56

Table 10
Option listing effects on ETFs

This table examines the option listing effects on the information environment of 85 ETFs between February 11, 2001 and February 28, 2010. For each listing ETF, a control ETF is chosen based on the predicted probability of option listing from the full-specification logistic model in Equation (1). Reported are the average treatment effects on the probability of information events (α); the probability of a symmetry liquidity shock (θ); log daily order arrival rate of informed trades (μ); log additional uninformed order arrival rate on liquidity shock days (δ); log daily order arrival rate of uninformed trades (ε); the adjusted probability of informed trading (*APIN*); and the probability of receiving a liquidity order from symmetric liquidity shocks (*PSOS*) based on Duarte and Young (2009) model in one year before and after option listing. For each variable, the percentage change is calculated as the natural logarithm of the post-listing value minus the natural logarithm of the pre-listing value. The cross-sectional mean and associated t-statistics calculated using year-clustered standard errors (in parentheses) are then reported for the listing stocks, the control stocks, and the paired difference between the two groups. *,**,***denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Listing ETFs	Control ETFs	Listing − Control
α	0.181**	0.164	0.017
	(2.12)	(1.57)	(0.12)
θ	0.208	0.030	0.179
	(1.37)	(0.22)	(0.85)
μ	0.175**	0.138	0.040
	(2.03)	(1.23)	(0.27)
δ	0.178	0.006	0.172
	(1.41)	(0.06)	(0.92)
ε	0.704***	0.224***	0.480***
	(8.96)	(3.25)	(4.76)
APIN	−0.139***	0.091	−0.230*
	(−5.04)	(0.60)	(−1.72)
PSOS	−0.103*	−0.166*	0.064
	(−1.73)	(−1.71)	(0.56)
N	85	85	85

Table 11

Option listing effects in firm characteristic portfolios

This table reports the option listing effects conditioning on the underlying stock's characteristics, including the total options trading volume (*OpVol*), the average options to stock volume ratio (O/S), average daily closing bid-ask spread in the year before listing (*Spread*), market capitalization (*Size*), number of analysts covering the stock (*Analyst*), average absolute earnings surprise ($|SUE|$) measured as the absolute difference between the actual earnings and the median analyst forecast scaled by the stock price at the end of the previous month, an earnings guidance dummy (*Guidance*) which is one for listing firms that provide any earnings guidance in the year before listing, and zero otherwise, average fraction of shares held by institutional investors in the four quarters before listing (*InstHolding*), the number of institutional investors at the time of listing (*NumInst*), and accounting accrual quality measured as the standard deviation of residuals from a regression of current accruals on lagged, current, and future cash flows from operations (*AccrualQuality*). The two options volume variables are calculated in the first year after listing and the other firm characteristics are calculated at the time of listing. For each characteristic, the listing stocks are sorted into quintile portfolios based on ascending order. The average option listing effects on the adjusted probability of informed trading (*APIN*) within each quintile portfolio are presented as well as the differences between the top and bottom quintiles with robust t-statistics.*,**,***denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *OpVol*	(2) O/S	(3) *Spread*	(4) *Size*	(5) *Analyst*	(6) $\lvert SUE \rvert$	(7) *Guidance*	(8) *InstHolding*	(9) *NumInst*	(10) *AccrualQuality*
Low	0.038	0.010	−0.031	−0.136	−0.099	−0.033	−0.106	−0.096	−0.131	−0.059
2	−0.060	−0.063	−0.083	−0.106	−0.065	−0.046		−0.076	−0.065	−0.075
3	−0.106	−0.102	−0.092	−0.095	−0.115	−0.075		−0.097	−0.067	−0.070
4	−0.143	−0.137	−0.095	−0.068	−0.066	−0.130		−0.121	−0.116	−0.097
High	−0.180	−0.149	−0.156	−0.037	−0.072	−0.146	−0.028	−0.020	−0.007	−0.138
High−Low	−0.218***	−0.160***	−0.125***	0.099**	0.027	−0.113***	0.079*	0.076**	0.123***	−0.080*
	(−5.27)	(−3.72)	(−2.97)	(2.42)	(0.58)	(−2.58)	(1.88)	(2.03)	(3.06)	(−1.86)

Table 12

Multivariate regressions of option listing effects

The table reports the OLS results of the option listing effect on *APIN*, the adjusted probability of informed trading based on the model of Duarte and Young (2009). The percentage change of *APIN* is calculated as the log of the post-listing value minus the log of the pre-listing value. The dependent variable of the regressions, the option listing effect, is the difference between the percentage change of the listing stock and that of the control stock matched on the propensity score of listing. *OpVol* is the average daily trading volume of all options on the same underlying stock in the first year after listing. O/S is the average daily ratio of options volume and the underlying stock trading volume. *Spread* is the average daily closing bid-ask spread in the year before listing. *Size* is market capitalization at the time of listing. *Analyst* is the number of analysts covering the stock. $|SUE|$ is the average absolute earnings surprise measured as the absolute difference between the actual earnings and the median analyst forecast scaled by the stock price at the end of the previous month. *Guidance* is an earnings guidance dummy which is one for listing firms that provide any earnings guidance in the year before listing, and zero otherwise. *InstHolding* is the average fraction of shares held by institutional investors in the four quarters before listing. *NumInst* is the number of institutional investors at the time of listing. *AccrualQuality* is accounting accrual quality measured as the standard deviation of residuals from a regression of current accruals on lagged, current, and future cash flows from operations. And *Trend* is a year indicator. Associated t-statistics calculated using year-clustered standard errors are in parentheses. *,**,***denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Intercept	0.486***	−0.297	0.258	0.278
	(4.63)	(−1.38)	(1.04)	(1.11)
OpVol	−0.061***		−0.060***	−0.06***
	(−5.37)		(−4.35)	(−4.35)
O/S	0.581**		0.637**	0.642**
	(2.22)		(2.12)	(2.13)
Spread		−0.033	−0.024	−0.029
		(−1.14)	(−0.82)	(−0.93)
Size		0.011	0.008	0.008
		(1.05)	(0.77)	(0.79)
Analyst		0.008	0.039	0.036
		(0.25)	(1.14)	(1.04)
$\|SUE\|$		−0.028*	−0.029*	−0.028*
		(−1.66)	(−1.70)	(−1.65)
Guidance		0.025	0.035	0.034
		(0.68)	(0.97)	(0.92)
InstHolding		−0.149	−0.088	−0.084
		(−0.42)	(−0.25)	(−0.24)
NumInst		0.001	−0.001	−0.001
		(0.36)	(−0.41)	(−0.34)
AccrualQuality		−0.646	−0.531	−0.534
		(−1.05)	(−0.85)	(−0.86)
Trend				−0.004
				(−0.47)

Table 13

Decomposing the option listing effects

This table reports the option listing effect on probabilities of directional informed trading estimated using the Duarte and Young (2009) model. For each of 1517 listing stocks between February 11, 2001 and February 28, 2010, a control stock is chosen based on the predicted probability of option listing from Model (3) in Table 2. For both listing and control stocks, Panel A reports the averages of the probability of an information shock being positive (β); the adjusted probability of informed trading for good news (*APIN_Good*); and the adjusted probability of informed trading for bad news (*APIN_Bad*) estimated in one year before and after the listing date. Panel B reports the treatment effect of option listing on these variables. For each variable, the percentage change is calculated as the natural logarithm of the post-listing value minus the natural logarithm of the pre-listing value. The cross-sectional mean and associated *t*-statistics calculated using year-clustered standard errors (in parentheses) are then reported for the listing stocks, the control stocks, and the paired difference between these two groups. Panels C and D replicate the analysis in Table 11 using *APIN_Good* and *APIN_Bad*. *,**,***denote statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: Averages of DY model parameters and constructs

	Listing stocks		Control stocks	
	Before	After	Before	After
β	0.588	0.566	0.572	0.569
APIN_Good	0.092	0.076	0.091	0.084
APIN_Bad	0.063	0.058	0.068	0.065

Panel B: Option listing effect

	Listing stocks	Control stocks	Listing − Control
β	-0.050^{***}	-0.007	-0.029^{***}
	(-5.48)	(-0.73)	(-3.04)
APIN_Good	-0.210^{***}	-0.061^{***}	-0.149^{***}
	(-15.72)	(-3.80)	(-5.93)
APIN_Bad	-0.101^{***}	-0.047^{**}	-0.054^{*}
	(-4.59)	(-2.21)	(-1.68)

Table 13 (continued)

	(1) *OpVol*	(2) O/S	(3) *Spread*	(4) *Size*	(5) *Analyst*	(6) $\lvert SUE \rvert$	(7) *Guidance*	(8) *InstHolding*	(9) *NumInst*	(10) *AccrualQuality*
Panel C: APIN_Good										
Low	−0.086	−0.100	0.004	−0.041	−0.054	−0.074	−0.179	−0.285	−0.080	−0.061
2	−0.040	−0.160	−0.247	−0.187	−0.230	−0.061		−0.096	−0.097	−0.217
3	−0.049	−0.127	−0.147	−0.153	−0.193	−0.084		−0.088	−0.097	−0.010
4	−0.259	−0.166	−0.101	−0.201	−0.110	−0.198		−0.119	−0.281	−0.215
High	−0.309	−0.207	−0.261	−0.173	−0.122	−0.219	−0.010	−0.164	−0.190	−0.191
High−Low	−0.223**	−0.107	−0.265**	−0.132	−0.069	−0.145*	0.169**	0.121	0.091	−0.131
	(−2.34)	(−1.27)	(−2.25)	(−1.23)	(−0.71)	(−1.65)	(2.51)	(1.43)	(1.03)	(−1.14)
Panel D: APIN_Bad										
Low	0.082	0.084	−0.020	−0.007	−0.003	−0.018	−0.063	−0.030	−0.102	−0.053
2	0.019	0.008	−0.092	−0.113	−0.094	−0.011		−0.104	−0.051	−0.013
3	−0.041	−0.152	−0.045	−0.053	−0.108	−0.012		−0.167	0.030	−0.101
4	−0.216	−0.160	−0.065	−0.048	−0.020	−0.087		−0.067	−0.082	−0.015
High	−0.126	−0.066	−0.066	−0.067	−0.036	−0.195	−0.011	0.026	−0.056	−0.140
High−Low	−0.208**	−0.150	−0.046	−0.060	−0.033	−0.177**	0.052	0.130	0.046	−0.087
	(−2.14)	(−1.62)	(−0.50)	(−0.67)	(−0.32)	(−2.00)	(0.77)	(1.58)	(0.51)	(−0.99)

Table 14

Option listing and price response to earnings surprise

The table investigates the option listing effect on stock price response to earnings surprise. For the listing stocks and matched control stocks in the study, four quarterly earnings announcements before and after the listing date are collected. Reported are the OLS regression results with year and firm fixed effects. The dependent variable is the cumulative abnormal return surrounding an earnings announcement. Earnings surprise SUE is calculated as the actual earnings minus the median analyst forecast then scaled by the stock price at the end of the previous month. $Listing$ is a dummy variable that equals one for option listing stocks and zero for control stocks. $After$ is a dummy variable that equals one for observations after the listing day and zero for those before the listing day. Associated t-statistics calculated using year-clustered standard errors are in parentheses. *,**,***denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
Intercept	0.001**	0.002**	0.003***
	(2.41)	(2.29)	(2.63)
SUE	0.002***	0.004***	0.002***
	(4.31)	(3.86)	(2.89)
$Listing$		-0.001	0.000
		(-0.94)	(-0.18)
$SUE * Listing$		-0.002^{*}	$-0.002)$
		(-1.89)	(-1.40)
$After$			0.000
			(0.26)
$SUE * After$			0.007*
			(1.79)
$Listing * After$			-0.001
			(-0.68)
$SUE * Listing * After$			-0.008^{***}
			(-3.20)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj. Rsq	0.121	0.121	0.122
N	19244	19244	19244

Table 15

Option listing effects on other stock market metrics

This table analyzes the treatment effects of option listing on $Spread$, the one-year average of daily percentage bid-ask spread; $AVOI$, the one-year average of absolute volume order imbalance; STD, the one-year standard deviation of daily returns; $RVol$, the one-year average of daily realized volatility; and $VPIN$, the order flow toxicity measure based on Easley, Prado, and O'Hara (2012). For each of 1517 listing stocks between February 11, 2001 and February 28, 2010, a control stock is chosen based on the predicted probability of option listing from the full-specification logistic regression in Column (3) of Table 2. For each dependent variable, X, the percentage change is calculated as the natural logarithm of the post-listing value minus the natural logarithm of the pre-listing value: $log(X_{after}) - log(X_{before})$. The cross-sectional mean and the associated t-statistics calculated using year-clustered standard errors (in parentheses) are then reported for the listing stocks, the control stocks, and the paired differences between these two groups. *,**,***denote statistical significance at the 10%, 5%, and 1% level, respectively.

Variable	Listing	Control	Listing - Control
Spread	-0.453^{***}	-0.281^{***}	-0.172^{***}
	(-26.65)	(-16.53)	(-10.12)
AVOI	-0.234^{***}	-0.133^{***}	-0.101^{***}
	(-33.43)	(-19.00)	(-11.22)
STD	-0.024^{**}	-0.019	-0.005
	(-2.40)	(-1.58)	(-0.42)
RVol	-0.240^{***}	-0.047	-0.193^{***}
	(-6.32)	(-1.24)	(-4.02)
VPIN	-0.193^{***}	-0.095^{***}	-0.098^{***}
	(-43.18)	(-22.14)	(-17.38)

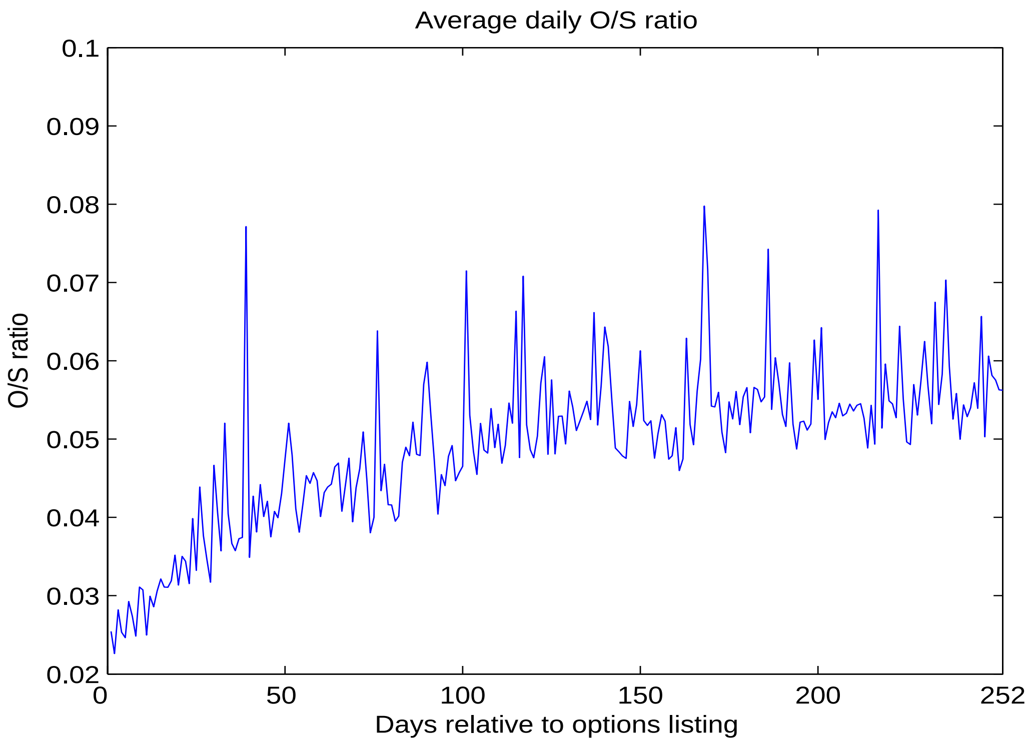

Figure 1
Options to stock volumes ratio in the first year after option listing
This figure plots the daily cross-sectional average of the O/S ratio in the first year after option listing for 1517 listing stocks between February 11, 2001 and February 28, 2010. The O/S is calculated as the total options volume divided by the total stock volume on the same day.