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Alejandro Bernales and Massimo Guidolin*

Abstract

We examine a number of unexplored factors that affect the *ex-post* adoption rates of newly listed stock options. We show that a variety of measures of information asymmetries for underlying stocks predict option adoption rates. This occurs even when we control for factors that have been found to be significant in earlier literature, such as stock volatility and volume. However, option listings induce a reduction in the strength of the information asymmetries in the underlying stock. Further, option bid-ask spreads start from low initial levels and increase over time, which is consistent with a modest initial aggressiveness of informed investors.

Keywords: Stock options; option listings; asymmetric information; adoption rates; option volume, open interest.

JEL Codes: D82; G10; G14; O31.

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1. Introduction

Since the first day of negotiations on the Chicago Board Option Exchange (CBOE) on April 26, 1973, when 911 plain vanilla contracts were opened for trading on 16 stocks, the U.S. equity option market has experienced an explosive growth. Between 1973 and 2011, in the United States alone, the equity option volume and the number of optioned stocks have grown on average by 34% and 19% per year, respectively. In 2011 over 1,534 million contracts have been traded on more than 3,684 stocks, for a total cleared premiums value in excess of 426 billion dollars.[1] Empirical evidence shows that the U.S. national system of options exchanges has become progressively more informationally efficient and better integrated with the underlying spot equity markets (see e.g., Battalio *et al.*, 2004). This development fits the stated goals of derivatives exchanges to foster efficiency and long-run viability of the financial system (see e.g., Mayhew and Mihov, 2004, p. 454). One of the important dimensions of efficiency in financial markets has long been identified with the removal of any information asymmetries between insiders and the general public of investors. Following a classical Grossman-Stiglitz's (1980) perspective, in this paper we ask whether stocks that are characterized—prior to option listing—by high degrees/likelihood of information asymmetries may enjoy greater chances of success (measured by option volume and open interest) when they are made optionable. This would therefore reduce the asymmetries *ex-post* and favour the overall efficiency of the financial system. We therefore empirically investigate whether and how popular, microstructure-based measures of information asymmetries (see e.g., Easley *et al.*, 2002) characterizing a stock prior to option introduction forecast a higher degree of ex-post success of options written on the same stock.

Because our paper investigates whether information asymmetries on individual stocks may predict the realized, *ex-post* success of options written on those stocks, it differs from a strand of research pursued, among others, by Mayhew and Mihov (2004) and Danielsen *et al.* (2007), through which financial economists have come to understand fairly well what are the factors that may lead a stock to be

[1] Information obtained from the Option Clearing Corporation (the common clearinghouse shared by all the option exchanges) web page, http:// www.optionsclearing.com

selected as an "optionable" one, i.e., a stock on which derivatives may be written. However, this is only an *ex-ante* perspective on the phenomenon: in spite of the enormous expansion of equity option markets, the newly listed options series have been characterized by rather heterogeneous adoption rates—as proxied by traded option volume and open interest—and hence, rather different success with investors. In fact, some of the options introduced have subsequently disappeared over time (i.e., the underlying stock has stopped being optioned) as a result of de-listings that may be imputed to low demand for the options themselves and not to the liquidation or merger of the underlying stock-issuing company.[2] To our knowledge, such an ex-post, realized perspective on option listing success is missing from the literature and of considerable importance to judge whether exchanges may effectively lure insiders to trade stock options, hence supporting the newborn derivative markets but also fostering the informational efficiency.

For instance, consider the option series written on Seagate Technology (ticker STX, an Irish-based technology company listed on the NADSAQ), that was introduced on the CBOE on Jan. 21, 2003. This option series (i.e., including all puts and calls that have been created and traded, spanning a range of strikes and maturities over time) has been remarkably successful: for instance, between 2008 and 2012, approximately 4.1 million Seagate options have been traded on the CBOE. In the week that followed the listing of Seagate options, also a new option series written on Sohu.com stock (ticker SOHU, a Chinese internet company listed on the NADSAQ) was introduced on the CBOE on Jan. 27, 2003. Yet—even though both companies seem to have remained healthy enough and both options sets have continuously traded since January 2003—the fate of the two option series has been very dissimilar, in the sense that between 2008 and 2012 less than only 600 thousands contracts written on Sohu.com have traded, roughly one-seventh the number of contracted traded on Seagate. What can explain this glaring difference between two option sets introduced at roughly the same time? Despite this latent and unexplained heterogeneity in the success of new option listings, to our knowledge there is no academic research that has empirically

[2] See "Exchanges Agree To Delist Options; More To Come", *Inside Market Data*, 26 Feb. 2006, Vol. 11 No 11.

investigated the factors that affect the actual, *ex-post* realized investors' adoption rates of newly listed options.

Because two important features of option markets are the presence of sophisticated investors and analysts, and the influential trading activity of informed agents, such as insiders (e.g., see Easley *et al.*, 1998b; Chakravarty *et al.*, 2004; Pan and Poteshman, 2006), we ask whether information asymmetries and/or analyst following may represent so-far neglected factors that may predict option listing success. In greater detail, first, we examine the determinants of the actual ex-post "success" (to be defined as adoption rates proxied in ways suggested by the micro-structure literature) of newly listed equity options, including factors that capture the liquidity, volatility, and market capitalization of the underlying stock. Interestingly, such an analysis is absent from the literature. Secondly, the high leverage that characterizes option markets, and the corresponding low margin requirements are particularly attractive to informed investors who can profit from their superior information on optioned stocks (see e.g., Black, 1975). Consequently, we emphasize the impact of information asymmetries on the success of option listings and place our emphasis on factors that are normally thought to measure the extent and depth of information differentials concerning optioned stocks. Thirdly, the empirical literature (e.g., Danielsen and Sorescu, 2001; Skinner, 1990) has widely recognized that option listings affect the asymmetric nature of information stocks and flows in the equity market. Therefore we also analyze the repercussions of option listings on information asymmetries, with a focus on the change of such measureable asymmetries between pre- and after-listing dates. Finally, we track the dynamics of average option bid-ask spreads after inception, which gives us indications on the dynamics of the extent of information-based trading in the aftermath of option introductions.

We use data from option listings on the U.S. equity option markets. Option listings are common examples of financial innovations in which new securities (option contracts) are introduced into the market (see e.g., Massa, 2002). In fact, option listings represent a rather special kind of security design innovation in that the number of option contracts traded is endogenously determined by investors: in option listings, a set of standardized contracts written on the same underlying stock are made available for trading on an option exchange.[3] However, for each new option (series) there is no initial "established number" of contracts that should be traded and this is different from other types of offerings in which the number of contracts is exogenously determined by the issuer and price adjusts to bring supply and demand in equilibrium. As a result, failure of the offering (e.g., an equity IPO) simply means a low trading price which may then be confounded by a myriad of complex, not-well-understood pricing factors. On the opposite, in the case of option listings, we can judge the success or failure on the sheer basis of traded volume and open interest, regardless of the realized, observed price for the newly created contracts.[4]

Studying the determinants of the option adoption process has also ramifications for our understanding of the effects and optimal design of innovation concerning financial securities. It is difficult to minimize the importance of a complete understanding of what determines the success of newly introduced derivatives. On the one hand, a traditional finance literature has emphasized that derivatives can and do improve market efficiency by lowering transaction costs (e.g., Merton, 1998), improving the quality of information flows (e.g., Boehmer *et al.*, 2010; Cao, 1999; De Jong *et al.*, 2006; Kumar *et al.*, 1998), and by reducing the overall level of aggregate, systemic risk (e.g., Klemkosky and Maness, 1980; Darby, 1994). On the other hand, it is under everybody's eyes the fact that unchecked processes of "financialization" based on the introduction of increasingly sophisticated securities (e.g., the collateralized mortgage obligations that have been often blamed for the worse excesses of the U. S. sub-prime bubble, see Coval *et al.*, 2009; or credit default swaps, see Boehmer *et al.*, 2010) may generate market instability and cause welfare losses to investors. Additionally, knowledge of the factors that influence the success of option

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[3] Differently from stock markets, where firms voluntarily apply to be listed, decisions to list options are made within the exchanges without any formal application by the stock-issuing company. For example, the bylaws of the CBOE include the criteria for options to be listed. These include share price, number of shareholders who are not insiders, and the trading volume of the underlying stock. Rule 5.4 lists the criteria that will cause the CBOE to stop listing options on a stock. The SEC also plays a role in determining the eligibility requirements for securities to be optioned, see e.g., http://www.sec.gov/rules.shtml.

[4] In option markets, investors themselves create the contracts in an endogenous process based on their demands and under the restrictions of standardization and clearing rules imposed by the option exchange.

listings may have policy implications especially with regard to the inspiring criteria that should regulate how option exchanges select optioned stocks.[5]

In this paper we consider option dollar-volume, option contract-volume, and open interest as alternative proxies for adoption levels of newly listed options (see Duffie and Jackson, 1989).[6] In addition, we use different measures as proxies for information asymmetries affecting stocks, including estimated, implicit indicators that rely on a range of microstructure models (e.g., *PIN* and adjusted *PIN*, where *PIN* means "probability of informed trading") as well as plausible observable proxies. We obtain a number of important results. First, we show that, even when we control for the effects of lagged volume and volatility, an elevated level of the information asymmetry indicators (measured in the year that precedes a listing) results in a higher rate of adoption among investors than it would otherwise be. In fact, our empirical results highlight that information asymmetries are as significant in forecasting the success of a listing as stock liquidity and volatility are. This positive relationship between the success of a listing and information asymmetries is consistent with few theoretical results (see e.g., Brennan and Cao, 1996; Vanden, 2008). The result that measures of information asymmetries are key predictors of option listing success is robust to using different proxies for the asymmetries, to a range of control variables, and to using either parametric or non-parametric econometric methods.

Second, we find that in the period immediately following an option listing, the option relative bid-ask spread displays on average a low initial level, with a tendency to increase over time. Such a low starting level for illiquidity costs, followed by an upward trend are somewhat surprising because the early "life" of an option should be marked—as one may expect after all kinds of financial innovations—by a relatively

[5] The existing literature seems to have ruled that out on purely ethical grounds. For instance, Mayhew and Mihov (2004) discuss the fact that "(...) exchanges may have been (...) wishing to emphasize the risk-management role and deemphasize the speculative role of options. More generally, we would suggest that an exchange interested in ensuring long-run viability should be concerned not only with generating immediate revenues, but should also consider other factors that promote long-run success. We would expect new exchanges to seek to invest in reputational capital (...)" (p. 454).
[6] The dollar-volume is the total value obtained by multiplying the number of option contracts that have been traded by their transaction prices and summing over a given period of time. The contract-volume (or simply, volume in what follows) simply cumulates the total number of contracts traded over time.

high illiquidity, so that comparatively *high* and not low bid-ask spreads are expected.[7] Nevertheless, despite the bid-ask spread surely includes a liquidity/inventory component, it is important to take into account that the other component of the spread reflects premiums that option market makers charge to execute orders in the presence of a non-zero probability of trading with informed agents (see e.g., Bartram *et al.*, 2008). In fact, the low initial values observed for the option relative bid-ask spread after listing can be explained by a modest level of early participation by informed investors in the new option market. It is the low volumes in the market of newly listed options that discourages informed traders away and hence causes relatively low bid-ask spreads. This is sensible because the early stages after option listings are characterised by a reduced trading volume, where even small transactions are noticeable and any trading activity by informed agents might be easily detected. As a result, informed investors will have incentives to hide their option trades by fragmenting them, or to simply wait for higher volumes, as reported by the empirical work in Chakravarty *et al.* (2004). Interestingly, the upward trend in the observed relative bid-ask spreads is more pronounced for option listings characterized by strong information asymmetries. This is because these listings imply that more informed investors shall need to start trading progressively, at a measured pace, to hide their presence as volume slowly picks up (see Mayhew *et al.*, 1995).

Third, also using a control sample methodology designed to correct for the endogeneity of option flotation, we find that information asymmetries significantly decrease after the listings. This is caused by the fact that option trading is expected to improve the informational efficiency of the security market as whole, in the sense that option trades contribute to reveal private information (e.g., Chern *et al.*, 2008; De Jong *et al.*, 2006; Kumar *et al.*, 1998; Senchack and Starks, 1993). In particular, option trades accelerate the rate of disclosure of information from informed investors as a result of the newly observable market activity (as predicted by theoretical models since Diamond and Verrecchia, 1987, and Jennings and Starks, 1986). Moreover, option listings create space and incentives for additional information collection and dissemination which may improve the analysis and interpretation of the information

[7] As standard in the literature, the inverse of the relative bid-ask spread is often used as a measure of liquidity, see among others Amihud and Mendelson (1986) and Conroy *et al.* (1990).

revealed by informed agents through their trading, as implied by the theoretical analyses by Cao (1999) and Massa (2002). For instance, we find that the number of analysts increases significantly after option introductions, similarly to Skinner (1990). However, our results are stronger because they extend to and are based on fine micro-structural measures of information asymmetries such as the probability of informed trading, which have been used widely in the literature as a proxy for asymmetric information.

Two earlier papers that analyze a related phenomenon, but only in an ex-ante perspective, are Mayhew and Mihov (2004) and Danielsen *et al.* (2007). They find that stock volatility and volume are the most important *ex-ante* factors used by option exchanges to select a stock as an optioned one. However, these papers do not study the *ex-post*, effectively realized adoption rate (success) that follows a listing. Our analysis also provides *ex-post* corroboration of the results in this early literature, by showing that option exchanges are on average "right" in terms of selecting optioned stocks using the factors in Mayhew and Mihov (2004) and Danielsen *et al.* (2007): stock liquidity and volatility are indeed good predictors of the actual, realized adoption rate after a listing.

Our empirical analysis also relates to a number of theoretical studies in which the introduction of derivatives in the presence of information asymmetries are jointly researched, although the emphasis of these papers is not specifically on the ex-post success of option listings. Brennan and Cao (1996) and Vanden (2008) present models in which information asymmetries are endogenously, positively related to option demand and volume. Cao (1999) finds that the introduction of derivatives could intensify the incentives to acquire additional information about the underlying asset payoffs. Massa (2002) develops a model with endogenous information acquisition when a derivative is introduced and where two types of agents exist, informed and uninformed investors. He shows that the incentives of the uninformed investors to purchase information depend on the market informational structure. Finally, a number of papers (among many, Duffie and Jackson, 1989; Duffie and Rahi, 1995) have studied the design of derivatives in a theoretical perspective, but without any empirical analysis of the effects of information asymmetries on the rate of option adoption.[8]

Section 2 further discusses our empirical hypotheses in the light of the literature. Section 3 describes the data and the micro-structure indicators of information asymmetry. Section 4 presents our main findings. Section 5 documents that option bid-ask display an upward trend that can be explained by informed traders hesitating before trading in thin markets. Section 6 analyzes the reduction in information asymmetries that follows the listing of options. Section 7 concludes.

2. Hypothesis Development

In this Section we develop three testable hypotheses using the existing literature on explanatory factors of option adoption as our logical background. Two papers provide such a starting point, Mayhew and Mihov (2004) and Danielsen *et al.* (2007). They find that stock volatility and volume are the most important *ex-ante* factors used by option exchanges to select a stock as an optioned one. However, these papers do not study the *ex-post*, effectively realized adoption rate (success) that follows a listing. Moreover, even though under rational expectations, one may expect the key ex-ante factors in the exchange decisions to also predict actual, ex-post option success, these papers do not extend their scope to an analysis of the role played by information asymmetries in explaining how and why option listings may meet with a rather mixed fortune.

In particular, as emphasized by Mahew and Mihov (2004) in an ex-ante perspective, newly opened option markets serve as venues for trading between investors with differences in beliefs. Therefore we expect that the underlying stock market return volatility will predict the ex-post realized option success. This occurs because for high volatility stocks, new information hits financial markets at a faster rate thus creating a higher potential for divergence of opinions among investors. However, their notion of “divergence of opinions” is not identical to the existence of

[8] In addition, a literature has investigated the factors that affect the ex-post realized adoption of futures contracts, for instance Nothaft *et al.* (1995) and Corkish *et al.* (1997). These studies find that stock volatility, liquidity, and market capitalization are key drivers. However, they do not study the interaction of asymmetric information and the adoption of derivative contracts.

information asymmetries, i.e., to the fact that a sub-set of investors may trade with the advantage of superior information: investors may simply interpret in different ways any symmetric information. However, the existence of information asymmetries clearly causes—at least before a sequence of trades reveals the superior information—the existence of differences of opinions among investors. We therefore hypothesize the existence of a causal link between the information asymmetries plaguing the market for the underlying stock prior to options listing and the ex-post realized success of such listings:

> *Hypothesis 1: High prior (to listing) information asymmetries affecting the market of the underlying stock predicts a high rate of adoption of newly introduced options.*

On the one hand, the general public of investors may wish to hedge the adverse effects of informed trading on their equity positions by trading options written on the stock. In this case, options markets will be perceived as venues in which uninformed investors try to shield themselves from informed investors' trades. On the other hand, informed investors may be eager for the stocks on which they have access to superior information to be optioned: options offer cheap ways in which private information may effectively be turned into profits. In fact, the literature (see e.g., Anand and Chakravarty, 2007; De Jong *et al.*, 2006, and references therein) tells us that there is strong empirical evidence of informed investors adopting fragmented trading strategies within option markets to try and maximize the trading profits from their private information. Also for this reason, we expect option listings to enjoy higher chances of ex-post realized success when the listings concern stocks that are characterized by pervasive information asymmetries.

Interestingly, if this causal link between information asymmetries and option listings were to be at work as our hypothesis 1 implies, then we expect not only the asymmetries to increase the chances of success of a listing, but to also heavily affect the way in which this success practically unfolds. Here one may naively expect that although a successful options market is characterized by high trading volume, this may follow a simple upward trend as the newly created market takes off. However, this conjecture fails to take into account the actual incentives of informed traders when it comes to operate in the option markets. If these markets are created to also provide informed investors with a cheap way to turn information into profits, we know (see e.g., Lee and Yi, 2001) then they will require adequate volumes to hide their trades behind the flow motivated by hedging and liquidity demands. This is consistent with the hiding strategies of informed agents in options markets reported by Anand and Chakravarty (2007).[9] Thus, the market makers intermediating the flow of trading in the newly created options markets will recognize this pattern of behavior of informed agents. This should lead them to progressively *increase* the component of the bid-ask spread which provides protection against dealing with traders with superior information.[10] This implies that our notion of a successful market may have straightforward implications for measures of volume and open interest, but not for measures of market liquidity such as the option bid-ask spread. However, absent a formal theoretical model, we expect only weak and variable links between the success of a listing and the option bid-ask spread, as summarized by:

Hypothesis 2: There is no simple, linear relationship between the rate of adoption of newly introduced options on a stock and their post-listing liquidity as measured by (relative) bid-ask spread measures that reflect an adverse selection component.

One more type of feedback occurring after option listing is worth of investigation: the changes in information asymmetries after the listing date. Here we expect the introduction of a new option to generate additional stock trading volume (the positive-sum-game described in Mayhew *et al.*, 1995) exactly for the stocks that

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[9] Anand and Chakravarty (2007) show that informed agents should optimally apply stealth trading strategies by fragmenting their orders into small (medium) trades for low (high) volume contracts. In addition, Biais and Hillion (1994) and Easley et al. (1998b) describe how an informed trader will arbitrage between spot and derivatives market when selecting where to trade, on the basis of their comparative depth and liquidity, and the amount of leverage achievable with options. DeJong et al. (2006) find that insiders trade aggressively in both the stock and the option, and typically trade in the market that affords the most profitable trading opportunity. Lee and Yi (2001) find that the adverse selection component of the bid–ask spread for all trade sizes is greater on the Chicago Board Options Exchange than on the New York Stock Exchange, which suggests that option traders are more information-motivated than stock traders are.

[10] Using intraday data for a sample of CBOE options, Lee and Yi (2001) have shown that large trades in the options market may be hardly anonymous, which might enable options market makers to screen large informed trades more effectively than in the stock market. This lack of anonymity in the options market will cause large investors with private information to behave differently than small investors. De Jong *et al*. (2006) have verified similar phenomena using an experimental set up. Kaul *et al.* (2004) have found that the adverse selection component of the underlying stock's spread explains a significant fraction of the option spread, i.e., that information asymmetries propagate from spot to derivatives markets.

have become optionable because characterized by high information asymmetries. If this is the case trading in the newly introduced options—even though this is optimally fragmented as described above—will increase the speed with which private information is incorporated into observed option and stock prices. As a result, measurable information asymmetries in the period following an option listing should decline, as in the theoretical analyses by Back (1993), Brennan and Cao (1996), Kraus and Smith (1996), and Vanden (2008):

Hypothesis 3: Option listings reduce the information asymmetries affecting the underlying stock.

Therefore, the causal link that our paper wants to emphasize has, after all, a "happy ending", if we assume that the goal of an efficient capital market is to compound all existing information into traded asset prices cheaply and quickly. The most resilient and successful option listings will concern underlying stocks plagued by strong information asymmetries. As a result, informed traders will progressively flock to the newly established option venue and do their best to extract the highest possible value from their information. As they do so, this makes the option market successful (because they generate volume as well as open interest), but also structurally not as liquid as initially "hoped" (and recorded, see Figure 1 in section 5). Moreover, the process of price discovery that they trigger leads to a decline in the strength of the information asymmetries in the sense that in the underlying stock market there are less information-driven trades (see e.g., Faff and Hillier, 2005), while the cheap and effective mechanisms of the options market favour a faster transmission of information into prices (see Chakravarty *et al.*, 2004). This last link of the chain has a classical Grossman and Stiglitz's (1980) flavour: informed traders are rewarded for their activity of acquiring information and taking it to the market; as they perform this role, they cause their privileged information to depreciate and to be incorporated into prices. The only, to us rather major, difference in the story of this paper is that—as a result of this virtuous mechanism—in the end the financial system finds itself enriched of a new and useful conduit for these information flows, the newly created option market.

3. Data and Construction of Asymmetric Information Measures

We use daily data on equity options (calls and puts) traded on the entire U.S. option market from the OptionMetrics database covering the period January 4, 1996 to October 30, 2009.[11] The data base contains daily information, including closing bid and ask quotes, volumes traded, and open interest. We calculate a proxy for the option dollar-volume by multiplying the number of transactions for each option contract by its end-of-day quote midpoint, and then aggregate this amount across all option contracts written on the same underlying stock, across maturities and strikes. All options that were listed for the first time in our sample period are selected and are the object of our investigation.[12] Because our goal consists of an analysis of the dynamics of the adoption process, in what follows we treat the listing date as the initial, "day zero" date across all option listings, even though it is clear that these occur at different points over the calendar period 1996-2009. This means that our empirical analysis is performed in event time and not in calendar time, although controls for the state of the market and of the economy that reflect calendar time conditions will be employed. Additionally, some exclusionary criteria are applied. All options whose underlying stock are affected by company events that may influence the measures of adoption (i.e., option dollar-volume, option volume, and open interest) such as splits, mergers, spin-offs, new equity issues, right offerings, or warrant issuing in the 12 months following day zero, are excluded.

The goal of our study is to analyze the role of asymmetric information in the option adoption process, and the behaviour of market participants when reacting to a new option listings. One key step therefore consists of the construction of measures of asymmetric information concerning the optioned stock. We resort to three alternative

[11] Between 1973 and 1975, options traded only on the Chicago Board Options Exchange (CBOE). In 1975 and 1976, option trading started on the American (Amex), Philadelphia, Midwest, and Pacific Stock Exchanges, but the Midwest exchange dropped out of the business in 1980. As of the end of our sample, options were also traded on the NYSE (ARCA), on the BATS exchange, on the BOX Exchange, on the International Securities Exchange (ISE), and on NASDAQ options circuit. Note that multiple listings of options are allowed and have become increasingly common after 1999. Since 1991 the SEC has also allowed the listing of options on securities other than common stock, such as preferred non-convertible stock, ADRs and country funds. However, in this paper we only consider optioned common shares of stock.

[12] Because multiple listings are possible, option may be introduced in one exchange even if the same (or at least, related) option contracts have been listed before in other exchanges. Therefore, we focus our attention exclusively on listing events in which the contracts are genuinely new and not already traded.

measures of asymmetric information. First, we calculate the probability of informed trading (*PIN*), which has been widely used in the literature since the seminal paper by Easley *et al.* (2002) (see e.g., Bharath *et al.*, 2009; Chan *et al.*, 2008; Roll *et al.*, 2009, for recent applications). Our second proxy of asymmetric information is the adjusted probability of informed trading (*AdjPIN*), an alternative measure of informed trading proposed by Duarte and Young (2009) to correct the fact that the standard *PIN* may often capture spurious liquidity effects. Finally, as a third measure of information asymmetries, we use the number of analysts which is a directly observable proxy for the level of asymmetric information (see Skinner, 1990). The use of the number of analysts is based on the premise that it should be easy for the market as a whole to detect any private information in trades when many highly trained observers, such as analysts are, were to analyze market activity, which should lead to a reduction in information asymmetries.[13,14]

The *PIN* and the *AdJPIN* indices are computed for each stock and they reflect the probability that orders concerning the stock may reflect informed trading. They are calculated from two different microstructure models that we summarize in Appendix A for the sake of completeness. Trade and Quote (*TAQ*) transaction data concerning the stocks underlying the option listings are used to compute estimates of *PIN* and *AdjPIN*. Resorting to *TAQ* data to measure asymmetric information scores effectively restricts our listing sample to optioned NYSE stocks. Data from *TAQ* are filtered using the same criteria as in Huang and Stoll (1996) and Danielsen *et al.* (2007). For example, we omit trades and quotes if they are flagged as being in a out of time sequence or involve either an error or a correction; we omit quotes if either the ask or bid price is zero or less; we omit trades if the price or volume is not greater than zero. *PIN* and *AdjPIN* measures are calculated both with reference to the year preceding and following the option listing.[15] Trades are classified as buys and sells

[13] The use of the number of analysts is however also supported by Easley *et al.* (1998a) who state that: "(...) high analysts stocks face a lower probability of information-based trading (...)" (p. 200). Also Roll et al. (2009) supplement their analysis based on PIN with the (inverse of the) number of analysts.

[14] Another possible proxy for asymmetric information is the dispersion of analysts' forecasts. However, we do not focus on this measure because Barry and Jennings (1992) have shown that diversity of opinions among analysts can increase even though the level of asymmetric information objectively declines.

[15] The estimation of *PIN* and *AdjPIN* on a pre- and post-listing annual basis is due to the fact that the level of accuracy of the estimates decreases enormously when these are computed over shorter periods of time, see e.g., Easley *et al.* (2002). For the purposes of this paper, a year is defined as a period of 252

following Lee and Ready's (1991) algorithm, as the likelihood functions presented in Appendix A use the daily number of buys and sells for each stock as data. Moreover, similarly to Easley *et al.* (2002), we exclude stocks for which we cannot find in TAQ at least 60 complete days of data concerning quotes and trades in the year prior to and the year following the listing of options written on a given stock, so to obtain reliable *PIN* and *AdjPIN* estimates.

We use Thomson's $I/B/E/S$ to extract data at monthly frequency concerning the total analyst following for each stock under investigation. We calculate the annual average of the monthly number of analysts publishing earnings forecasts for each of the newly optioned stocks; this estimate is produced for both the year before and the year after a listing. Because *PIN* and *AdjPIN* estimate the strength of the information asymmetries concerning a given stock and earlier literature (see e.g., Easley *et al.*, 1998a) has argued that low analyst following implies high information asymmetries, we also consider the inverse of the average of the number of analysts (*InvAnlst*) following a stock as a measure of information differentials alternative to *PIN* and *AdjPIN*.

Finally, the equity data required to compute the control variables used in this study (stock volatility, stock dollar-volume, and market capitalization) within our formal econometric analyses, are all obtained from the daily CRSP database and were available for all stocks for which new options were listed, as one would expect.

As a result of the merging of all these data sets as well as of the exclusionary criteria listed above, we obtain a final sample of 891 option listings for which we can estimate appropriate *PIN*, *AdjPIN*, and *InvAnlst* measures for both the year prior to and the year following the listings, over our 1996-2009 sample. Table 1 reports summary statistics for the key variables in this paper: $DVlm_{OP,1Y}$, $Vlm_{OP,1Y}$, and $OInt_{OP,1Y}$ are the average of the daily option dollar-volume, option volume (measured as number of traded contracts), and open interest, respectively, in the year after the option listing; $BAre_{OP,1Y}$ is the average of the relative bid-ask spread for the option during the year following the listing. PIN_{0Y}, $AdjPIN_{0Y}$, and $InvAnlst_{0Y}$ are the *PIN*

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trading days that precede (follow) the listing, with day zero excluded from both the prior and post-periods.

estimate, the *AdjPIN* estimate, and the inverse of the average number of analysts, referring to the year prior to listing; PIN_{1Y}, $AdjPIN_{1Y}$, and $InvAnlst_{1Y}$ are the *PIN*, the *AdjPIN*, and the inverse of the average number of analysts, concerning the year following the listing.[16] Interestingly, Table 1 shows preliminary evidence concerning a possible relation between changes in the strength of information asymmetries and the fact that options may be newly listed: The mean of the *PIN* estimates, the *AdjPIN* estimates, and the inverse number of analysts all strongly decline after the listing date, by −25.05%, −23.52%, and −24.24%, respectively. Simple tests for differences in means (proportions, under the assumption of constant variance) reveal that all these changes in information asymmetry indices are strongly statistically significant. For instance, the cross-sectional average of *AdjPIN* declines from 0.17 in the year prior to listing, to 0.13 in the year that follows the listing; the cross-sectional median for *AdjPIN* declines from 0.16 in the year prior to listing, to 0.13 in the year that follows the listing. Estimates of the decline in measured information asymmetries are even stronger in the case of *PIN* and *InvAnlst*. In section 5, we further test the significance of these changes using formal econometrics and for different sub-samples.

[Insert Table 1 here]

4. Key Empirical Findings

We use the option dollar-volume, the option volume, and the open interest as measures of adoption for newly listed options. The option dollar-volume and the option volume are selected because these are the main measure of success tracked by option exchanges when they assess a decision of listing new derivative securities (see Duffie and Jackson, 1989).[17] In addition, we use the open interest as a measure of the level of success of an option because in this market the number of contracts is established in an endogenous process based on investors' demands. Therefore, after

[16] Appendix B reports the cross-sectional distribution of the parameter estimates for the micro-structure models described in section 3 which are used to calculate *PIN* and *AdjPIN* (see Tables AI and AII).

[17] Quoting Mayhew and Mihov (2004): "Presumably, the main objective for an exchange is to maximize long-term profits for its members. In practice, according to industry sources, this amounts to listing those options expected to generate the highest trading volume." (p. 450)

an option listing, the open interest truly represents the willingness of investors to participate in and trade the newly listed securities.

The first objective of our study is to examine the different factors that can predict the *ex-post, realized* success of equity option listings. As an initial step, we use simple regressions which are estimated to test the significance of the determinants of option adoption. In the regressions, the dependent variables are the adoption levels (i.e., $DVlm_{OP,1Y}$, $Vlm_{OP,1Y}$, and $OInt_{OP,1Y}$), while the explanatory variables are the asymmetric information measures and a set of factors related to the liquidity, the volatility, and the market capitalization of the underlying asset in the year before the listing date. The asymmetric information measures are the probability of informed trading (PIN_{0Y}), the adjusted probability of informed trading ($AdjPIN_{0Y}$), and the inverse of the number of analysts ($InvAnlst_{0Y}$) in the year prior to the listing date. Further control variables (again, all calculated with reference to the year prior to listing) are included to coincide with the same "ex-ante" factors that Mayhew and Mihov (2004) identify as the main predictors of stock selection by exchanges for option listing: stock dollar-volume, distinguishing between its long-term ($DVlm_{S,252,0Y}$) and short-term ($DVlm_{S,21,0Y}$) components (daily averages using the previous 252 and 21 trading days, respectively); stock volatility, distinguishing between its long-term ($SDev_{S,252,0Y}$) and short-term ($SDev_{S,21,0Y}$) components (the annualized standard deviation of stock daily log returns over the 252 and 21 trading days, respectively); and total stock market capitalization ($Size_{0Y}$) for the year prior to listing.[18] As discussed in section 2, the inclusion of these control factors is important because while prior underlying stock volume and volatility may relate to ex-post realized option success because of the existence differences of opinions among traders that spill over from the spot to the derivatives market, prior measures of information asymmetries only capture the existence of objective differences in the information sets among traders. Moreover, it is clearly important for us to show that information

[18] Results are not sensitive to defining the explanatory variables with reference to the period that goes between 252 and 20 trading days before the option introduction, as in Danielsen *et al.* (2007). As they argue in their paper, the exclusion of the 20 trading sessions before option trading starts is sensible if the goal of the study is to isolate which factors are actually taken into account by options exchanges that rule over which stocks should be optioned, which is however not our objective here.

asymmetries predict ex-post realized option success even when the standard ex-ante factors—stock trading volume and volatility—are taken into account.

Therefore, our formal analysis is described by three simple linear models:

$$\begin{aligned} log\left(DVlm_{OP,1Y}\right) &= \phi + \beta_1 Asymmetry_{0Y} + \gamma_1 log\left(DVlm_{S,252,0Y}\right) + \gamma_2 \frac{DVlm_{S,21,0Y}}{DVlm_{S,252,0Y}} \\ &+ \gamma_3 SDev_{S,252,0Y} + \gamma_4 \frac{SDev_{S,21,0Y}}{SDev_{S,252,0Y}} + \gamma_5 log(Size_{\,0Y}) + \varepsilon, \end{aligned} \tag{1a}$$

$$\begin{aligned} log(Vlm_{OP,1Y}) &= \phi + \beta_1 Asymmetry_{0Y} + \gamma_1 log(DVlm_{S,252,0Y}) + \gamma_2 \frac{DVlm_{S,21,0Y}}{DVlm_{S,252,0Y}} \\ &+ \gamma_3 SDev_{S,252,0Y} + \gamma_4 \frac{SDev_{S,21,0Y}}{SDev_{S,252,0Y}} + \gamma_5 log(Size_{\,0Y}) + \varepsilon, \end{aligned} \tag{1b}$$

and

$$\begin{aligned} log(OInt_{OP,1Y}) &= \phi + \beta_1 Asymmetry_{0Y} + \gamma_1 log(DVlm_{S,252,0Y}) + \gamma_2 \frac{DVlm_{S,21,0Y}}{DVlm_{S,252,0Y}} \\ &+ \gamma_3 SDev_{S,252,0Y} + \gamma_4 \frac{SDev_{S,21,0Y}}{SDev_{S,252,0Y}} + \gamma_5 log(Size_{\,0Y}) + \varepsilon \end{aligned} \tag{1c}$$

where the variable $Asymmetry_{0Y}$ is identified with (a transformation of) either *PIN*, *AdjPIN*, or *InvAnlst*, ε is a random (measurement) error, and $log(\cdot)$ is the natural logarithm.[19] The short term components of liquidity and volatility are expressed in terms relative to the long-term components, to separate the two effects, i.e., $DVlm_{S,21,0Y}/DVlm_{S,252,0Y}$ and $SDev_{S,21,0Y}/SDev_{S,252,0Y}$ as in Mayhew and Mihov (2004).

The estimated coefficients from the models in equations (1a)-(1c) are reported in Table 2. The results in Table 2 are consistent with an *ex-ante* selection policy by option exchanges that consists in introducing option contracts only/principally written on stocks with high volume and high volatility, as already found by Mayhew and Mihov (2004) and Danielsen *et al.* (2007). Table 2 shows that also the *ex-post* levels of option adoption are positively and significantly related to stock volume and volatility in the year prior to listing. The long-term and short-term components of the stock dollar-volume are positively and significantly related to all the option adoption measures (fourth and fifth columns, respectively, in Table 2). The economic

[19] Because *PIN*, *AdjPIN*, and *InvAnlst* are either constructed as or are scaled to range between zero and one, their values are logistically transformed before statistically correlating them with other variables.

magnitude of such an effect is indeed large: for instance, holding all other factors the same and assuming that information asymmetries are measured by *AdjPIN*, a 1% increase in measured *stock* volume in the year prior to listing, increases post-listing *option* dollar-volume by 0.83%. A 1% increase in the measured short-term relative *stock* dollar-volume component starting from the cross-sectional average of this relative value—i.e., when more of the same one year prior volume comes from the short-term—raises increases post-listing *option* dollar-volume by 0.41%. However, only the long-term component of stock volatility is positively and significantly related the option adoption (sixth column in Table 2); the relationship between listing success and the short-term component of stock volatility is instead negative but insignificant (seventh column in Table 2).[20] The negative coefficients observed for the short-term component of stock volatility are however consistent with the results in Mayhew and Mihov (2004) who find evidence of a tendency in option exchanges to list options in periods when there is a decreasing stock volatility, probably a proxy for quiet market states. This finding shows that Mayhew and Mihov's results concern not only how option exchanges select stocks to become optioned, but also the fact that the exchanges are rightly using these factors to single stocks out, because volume and volatility are also precisely estimated and economically meaningful predictors of actual listing success.

[Insert Table 2 here]

We expect the underlying stock market volume to be an important predictor of ex-post realized option success because we impute rational expectations to stock option exchanges. These are member-owned organizations in which listing decisions are made by the members whose profits are an increasing function of trading activity. If the exchanges are on average right in their choice, they will introduce new option contracts that are ex-post successful, in the sense that the strong volume in the spot market is correctly anticipated to move to (or even, spill over to, in a positive-sum-game) high volume in the derivatives market. Similarly, we expect that the underlying stock return volatility will predict the ex-post realized option success. This occurs

[20] The economic effect of a 1% increase in long-term stock return volatility is however rather sizeable, a 26.7% increase in dollar-volume for options when information asymmetries are measured by *AdjPIN*.

because for high volatility stocks, new information hits financial markets at a faster rate thus creating a higher potential for divergence of opinions among investors that can be traded on and/or hedged by taking appropriate positions in derivatives.

However, stock volume and volatility do not represent end of the story, as far as ex-post adoptions are concerned: Table 2 also shows that the success of a listing is positively and significantly related to prior information asymmetries, even when one controls ex-post for Mayhew and Mihov's factors. Table 2, columns 1-3 all show evidence of a positive and significant relationship between *PIN, AdjPIN*, and *InvAnlst* (in the year prior to listing) and adoption levels (in the year following listings). The economic effects are quite large: for instance, holding all other factors constant, a 1% increase in *AdjPIN* (starting from its cross-sectional mean prior to listing, in Table 1) leads to an increase in post-listing option dollar-volume of 4.39%; the comparables values of the estimated elasticities for *PIN* and *InvAnlst* are 6.11 and 0.87, respectively. Results are similar as far as the effects on contract volume and open interest are concerned. For instance, a 1% increase in *AdjPIN* (starting from its cross-sectional mean prior to listing) leads to an increase in post-listing option contract volume of 4.39% and in open interest of 13.00%. Note that in the light of the recorded declines (see Table 1) in the values of *AdjPIN* (−25.05%), *PIN* (−23.52%), and *InvAnlst* (−24.24%) between prior and post-listing dates, an experiment based on a 1% change in these indicators is extremely realistic. Therefore, Table 2 supports the existence of significant, positive effects of information asymmetries on the adoption of new option contracts, consistently with our hypothesis 1.

Table 2 also shows that the total market capitalization of the underlying stock prior to listing shows a negative relationship with option success, although with insignificant coefficients (eighth column). This negative association is also coherent with our argument that information asymmetries are positive predictors of the success of equity option listings: larger firms normally suffer from lower information asymmetries because they receive more attention from analysts and regulators (see e.g., Bhushan, 1989), and they are generally more mature and successful firms which tend to benefit from effective mechanisms to provide information disclosure to investors (see, e.g., Diamond and Verrecchia, 1991). Should this be the case, then our indicators of information asymmetries in the first three columns prove to do a good job in picking up most of the effects on listing. This is also consistent with Mayhew and Mihov's (2004) result that firm size was an important determinant of listing through the 1980s, but became unimportant in the 1990s (our data start in 1996, when Mayhew and Mihov's end), and with the findings in Danielsen *et al.* (2007) that the market value of equity has a negative relation with the likelihood of option listing, consistent with smaller stocks being favoured as optionable candidates.

Moreover, to check whether the results are sensible to details of our logistic regression framework, we also use a matched sample analysis of option listings, with the objective of testing through a different econometric approach the positive relationship between asymmetric information and the success of option listings. To this purpose, we match the quartile of option listings for which there is evidence of strong information asymmetries on the underlying stock in the year prior to listing with the quartile of option listings that have low prior levels of asymmetric information. In practice, we follow Easley *et al.* (1998b) and select pairs of option listings that differ in prior underlying asymmetric information as much as possible but that are as similar as possible according to other matching criteria. Such a control sample methodology is designed to correct for the endogeneity of option listing. To achieve the goal of maximizing the difference in the informational dimension, the pairs are selected in the upper and lower quartiles of the cross-sectional distribution of *PIN*, *AdjPIN*, and *InvAnlst*, respectively, computed as usual with reference to the year prior to the listing date. Three matching criteria are simultaneously used: the industry to which the stock/firm belongs; the average daily stock dollar-volume over the 252 trading days before listing; the volatility of the underlying stock returns estimated as the annualized daily standard deviation over the 252 trading days prior to listing.[21] Once we have built the two matched samples, we apply the paired-sample sign test and the Wilcoxon signed-rank test to option adoption rates measured as option dollar-volume, contract volume, and open interest in the year *following* option

[21] For instance, suppose we want to match an option listing i with an option listing j. Option listings i and j have underlying stock dollar-volumes $DVlm_{S,i}$ and $DVlm_{S,j}$, and underlying stock volatilities $SDev_{S,i}$ and $SDev_{S,j}$, respectively. Given a listing i, when possible our algorithm selects j in the same industry as i by further minimizing the sum of the absolute relative differences between stock volumes and return volatilities, i.e., $\min_j[|(DVlm_{S,i} - DVlm_{S,j})/ DVlm_{S,i}| + |(SDev_{S,I} - Sdev_{S,j})/SDev_{S,i}|]$.

listings. Therefore, if high information asymmetries prior to listing positively affect the listing success, the upper quartile of listings ranked by *PIN*, *AdjPIN*, and *InvAnlst* (i.e., the quartile with options with the strongest prior asymmetric information) should display the highest values of the adoption indices in the first year of the option "life".

In Table 3, Panels A and B, the matched pairs from the lower and upper quartiles of option listings ranked by *PIN* and *AdjPIN* are used to test the differences in option success. The null hypothesis of no differences in adoption is tested against the one-sided alternative of higher adoption rates in the upper quartile vs. the lower quartile. Table 3, Panel A (Panel B) shows that out of 152 (141) pairs of matched listings, 95 (89), 92 (92), and 93 (86) of the pairs have larger levels of dollar-volume, contract volume, and open interest, respectively, in the group of listings characterized by elevated prior information asymmetries.[22] In addition, in Panel A (Panel B), the median of the percentage differences in option dollar-volume, contract volume, and open interest between listings from the upper vs. the lower quartiles are 152.1% (200.7%), 103.0% (186.7%), and 163.3% (238.4%), respectively. These are very large differences. The null hypothesis of no differences (i.e., of a zero median percentage change) can be rejected at the 1% level using both tests (paired-sample sign and Wilcoxon signed-rank tests), both measures of asymmetric information, and all adoption measures. Consequently, the rejection of the null hypothesis of equal adoption rates independently of the strength of the underlying information asymmetries in Table 3, Panels A and B, implies that we can also reject the null that prior information asymmetries do not affect the success of option listings.

[Insert Table 3 here]

Table 3, Panel C shows results similar to those in Panels A and B, although in this case the lower and upper quartiles are selected sorting the cross-section of

[22] The number of option listings in the lower and upper quartiles is 222 (891/4 = 222.75). However the number of pairs matched from the lower and upper quartiles is less than 222 because the matching criteria do not always allow perfect matching. The main matching constraint is that the two extreme quartiles contain different numbers of listings in different industries, and therefore this criterion reduces the number of pairs of listings that we are able to analyze. In addition, we impose a constraint by which the maximum absolute total relative difference used in the matching process cannot exceed 40% for the stock dollar-volume and return volatilities, i.e., we prevent poorly matching pairs to be formed.

listings on the basis of the inverse of the number of analysts following the underlying stocks. In Panel C, the null hypothesis of no difference in the adoption rates is tested against the one-sided alternative of faster adoption in the upper quartile group than in the lower quartile. We find that out of 146 pairs of matched listings 99, 97, and 96 of the pairs have higher dollar-volume, contract volume, and open interest in the upper quartile group than in the lower quartile. The null hypothesis of no difference in the rate of listing success is also rejected at the 1% level using both tests and all adoption measures.

However, because our analysis has focussed on listings using as its base date the official start of negotiations, one may object that Table 3 may be affected by considerable non-synchronicity, in the sense that many or even most of the pairs of listings may implicitly compare options that have been newly introduced in the market at very different times. Therefore we have reproduced in Table 4 a similar matched sample analysis as in Table 3, but this time making sure that the matched pairs are not separated in calendar time by more than 252 trading days.[23] Table 4 shows that the effects of prior information asymmetries on option listing success are even stronger after including this additional time-window constraint when building the matched pairs. The null hypothesis of no differences in adoption rates is again rejected at the 1% level, against the one-sided alternative of finding higher rates in the upper quartile group using both tests, the three measures of asymmetric information, and all adoption measures.

[Insert Table 4 here]

Consequently, the results in Tables 3 and 4 are consistent with the empirical evidence presented in Table 2 that stronger information asymmetries characterizing the underlying stock predict a greater success—as measured by the strength of adoption—for any options written on the same stock, when these are eventually listed. This is consistent with our key hypothesis 1. Therefore, an important implication of these findings for the actual, *ex-post* dynamics of option trading and

[23] For example, suppose we match an option listing *i* with an option listing *j*. We use the same matching criteria as in Table 3, but if option *i* is listed on day *t*, option *j* is now required to have been listed over the period [t-252, t+252] for the pair to be matched.

open interest is that option exchanges should also take prior asymmetric information measures into account when *ex-ante* making listing decisions.

5. Relative Bid-Ask Spreads and Informed Trading Activity in Option Markets after New Listings

In our analyses we have also found that that the option relative bid-ask spread, $BAre_{OP}$, starts at low initial levels but subsequently displays a tendency to progressively increase.[24] This pattern of the $BAre_{OP}$ is presented in Figure 1, which shows the evolution of the cross-sectional daily average (for the complete sample of all listings) of $BAre_{OP}$ and the option dollar-volume in each month over the first year after listing. The low starting level of $BAre_{OP}$ is particularly interesting because in the early "life" of a (set of) option contracts these are normally characterized by substantial illiquidity, as one would expect of all newly created securities. Therefore, high and not low $BAre_{OP}$ values should be expected because the inverse value of the relative bid-ask spread is as a standard proxy to measure liquidity in the literature (see e.g., Amihud and Mendelson, 1986).

[Insert Figure 1 here]

We conjecture that the initial low levels of $BAre_{OP}$ can be explained by a modest level of informed option trading activity in the early stages after option listings. On the one hand, even though it is well known that bid-ask spreads contain an inventory/liquidity component, the spread also reflects a component caused by the possibility of informed traders inflicting losses to market makers (see e.g., Copeland and Galai, 1983; Glosten and Milgrom, 1985); such a component is therefore an increasing function of any information asymmetries. This asymmetric information component has been characterized in models that capture the adverse selection problem faced by market makers.[25] On the other hand, immediately after the listing

[24] The relative bid-ask spread (BAre) is defined as BAre = (Ask Price – Bid Price)/(0.5(Ask Price + Bid Price)).

[25] The *PIN* and the *AdjPIN* estimates obtained from underlying stock data using the microstructure model in Appendix A rely exactly on these arguments. An alternative proxy for the probability of informed trading could be given by *PIN* or *AdjPIN* estimated from intra-day option data. However, it would be difficult to obtain reliable *PIN* and *AdjPIN* estimates bases on options data because of the modest trading activity that usually characterizes the immediate post-listing periods.

date, option contracts tend to be characterized by moderate volume at best, which only slowly grows over time (see Figure 1). Therefore, in the early stages after a listing, informed trades could be easily detected. As a result, rational informed investors are deterred from trying to hide their trades by fragmenting them and decide instead to optimally wait for volumes to pick up over time. Consequently, one may indeed see $BAre_{OP}$ start out low and progressively increase as volumes—hence the possibility to fragment informed trades in sequences of smaller, hard-to-detect orders as characterized by Anand and Chakravarty (2007)—pick up.

To corroborate this conjecture, we use a two-pronged strategy, in Tables 5 and 6. In a first step, we analyze matched samples to test the significance of the growth in $Bare_{OP}$ over time (see Table 5, Panel A), using the following logic. We calculate cross-sectional averages of relative bid-ask spreads with reference to both the first and the thirteenth months after listing, matched in pairs of $BAre_{OP}$ values. Paired-sample sign and the Wilcoxon signed-rank tests are then applied to test whether relative bid-ask spreads increase significantly between the first month and the initial thirteenth months over the option 'life'. The null hypothesis of no change in $BAre_{OP}$ is tested against the one-sided alternative of an increase in $BAre_{OP}$. Table 5, Panel A, shows that out of the 891 option listings in our sample, 689 display a widening $BAre_{OP}$ when one compares the thirteenth- with the first-month after listing; the median percent increase is a stunning 40.59%, with the median relative bid ask spread growing from 0.32 just after listing to 0.44 13 months after listing. The null hypothesis of no difference is formally rejected at 1% under both types of tests, paired-sample sign and the Wilcoxon signed-rank tests.

[Insert Table 5 here]

Furthermore, to check for potential biases in the results in Table 5 due to variations in market conditions after listings, we use a further control group of 891 equity options with at least three years of market activity after their listing dates. The spirit of the test is to verify that long after the listing, the relative bid ask spread stabilizes as the flow of access of informed traders to the options market does (or, alternatively, as information asymmetries disappear, see section 6 and hypothesis 3). Therefore each of the newly listed contract series in Table 5 is matched to a "seasoned" stock option. The matching is performed using the same criteria behind Tables 3 and 4: the underlying stock industry, the underlying stock return volatility (annualized standard deviation of daily returns over the 252 trading days prior to listing), and underlying stock volume (mean of daily dollar-volume over the 252 trading days prior to listing). In Table 5, Panel B, no significant increasing (or decreasing) patterns for option relative bid-ask spreads are found for the control sample of seasoned listings. It seems that past the thirteen month after listing, the relative bid ask spread stabilizes at around 0.46-0.47. In fact, the percent change in $BAre_{OP}$ between the first and thirteenth month following the listing date for the baseline sample of listings (Table 5, Panel A) is strongly significantly larger than the percentage change observed for the seasoned controls (data from Table 5, Panel B), using both the paired-sample sign and the Wilcoxon signed-rank tests. In addition, in an unreported test, we verify that the percent change in BAreOP for option listings in Tables 5 Panel A is significantly more positive than the same percent changes in BAreOP of the control group (Tables 5 Panel B).

Additionally, we perform a matched sample analysis to evaluate the impact of any fragmentation strategies implemented by informed option traders on the changes in relative bid-ask spread (*ΔBare*). In Table 6, we match the group of option listings for which we have evidence of strong information asymmetries on the underlying asset in the year prior to option listings with listings that have instead low prior levels of asymmetric information (i.e., listings in the upper vs. lower quartiles of *PIN*, *AdjPIN*, and *InvAnlst*, respectively). We use the same matching criteria as before and apply to the resulting sample of matched pairs the usual sign- and signed-rank tests to the null of no change in *ΔBare*. The intuition is that only when an option listing is successful, it is the case that informed investors may progressively ripe the advantages of growing volumes to hide their trades. However, this is exactly what a rational market maker would anticipate, thus ending up widening the relative bid-ask spreads over time.

[Insert Table 6 here]

Table 6 shows that the listings characterized by previously high levels of information asymmetries imply larger changes in the option relative bid-ask spread than the listings with low prior asymmetric information. For instance, Table 6, Panel

A, shows that out of 152 pairs of matched option listings 89 of the pairs have larger *ΔBare* values in the quartile characterized by elevated prior information asymmetries, as ranked by *PIN*. The null hypothesis of no differences in *ΔBare* can be rejected with p-values always inferior to 5%, using both tests and all measures of asymmetric information. The results reported in Table 6 are consistent with our conjecture that informed option traders would wait for sufficient volume to flood the market before implementing their typical stealth strategies. Hence option listings concerning stocks plagued by strong information differentials would only eventually attract—also because these are truly the options that are most successful on average, also thanks to the trading activity of these informed investors—a large number of informed option traders who however would avoid trading in the immediate aftermath of listing.

Finally, in Table 7 we have repeated the same analysis as in Table 6 when we include an additional constraint by which matched pairs are formed under the additional restriction of the any pair of listings having occurred within 252 trading days (similarly to the time-window constraint already applied in Table 4). The goal of this further restriction is to prevent results to be driven by paired samples characterized by large disparities in the calendar dates of the listings. The null hypothesis of no difference in *ΔBare* is again rejected with p-values well below a 5% size, against the one-sided alternative of larger *ΔBare* values in the upper vs. the bottom quartiles, and using both tests and all measures of asymmetric information.

[Insert Table 7 here]

6. The Effect of Option Listings on Information Asymmetries

As already conjectured in section 2, the ex-post dynamics triggered by the introduction of new option may eventually record a "happy ending". In spite of the fact that optioned stocks characterized by stronger information asymmetries score the greater success and that this may initially happen at the expenses of the liquidity in the derivatives market, the introduction of option-style derivative contracts end up improving market quality, in the sense that markets may become increasingly informationally efficient. In our empirical tests, we find indeed that information asymmetries decline after options are newly listed. Such a decline derives from a learning process by the uninformed agents that are now able to exploit the visibility of the trades by the informed traders in options to infer their private information.[26] Moreover, after an option listing, it is customary that multiple standardized option contracts on the same underlying asset are simultaneously introduced (for instance, along the strike and maturity dimensions), so that there are strong incentives for all investors towards collecting increasing amounts of information concerning the underlying asset's payoffs (see e.g., Cao, 1999; Massa, 2002). Therefore, option listings ought to induce an increase in the number of market analysts following the underlying stock (e.g., Skinner, 1990) as well as a decline in the fraction of trades that are backed by private information, as the latter asymptotically vanishes (or, its exploitability declines) in a market in which option trades contribute to the efficient dissemination of company news. In fact, the tendency for the number of analysts to increase is also instrumental to further reductions in information asymmetries, as the scrutiny of news and trades offered by skilled professional facilitates the detection of any private information.

Similarly to section 4, we use the *PIN* and the *AdjPIN* measures to analyze any changes in information asymmetries that follow option listings. For each newly listed option, we compare two estimates of *PIN* and *AdjPIN*: the values estimated over the year that precedes the listing date (PIN_{0Y} and $AdjPIN_{0Y}$) and the values estimated over the year following the listing (PIN_{1Y} and $AdjPIN_{1Y}$). The paired-sample sign and the Wilcoxon signed-rank tests are then applied to the different *PIN* and *AdjPIN* estimates. In Tables 8 and 9, the null hypothesis of no change in the asymmetry measures is tested against the one-sided alternative of a decrease after the listing. The two tests are applied to a few alternative sub-samples (in descending order in the table): the complete sample of listings; the listings in the lower and upper quartiles as computed by using $DVlm_{OP,1Y}$; the listings in the lower and upper quartiles by $Vlm_{OP,1Y}$; and listings in the lower and upper quartiles by $OInt_{OP,1Y}$. Reporting results sorted by quartiles of measures of adoption helps to test whether it is the newly admitted trading in options that cause the decline in measured information asymmetries. If that

[26] The main cognitive mechanism followed by uninformed investors may consist of a learning-by-observing process which assumes that agents do not live in an isolated environment and in which, on the opposite, their surroundings represent a source of additional knowledge (e.g., see Bikhchandani *et al.*, 1998; DeLong and DeYoung, 2007).

is the case, the decline in the latter should be stronger the higher is the success of a listing, i.e., for listings in the upper quartiles of $DVlm_{OP,1Y}$, $Vlm_{OP,1Y}$, and $OInt_{OP,1Y}$. Table 8 concerns *PIN* while Table 9 concerns *AdjPIN*. In both tables, we find that information asymmetries concerning optioned stocks substantially decline after options are listed. This means that the data fail to reject our hypothesis 3 from section 2. For instance, Table 8, first row (Table 9, first row) shows that out of the 891 option listings in our complete sample, 532 (558) have lower *PIN* (*AdjPIN*) values after the listing date, with a median percent change of -22.5% (-20.0%). Moreover, in both cases the null hypothesis of no differences in *PIN* and *AdjPIN* estimates before and after option listings is rejected with p-values smaller than 5% using both paired-sample sign and the Wilcoxon signed-rank tests and for all quartiles.

[Insert Table 8 here]

[Insert Table 9 here]

However, in Tables 8 and 9, we also note that—as expected—the listings in the higher quartiles of success (independently of how this is measured) imply larger effects compared to option listings in the lower quartiles. For instance, in Table 9, last two panels, *AdjPIN* declines by a median 14.9% in the case of the bottom post-listing open interest quartile vs. a much larger 30.6% decline in the case of the upper post-listing open interest quartile, which is more than double. The higher impact recorded in the upper quartile listings are consistent with a learning-by-observing hypothesis à la DeLong and DeYoung (2007): in the upper quartiles built sorting by adoption rates, market activity following a listing is, by construction, stronger than for other quartiles, so that large amounts of private information may be revealed through trading in newly listed options. This is related to recent findings by Roll *et al.* (2009) concerning the trading of seasoned options: they report that "liquidity-attracts-liquidity" so that highly traded options increase firm value because, besides completing markets, they stimulate informed trades and therefore informational efficiency.

Furthermore, to check for potential biases in the results in Tables 8 and 9 due to variations in market conditions after listings are decided, we use a further control group of 891 equity options with at least three years of market activity after their listing dates. The spirit of the test is to verify that long after the listing, the reduction effects on measurable information asymmetries become negligible, or at least rather weak, which is also consistent with the learning-by-observing hypothesis: initial effects from learning from the trading environment ought to be stronger than steady-state effects. Therefore each of the newly listed contract series in Tables 8 and 9 is now matched to a "seasoned" stock option. The matching is performed using the same criteria behind Tables 3 and 4.

Tables 10 and 11 reproduce the analysis in Tables 8 and 9 using the control group of seasoned options. Table 10 shows that there are no significant reductions in information asymmetries concerning the underlying stocks for options in this control group. For example, Table 10, first row (Table 11, first row) shows that out of the 891 equity options in the complete control group, 458 (463) have lower *PIN* values (*AdjPIN* values) after the listing date but with a median percent change of only -1.35% (-1.59%). The null hypothesis of no changes in *PIN* and *AdjPIN* estimates after the introduction date cannot be rejected at conventional significance levels for all sub-groups based on quartiles and using both the paired-sample sign and the Wilcoxon signed-rank tests. In addition, in unreported tests, we verify that the percent change in *PIN* and *AdjPIN* of matched listings in Tables 8 and 9 over the year prior to and the year following listing are significantly more negative than the same percent changes in *PIN* and *AdjPIN* of their controls (Tables 10 and 11), also in this case using paired-sample sign and Wilcoxon signed-rank tests at a 5% size. Therefore, Tables 10 and 11 strengthen earlier evidence that changes in information asymmetries are fundamentally related to option listings and not to the mere fact that options are traded, independently of their recent introduction.

[Insert Table 10 here]

[Insert Table 11 here]

Additionally, similarly to Damodaran and Lim (1991) and Skinner (1990), we find that the number of analysts significantly increases after option listings, which is the evidence presented in Table 12. In Table 12 the paired-sample sign and the

Wilcoxon signed-rank tests are applied to matched pairs based on the inverse of the number of analysts following (i.e., publishing earnings forecasts) on average the stock during the year prior ($InvAnlst_{0Y}$) and following ($InvAnlst_{1Y}$) the listing date. The null of no difference in the (inverse of the) number of analysts is tested against the one-sided alternative of a decline (which would imply that $InvAnlst_{1Y}$ increases over $InvAnlst_{0Y}$). Table 12 shows that out of the 891 listings in the complete sample, 610 imply a lower value for *InvAnlst* (i.e., more analysts follow the stock) after the listing, with a median percent change of -22.4%. The null hypothesis of no differences for all the quartile sub-samples is always rejected at the 1% level using both tests. Like Tables 8 and 9, also Table 12 implies that information asymmetries abate after option are listed, both directly if we take $InvAnlst_{Y}$ as an index of such asymmetries and indirectly, as the growth in the number of analysts producing (or even re-proposing already known) public news reports has been shown to help tame any information differences (see Tetlock, 2010). Also in Table 12, such an increase in the number of analysts is stronger the more successful listings are.

[Insert Table 12 here]

Finally, we repeat the same analysis as in Table 12, but using our control group of seasoned equity options already defined for the purpose of preparing Tables 10 and 11. Table 13 emphasizes once more that there is no significant increase in the number of analysts of seasoned equity options long after the initial listing date. Table 13 shows that out of the 891 matched, seasoned listings in our complete sample, 461 have a lower level in the *InvAnlst* after the listing date, but with a median percent change of a puny −1.77%. The null hypothesis of no differences in *InvAnlst* cannot be rejected for all quartiles sub-samples using any of the tests employed so far. Moreover, in an unreported analysis we observe that the percentage change in the inverse number of analysts of matched option listings (statistics from Table 12) between the year prior to and the year following the listing is significantly more negative than the same value for their controls (statistics from Table 13) at a 1% level.

[Insert Table 13 here]

7. Conclusions

Option listings represent one often seen (one would say, routine) case of financial innovation in which completely new derivatives securities are introduced into the market for the first time by option exchanges. Consequently, understanding the option adoption process has enormous importance for both policy (i.e., normative) and positive perspectives, also because one would hope that a deeper insight into the dynamics of the process may lead to a better understanding of the dynamics of the success and/or failure of even more sophisticated derivative securities. In addition, knowledge of the factors that affect the success of newly listed options is of extreme relevance to option exchanges, which are in charge of selecting optionable stocks and are likely to do so with a view to long-run profit maximization.

Differently from earlier literature that has focussed on the ex-ante decision (by option exchanges) to make stocks optioned, our study has examined the determinants of the actual, *ex-post* success of stock option listings, and particularly the role that asymmetric information plays in affecting the adoption process. We use data from option listings on the U.S. equity option markets over a relatively long period of time, 1996-2009. Our first and crucial result is that, using different proxies for information asymmetries common to the microstructure literature, an elevated level of asymmetric information affecting the underlying stock prior to listing results in an ex-post higher rate of adoption. Importantly, information asymmetry measures remain a key predictor of newly traded option success, even after controlling for the factors that the earlier literature as indicated as responsible for the exchange choice to turn certain stocks into optioned ones.

Second, we find that option listings reduce asymmetric information. Third, we obtain empirical evidence to support a view by which informed option traders slowly enter the newly created markets because of their need to exploit sufficient volumes to "hide" their informed trades. As a result—because it reflects the probability that market makers perceive of dealing with these informed investors—the option relative bid-ask spread is observed to be initially low and to progressively increase as an option market takes off. This counterintuitive result (one would naively expect bid-ask spreads to narrow as volume and the importance of a market pick up) appears to be stronger for options written on stocks characterized by large information differentials, which are however also the option listings that are mostly likely to be successful.

Interestingly, the literature has long debated whether option listings ought to affect the liquidity and volatility of the underlying stock market. For example, Branch and Finnerty (1981), Conrad (1989), Damodaran and Lim (1991), Skinner (1989), and Sorescu (2000) have tested whether option listings influence stock volatility but also warned that if exchanges list options in response to or in anticipation of changing volatility, selection bias may introduce a spurious relation between listings and volatility. Using a control-sample design that allays the endogeneity concerns, Mayhew and Mihov (2004) report that optioned stocks tend to experience a larger volatility increase, or a smaller decrease, than options in their control sample; however their result remains mixed. Interestingly, similar ambiguous theoretical (see Cao, 1999; Massa, 2003) and empirical (see e.g., Damodaran and Lim, 1991; Skinner, 1989) findings concern the effects of option introductions on the volume of the underlying stock, because in a few cross-sectional studies it has been reported that the increase in volume may disappear after controlling for aggregate market volume. Although unreported empirical tests have confirmed these weak results concerning the impact of listings on volumes and volatility of the underlying stocks in our data, we refrain from dealing with these issues in a systematic way, also because it is possible that the impact on information asymmetries (section 6) and the way informed investors try to hide their informed trades (section 5) may represent the underlying, latent phenomenon that drives the confounding results on post-listing stock volatility in the earlier literature.

Finally, the econometric approach used in our paper is simple and intuitive because we limit ourselves to use standard regression analysis and, even more frequently, matched-pair tests of differences in medians for the various quantities of interest. However, it is clear that more sophisticated and (possibly) more powerful econometric techniques may allow us to expand our study to other issues that remain to be addressed. For instance, apart from the obvious need to generalize our results to other, more complex (such as over-the-counter) derivatives, an exploration of whether there are windows of opportunity for exchanges to optimally time the introduction of new option contracts on the basis of the underlying asymmetries in information has been left for future research.

Appendix A: Asymmetric Information Measures

PIN and *AdjPIN* are measures derived from models of a market maker's learning process, characterised by a Bayesian procedure. A market maker faces a price-setting decision problem in which trades (from both uninformed and informed investors) are taken as the inputs and transaction prices are the outputs. Developed by Easley *et al.* (1996), the *PIN* index is estimated within a specific microstructure model by way of inferences from the order flow and taking its effects on the market maker's beliefs into account. The intuition behind the model by Easley *et al.* (1996) is that *PIN* can identify the arrival of informed trades from abnormal features of the order flow imbalance process.

However, Duarte and Young (2009) argue that abnormal order flow imbalances might also be due to liquidity shocks or changes in the demand for immediacy (e.g., see Grossman and Miller, 1988). Therefore, *PIN* may also capture liquidity effects. To address this issue, Duarte and Young (2009) introduce *AdjPIN*, which is based on an extension of the model by Easley *et al.* (1996) that takes into account order flow shocks and allows for a non-zero correlation between buy and sell orders. In this section, we will briefly describe the generalized model presented in Duarte and Young (2009) to obtain *AdjPIN*, and then explain how the model may be simplified (restricted) to deliver Easley *et al.*'s *PIN*.

Suppose that there are three types of agents in a simple securities market model: a risk-neutral market maker; uninformed investors; and informed investors. Suppose that the uninformed and informed investors trade a single risky asset over $i = 1, \dots, I$ trading days, with time evolving continuously within each single trading day and represented by $t \in [0, T]$. Prior to each day and with a probability $\alpha \in (0,1)$, an "information event" may take place. Such an event may provide bad or good news with probabilities $\delta \in (0,1)$ or $(1-\delta)$, respectively. Let $V \equiv (V_{n,i}, V_{b,i}, V_{g,i})$ be a vector of random variables that represent the asset price on day i, conditional on the absence of news, the arrival of bad news, or the arrival of good news, respectively, with $V_{b,i} < V_{n,i} < V_{g,i}$.

On each day buy and sell orders from uninformed traders are submitted stochastically according to two Poisson processes with rates ξ_B and ξ_S for buy and sell orders, respectively. Buy and sell orders from informed investors are instead generated by two additional Poisson processes, with rates μ_B and μ_S for buy and sell orders, respectively; these informed orders occur only on days characterized by an information event, because they derive from the desire of informed agents to use their private knowledge to support their trades. Finally, on each day an event can happen with probability η that causes an increase in both informed and uninformed, and both buy and sell order flows (such event is called a *symmetric order-flow shock*). In the case of a symmetric order-flow shock the additional arrival rate for buys is λ_B and for sells is λ_S. Figure A1 shows a diagram of market dynamics according to the assumptions above.

[Insert Figure A1 here]

On each day, the market randomly follows the path associated with one of the three main branches (i.e., no-news, bad-news, or good-news) in Figure A1. At the beginning of each trading session, the market maker does not know which branch will be followed, but she then continuously learns and updates her beliefs from the orders that she receives throughout the session, following an optimal Bayesian scheme. Furthermore, the market maker's prior beliefs are represented by a vector $P(t) \equiv (P_n(t), P_b(t), P_g(t))$, where each of the three probability measures refers to no-news, bad-news, and good-news, respectively. Consequently, the market maker's expected asset price, conditional on the information received on or before time t is:

$$E[V_i|\Im_t] = P_n(t)V_{n,i} + P_b(t)V_{b,i} + P_g(t)V_{g,i}, \tag{A1}$$

where $\Im_t$ denotes the information set available as of time t. Let S_t (B_t) denote the event that a sell (buy) order reaches the market maker at time t. For simplicity, we rule out the possibility that at time t both a buy and a sell order may arrive at the market maker at the same time. In case of a sell order, the market maker will update her beliefs using Bayes rule, by which her posterior probability of no-news given a sell order at time t is:

$$P_n(t|S_t) = \frac{P_n(t)(\xi_S + \eta\lambda_S)}{\xi_S + \eta\lambda_S + P_b(t)\mu_S}. \tag{A2}$$

Similarly, the market maker's posterior probability of bad-news given a sell order is:

$$P_b(t|S_t) = \frac{P_b(t)(\xi_S + \eta\lambda_S + \mu_S)}{\xi_S + \eta\lambda_S + P_b(t)\mu_S}, \tag{A3}$$

while the probability of good news under the same conditions is:

$$P_g(t|S_t) = \frac{P_g(t)(\xi_S + \eta\lambda_S)}{\xi_S + \eta\lambda_S + P_b(t)\mu_S}. \quad \text{(A4)}$$

Consequently, the expected bid price at time t, $b(t)$, is the expected asset price assessed by the market maker conditional on S_t:

$$b(t) = \frac{P_n(t)(\xi_S + \eta\lambda_S)}{\xi_S + \eta\lambda_S + P_b(t)\mu_S}V_{n,i} + \frac{P_b(t)(\xi_S + \eta\lambda_S + \mu_S)}{\xi_S + \eta\lambda_S + P_b(t)\mu_S}V_{b,i} + \frac{P_g(t)(\xi_S + \eta\lambda_S)}{\xi_S + \eta\lambda_S + P_b(t)\mu_S}V_{g,i}. \quad \text{(A5)}$$

The bid price can then be re-written by substituting equation (A1) into equation (A5) as:

$$b(t) = E[V_i|\Im_t] - \left(E[V_i|\Im_t] - V_{b,i}\right)\frac{P_b(t)\mu_S}{\xi_S + \eta\lambda_S + P_b(t)\mu_S}. \quad \text{(A6)}$$

In equation (A6) the bid price is the expected price of the market maker ($E[V_i|t]$), minus the expected loss in case an informed investor places a sell order ($E[V_i|t] - V_{b,i}$), multiplied by the probability that the sell order is triggered by informed trading, (i.e., $P_b(t)\mu_S/(\xi_S + \eta\lambda_S + P_b(t)\mu_S)$). Equation (A6) implies that the market maker charges a premium to execute sell orders to account for the possibility of dealing with informed traders. In a similar way, the ask price, $a(t)$, takes the form:

$$a(t) = E[V_i|t] + \left(V_{g,i} - E[V_i|t]\right)\frac{P_g(t)\mu_B}{\xi_B + \eta\lambda_B + P_g(t)\mu_B}. \quad \text{(A7)}$$

In equation (A7) the ask price is the expected price of the asset ($E[V_i|t]$) plus a premium represented by the expected loss should the buy order come from an informed trader ($V_{g,i} - E[V_i|t]$), multiplied by the probability of informed trading supporting the buy order (i.e., $P_g(t)\mu_B$ $/(\xi_B + \eta\lambda_B + P_g(t)\mu_B)$).

Duarte and Young (2009) demonstrate how the micro-structural model in equations (A1)-(A7) can be used to extract estimates of the probability that a trade is information-based, *AdjPIN*. Therefore, defining the initial prior probability vector as $P(0) \equiv (1 - \alpha, \alpha\delta, \ \alpha(1 - \delta))$, on any day i, *AdjPIN* may be computed as:

$$AdjPIN = \frac{\alpha(\delta\mu_S + (1-\delta)\mu_B)}{\alpha(\delta\mu_S + (1-\delta)\mu_B) + \xi_B + \xi_S + \eta(\lambda_B + \lambda_S)}. \quad \text{(A8)}$$

Equation (A8) shows that *AdjPIN* is zero when there is no informed trading (μ_S = μ_S = 0) and/or if the number of uninformed trades goes to infinity ($\xi_B \to \infty$ and/or $\xi_S \to \infty$). In contrast, *AdjPIN* is one if there is no uninformed trading and symmetric order-flow shocks $\left((\xi_B + \xi_S + \eta(\lambda_B + \lambda_S)\,) = \ 0\right)$ or when the number of informed trades goes to infinity ($\mu_B \ \to \infty$ and/or $\mu_S \ \to \infty$). Additionally, and again from the microstructure model in equations (A1)-(A7), on any day the likelihood function induced by this model is:

$$
\begin{aligned}
L(\theta|(B,S)) = {} & \alpha\delta\eta\left\{e^{-(\xi_B+\lambda_B)}\frac{(\xi_B+\lambda_B)^B}{B!}e^{-(\xi_S+\lambda_S+\mu_S)}\frac{(\xi_S+\lambda_S+\mu_S)^S}{S!}\right\} \\
& + \alpha\delta(1-\eta)\left\{e^{-(\xi_B)}\frac{(\xi_B)^B}{B!}e^{-(\xi_S+\mu_S)}\frac{(\xi_S+\mu_S)^S}{S!}\right\} \\
& + \alpha(1-\delta)\eta\left\{e^{-(\xi_B+\lambda_B+\mu_B)}\frac{(\xi_B+\lambda_B+\mu_B)^B}{B!}e^{-(\xi_S+\lambda_S)}\frac{(\xi_S+\lambda_S)^S}{S!}\right\} \\
& + \alpha(1-\delta)(1-\eta)\left\{e^{-(\xi_B+\mu_B)}\frac{(\xi_B+\mu_B)^B}{B!}e^{-(\xi_S)}\frac{(\xi_S)^S}{S!}\right\} \\
& + (1-\alpha)\eta\left\{e^{-(\xi_B+\lambda_B)}\frac{(\xi_B+\lambda_B)^B}{B!}e^{-(\xi_S+\lambda_S)}\frac{(\xi_S+\lambda_S)^S}{S!}\right\} \\
& + (1-\alpha)(1-\eta)\left\{e^{-(\xi_B)}\frac{(\xi_B)^B}{B!}e^{-(\xi_S)}\frac{(\xi_S)^S}{S!}\right\}
\end{aligned}
\tag{A9}
$$

where $\theta \equiv (\alpha, \delta, \eta, \xi_B, \xi_S, \mu_B, \mu_S, \lambda_B, \lambda_S)$ is the parameter vector, and B (S) is the (integer) number of buy (sell) orders for that day. In equation (A9), each element represents the likelihood function of each of the branches in the diagram in Figure 1, which are weighted by their probabilities. Furthermore, following Easley *et al.* (1996) and Duarte and Young (2009), under sufficiently strong independence conditions imposed on the dynamics across the I days in a data sample (e.g., if all process are independently and identically distributed over time), the total likelihood function is:

$$L(\theta|M) = \prod_{i=1}^{I} L(\theta|B_i, S_i), \tag{A10}$$

where (B_i, S_i) is the (integer) number of buy (sell) trades on day i. Equation (A10) is maximized over θ given the data sample to obtain maximum-likelihood estimates of the parameters, which can then be used to compute $AdjPIN$ from equation (A8).

At this point, it is easy to see that the original model introduced in Easley *et al.* (1996) is just a restricted version of Duarte and Young's (2009). On the one hand, in Easley *et al.* (1996) the number of buyer-initiated trades has the same distribution as the number of seller-initiated trades (i.e., μ_B = μ_S = μ). On the other hand, Easley *et al.* (1996) do not include the possibility of order flow shocks, so that they implicitly set $\eta = 0$. Therefore, if we take equation (A8) to represent the probability of informed trade (i.e., the simple PIN), this simplifies to:

$$PIN = \frac{\alpha\mu}{\alpha\mu + \xi_B + \xi_S}. \tag{A11}$$

In this case, the likelihood function for each single observation is:

$$L^*\big(\theta^*\big|(B,S)\big) = \alpha\delta\left\{e^{-(\xi_B)}\frac{(\xi_B)^B}{B!}e^{-(\xi_S+\mu)}\frac{(\xi_{S+}\mu)^S}{S!}\right\} + \alpha(1-\delta)\left\{e^{-(\xi_B+\mu)}\frac{(\xi_B+\mu)^B}{B!}e^{-(\xi_S)}\frac{(\xi_S)^S}{S!}\right\}(1 - \alpha)\left\{e^{-(\xi_B)}\frac{(\xi_B)^B}{B!}e^{-(\xi_S)}\frac{(\xi_S)^S}{S!}\right\} \quad \text{(A12)}$$

where $\theta^* \equiv (\alpha, \delta, \xi_B, \xi_S, \mu)$ is the parameter vector for the Easley *et al.*'s version. Correspondingly, the total likelihood function is:

$$L^*(\theta^*|M) = \prod_{i=1}^{I} L^*(\theta^*|B_i, S_i) \quad \text{(A13)}$$

Appendix B: Maximum Likelihood Parameter Estimates

This appendix provides details concerning the parameters estimated from the microstructure models in Appendix A, which are used to calculate the *PIN* and the *AdjPIN* estimates used in Sections 3-6 of the paper. Table BI and Table BII present the cross-sectional distribution of the estimated parameters using Easley *et al.*'s (1996) and the Duarte and Young's (2009) models, respectively, for the year prior to and the year following the option listing date and for each stock. The parameters are estimated by maximizing the sample likelihood functions in equations (A10) and (A13), and the *PIN* estimates are calculated from equation (A11) while the *AdjPIN* estimates are then calculated from equation (A8).

[Insert Table BI here]

[Insert Table BII here]

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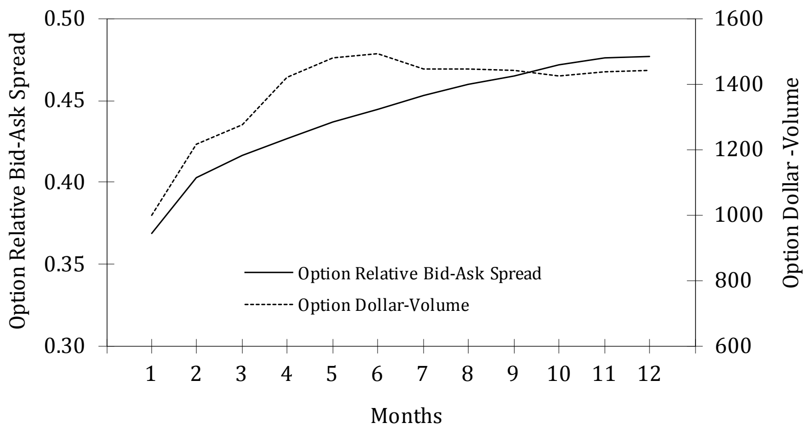

Figure 1. Evolution of the option dollar-volume and the option relative bid-ask spread. The figure presents the evolution of the cross-sectional mean in each month of the average for the daily option dollar-volume and the relative option bid-ask spread in the 12 months following the listing date. The relative bid-ask spread (*BAre*) is defined as *BAre* = (*Ask Price* – *Bid Price*)/(0.5(*Ask Price* + *Bid Price*)).

Table 1
Summary Statistics

The table contains cross-sectional statistics of the main variables used in the study. $DVlm_{OP,1Y}$, $Vlm_{OP,1Y}$, and $OInt_{OP,1Y}$ are the averages of the daily option dollar-volume, option contract volume, and open interest, respectively, in the first year after the option listing. $BAre_{OP,1Y}$ is the average of the option relative bid-ask spread in the year following the listing date, where *BAre* = (*Ask Price* – *Bid Price*)/(0.5(*Ask Price* + *Bid Price*)). PIN_{0Y}, $AdjPIN_{0Y}$, and $InvAnlst_{0Y}$ are the *PIN* and *AdjPIN* estimates, and the inverse of the average of the number of analysts, respectively, for the year prior to option listing. PIN_{1Y}, $AdjPIN_{1Y}$, and $InvAnlst_{1Y}$ are the *PIN* and *AdjPIN* estimates, and the inverse function of the average of the number of analysts, respectively, for the year immediately after option listing.

Variable	Mean	Median	Std. Dev.	Skewness	Kurtosis	Min.	Max.	Obs.
$DVlm_{OP,\,1Y}$	1335.79	124.44	31064.85	35.57	832.56	0.28	9012509.12	891
$Vlm_{OP,\,1Y}$	498.72	74.40	7212.01	29.51	880.45	0.38	214713.33	891
$OInt_{OP,\,1Y}$	8835.03	1833.14	108539.05	29.41	876.35	25.51	3228950.54	891
$BAre_{OP,\,1Y}$	0.44	0.42	0.15	0.69	3.81	0.11	1.11	891
PIN_{0Y}	0.20	0.19	0.06	0.43	2.91	0.08	0.37	891
PIN_{1Y}	0.15	0.14	0.04	0.84	3.98	0.08	0.27	891
$AdjPIN_{0Y}$	0.17	0.16	0.05	0.24	4.37	0.02	0.33	891
$AdjPIN_{1Y}$	0.13	0.13	0.03	0.56	5.42	0.03	0.23	891
$InvAnlst_{0Y}$	0.33	0.27	0.23	1.31	4.25	0.04	1.00	891
$InvAnlst_{1Y}$	0.25	0.20	0.17	2.37	9.86	0.04	1.00	891

Table 2

Regression Analysis of the Impact of Different Factors on Ex-Post Option Adoption Rates

The table reports regressions of measures of success of new and recently listed stock options on a range of explanatory factors. Panel A, B, and C present the estimated coefficients of equations (14a), (14b), and (14c), respectively. $Ln(\cdot)$ is the natural logarithmic function. $DVlm_{OP,1Y}$,$Vlm_{OP,1Y}$, $OInt_{OP,1Y}$, PIN_{0Y}, $AdjPIN_{0Y}$, and $InvAnlst_{0Y}$ are defined in Table 1. Since *PIN*, *AdjPIN*, and *InvAnlst* range between zero and one, their estimates are logistically transformed before being used as explanatory variables in the regressions. The other variables used are: underlying stock volume, distinguishing between long-term ($DVlm_{S,252,0Y}$) and a short-term ($DVlm_{S,21,0Y}$) components, which are calculated as the average daily stock dollar-volume using the 252 and 21 trading days preceding the listing date, respectively; the underlying stock return volatility, distinguishing between long-term ($SDev_{S,252,0Y}$) and short-term ($SDev_{S,21,0Y}$) components, calculated as the annualized standard deviation of daily log returns over the 252 and 21 trading days preceding the listing date, respectively; and the distinguishing between stock market capitalization ($Size_{0Y}$) calculated with reference to the year to listing. ***, **, and * denote significance at 1%, 5%, and 10%, respectively (*t*-statistics are in parentheses).

PIN_{0Y}	$AdjPIN_{0Y}$	$InvAnlst_{0Y}$	$Ln(DVlm_{S,252,0Y})$	$DVlm_{S,21,0Y}/DVlm_{S,252,0Y}$	$SDev_{S,252,0Y}$	$SDev_{S,21,0Y}/SDev_{S,252,0Y}$	$Ln(Size_{0Y})$	Const.	Obs.	R^2
Panel A: Dependent Variable $Ln(DVlm_{OP,1Y})$										
0.45			0.91	0.40	1.29	-0.26	-0.22	-9.28	891	0.41
(2.02)**			(11.73)***	(10.76)***	(3.91)***	(0.97)	(1.03)	(9.83)***		
	0.49		0.83	0.41	1.18	-0.31	-0.15	-10.24	891	0.43
	(2.72)***		(11.83)***	(11.23)***	(3.16)***	(2.78)	(0.77)	(11.31)***		
		0.83	1.04	0.48	0.71	-0.46	-0.08	-11.51	891	0.48
		(3.16)***	(12.16)***	(11.02)***	(3.63)***	(1.81)*	(0.85)	(11.20)***		
Panel B: Dependent Variable $Ln(Vlm_{OP,1Y})$										
0.43			0.85	0.43	0.22	-0.39	-0.25	-7.01	891	0.37
(2.51)**			(11.24)***	(9.02)***	(2.63)***	(0.85)	(1.54)	(6.28)***		
	0.49		0.71	0.35	0.12	-0.33	-0.12	-8.35	891	0.42
	(2.88)***		(10.66)***	(10.04)***	(3.21)***	(0.92)	(1.45)	(8.24)***		
		0.81	0.86	0.41	0.19	-0.50	-0.16	-7.74	891	0.36
		(3.21)***	(10.38)***	(9.74)***	(3.39)***	(1.39)	(1.84)*	(7.82)***		
Panel C: Dependent Variable $Ln(OInt_{OP,1Y})$										
0.33			0.69	0.35	0.04	-0.35	-0.20	-2.64	891	0.31
(2.66)***			(9.16)***	(10.47)***	(2.52)**	(0.32)	(1.18)	(3.95)***		
	0.32		0.62	0.29	0.07	-0.32	-0.17	-3.04	891	0.33
	(2.94)***		(9.58)***	(8.82)***	(2.76)***	(0.55)	(1.33)	(3.21)***		
		0.79	0.78	0.36	0.05	-0.43	-0.13	-3.53	891	0.35
		(3.44)***	(10.08)***	(9.45)***	(3.28)***	(0.41)	(1.68)*	(3.91)***		

Table 3

Matched Sample Analysis of Option Listings to Assess the Effect of Asymmetric Information on Option Adoption Rates

The table reports a matched sample analysis of option listings in relation to the effects of prior information asymmetries on the adoption rate during the first year after listing. PIN_{0Y}, $AdjPIN_{0Y}$, $InvAnlst_{0Y}$, $DVlm_{OP,1Y}$, $Vlm_{OP,1Y}$, and $OInt_{OP,1Y}$ are defined in Table 1. In Panels A, B, and C the matched pairs consist of listings in the lower and upper quartiles using *PIN*, A*djPIN*, and *InvAnlst*, respectively to sort listings, all calculated with reference to the year prior to listing. The matching criteria for the pairs of listings are the underlying stock industry, the underlying stock return volatility, and the underlying stock dollar-volume. *OAdp* is the measure of option adoption using either $DVlm_{OP,1Y}$, $Vlm_{OP,1Y}$, or $OInt_{OP,1Y}$; while $OAdp_{LQ}$ ($OAdp_{UQ}$) is the measure of option adoption for the listings in the lower (upper) quartile ranked by measures of asymmetric information. The table reports both the paired-sample sign test and the Wilcoxon signed-rank test which are applied to pairs of option listings in relation to adoption levels. The null hypothesis of no difference in rates of option adoption is tested against the one-sided alternative of larger $OAdp_{UQ}$ values than $OAdp_{LQ}$. For instance, the first row of Panel shows that out of 152 pairs of matched listings, 95 have higher adoption levels using as proxy $DVlm_{OP,1Y}$ in the upper quartile than in the lower quartile of options ranked by *PIN* values in the year prior to the listing date. [a], [aa], and [a] denote significance at 1%, 5%, and 10%, respectively, for the paired-sample sign test. [bbb], [bb], and [b] indicate significance at 1%, 5%, and 10%, respectively, for the Wilcoxon signed-rank test.

OAdp	Obs.	#($OAdp_{LQ} < OAdp_{UQ}$)	%($OAdp_{LQ} < OAdp_{UQ}$)	Median $OAdp_{LQ}$	Median $OAdp_{UQ}$	Median % Change ($OAdp_{UQ}/OAdp_{LQ}$-1)
	Panel A: Differences in Option Adoption (Year Following Opt. Listings) between the Groups in the Lower and Upper Quartiles by the PIN_{0Y} (Year Prior to Opt. Listings)					
$DVlm_{OP,1Y}$	152	95	62.50%	72.83	172.80	152.05%[aaa,bbb]
$Vlm_{OP,1Y}$	152	92	60.53%	49.76	104.28	102.99%[aaa,bbb]
$OInt_{OP,1Y}$	152	93	61.18%	1324.41	2796.76	163.29%[aaa,bbb]
	Panel B: Differences in Option Adoption (Year Following Opt. Listings) between the Groups in the Lower and Upper Quartiles by the $AdjPIN_{0Y}$ (Year Prior to Opt. Listings)					
$DVlm_{OP,1Y}$	141	89	63.12%	58.39	188.73	200.68%[aaa,bbb]
$Vlm_{OP,1Y}$	141	92	65.25%	43.78	113.39	186.69%[aaa,bbb]
$OInt_{OP,1Y}$	141	86	60.99%	1182.11	2953.81	238.43%[aaa,bbb]
	Panel C: Differences in Option Adoption (Year Following Opt. Listings) between the Groups in the Lower and Upper Quartiles by the $InvAnlst_{0Y}$ (Year Prior to Opt. Listings)					
$DVlm_{OP,1Y}$	146	99	67.81%	71.13	160.27	131.07%[aaa,bbb]
$Vlm_{OP,1Y}$	146	97	66.44%	51.47	95.16	121.06%[aaa,bbb]
$OInt_{OP,1Y}$	146	96	65.75%	1462.78	2294.50	89.54%[aaa,bbb]

Table 4

Matched Sample Analysis of Option Listings to Assess the Effect of Asymmetric Information on Option Adoption Rates under a Time-Window Constraint

The table reports a similar matched sample analysis as in Table 3, but in this case the matching reflects an additional constraint by which matched pairs must both belong to a time-window of 252 trading days from the baseline listing. For instance, in the case of the matching of a listing *i* with a listing *j*, we use the same matching criteria as in Table 3, but if the listing *i* has occurred on day *t*, the listing *j* must fall in the interval [t-252, t+252]. PIN_{0Y}, $AdjPIN_{0Y}$, $InvAnlst_{0Y}$, $DVlm_{OP,1Y}$, $Vlm_{OP,1Y}$, and $OInt_{OP,1Y}$ are defined in Table 1. In Panels A, B, and C the matched pairs consist of option listings in the lower and upper quartiles using *PIN*, *AdjPIN*, and *InvAnlst*, respectively, all calculated in the year prior to listing. *OAdp* is the level of option adoption using either $DVlm_{OP,1Y}$, $Vlm_{OP,1Y}$, or $OInt_{OP,1Y}$; while $OAdp_{LQ}$ ($OAdp_{UQ}$) is the measure of option adoption for option listings in the lower (upper) quartile. The table reports both paired-sample sign test and Wilcoxon signed-rank test which are applied to the pairs of listings in relation to adoption levels. The null hypothesis of no difference in adoption rates is tested against the one-sided alternative of $OAdp_{UQ}$ exceeding $OAdp_{LQ}$. For instance, the first row of Panel A shows that out of 41 pairs of matched listings, 33 implied higher adoption rates using as a proxy $DVlm_{OP,1Y}$ in the upper than in the lower quartiles ranked by *PIN* values in the year prior to listing. [a], [aa], and [a] denote significance at 1%, 5%, and 10%, respectively, for the paired-sample sign test. [bbb], [bb], and [b] indicate significance at 1%, 5%, and 10%, respectively, for the Wilcoxon signed-rank test.

OAdp	Obs.	#($OAdp_{LQ} < OAdp_{UQ}$)	%($OAdp_{LQ} < OAdp_{UQ}$)	Median $OAdp_{LQ}$	Median $OAdp_{UQ}$	Median % Change ($OAdp_{UQ}/OAdp_{LQ}$-1)
	Panel A: Differences in Option Adoption (Year Following Opt. Listings) between the Groups in the Lower and Upper Quartiles by the PIN_{0Y} (Year Prior to Opt. Listings)					
$DVlm_{OP,1Y}$	41	33	80.49%	69.31	174.94	168.17%[aaa,bbb]
$Vlm_{OP,1Y}$	41	30	73.17%	51.36	107.63	111.49%[aaa,bbb]
$OInt_{OP,1Y}$	41	32	78.05%	1258.71	2900.44	172.91%[aaa,bbb]
	Panel C: Differences in Option Adoption (Year Following Opt. Listings) between the Groups in the Lower and Upper Quartiles by the $InvAnlst_{0Y}$ (Year Prior to Opt. Listings)					
$DVlm_{OP,1Y}$	38	29	76.32%	50.56	197.26	208.34%[aaa,bbb]
$Vlm_{OP,1Y}$	38	31	81.58%	40.21	118.40	193.83%[aaa,bbb]
$OInt_{OP,1Y}$	38	27	71.05%	1068.03	3262.49	245.48%[aaa,bbb]
	Panel C: Differences in Option Adoption (Year Following Opt. Listings) between the Groups in the Lower and Upper Quartiles by the $InvAnlst_{0Y}$ (Year Prior to Opt. Listings)					
$DVlm_{OP,1Y}$	37	33	89.19%	67.16	167.83	140.36%[aaa,bbb]
$Vlm_{OP,1Y}$	37	29	78.38%	47.48	98.53	129.33%[aaa,bbb]
$OInt_{OP,1Y}$	37	31	83.78%	1390.10	2340.01	95.82%[aaa,bbb]

Table 5

Increase in the Option Relative Bid-Ask Spread After Option Listings

The table presents a matched sample analysis of the effects of option listings on changes in the option relative bid-ask spread for the baseline sample of options (Panel A) and for a control group (panel B). The relative bid-ask spread (*BAre*) is defined as *BAre* = (*Ask Price* – *Bid Price*)/(0.5(*Ask Price* + *Bid Price*)). $BAre_{OP,1M}$ ($BAre_{OP,13M}$) is the average relative bid-ask spread in the first (thirteenth) month after listing. In Panel A, the matched pairs concern the same option listing but *BAre* is measured in different time periods (in the first and thirteenth months after listing). The table reports both the paired-sample sign test and the Wilcoxon signed-rank test applied to the change from $BAre_{OP,1M}$ to $BAre_{OP,13M}$. The null hypothesis of no change in $BAre_{OP}$ is tested against the one-sided alternative of $BAre_{OP,13M}$ being larger than $BAre_{OP,1M}$. For instance, the first row shows that out of 891 pairs of matched $BAre_{OP}$ values in the complete sample of option listings, 689 have larger $BAre_{OP}$ levels in the thirteenth month than in the first month. In Panel B, the control group is created by selecting a seasoned equity option (with at least three years of market activity subsequent to its listing) to match each listing in the original sample. The matching criteria are defined in Table 7. All the statistics in Panel B are calculated using data from the equity options in the control group and have structure similar to Panel A. [a], [aa], and [a] denote significance at 1%, 5%, and 10%, respectively, for the paired-sample sign test. [bbb], [bb], and [b] indicate significance at 1%, 5%, and 10%, respectively, for the Wilcoxon signed-rank test.

Diff. in Option Relative Bid-Ask Spreads between the First and Thirteenth Months Following Option Listings Using Multiple Sub-Samples						
	Obs.	#($BAre_{OP,1M}$ < $BAre_{OP,13M}$)	%($BAre_{OP,1M}$ < $BAre_{OP,13M}$)	Median $BAre_{OP,1M}$	Median $BAre_{OP,13M}$	Median % Change ($BAre_{OP,13M}/BAre_{OP,1M}$-1)
	Panel A: Complete Sample of Equity Options					
$BAre_{OP}$	891	689	77.33%	0.32	0.44	40.59%[aaa,bbb]
	Panel B: Control Group of Equity Options					
$BAre_{OP}$	891	441	49.49%	0.47	0.46	-2.09%

Table 6

Matched Sample Analysis of the Impact of Options Listings on the Change in Option Relative Bid-Ask Spreads

The table presents a matched sample analysis of the effects of option listings and stealth strategies by informed traders on the change in the option relative bid-ask spread. $BAre_{OP,1M}$ ($BAre_{OP,13M}$) is the average of the option relative bid-ask spread in the first (thirteenth) month after option introduction. The change in the option relative bid-ask spread is defined as $\Delta Bare = BAre_{OP,13M}/BAre_{OP,1M}$. PIN_{0Y}, $AdjPIN_{0Y}$, and $InvAnlst_{0Y}$ are defined in Table 1. In Panels A, B, and C the matched pairs consist of listings in the lower and upper quartiles built using *PIN*, *AdjPIN*, and *InvAnlst*, respectively which are calculated in the year prior to the listing date. The matching criteria to form pairs of option listings are the underlying stock industry, the underlying stock return volatility, and the underlying stock dollar-volume. $\Delta Bare_{LQ}$ ($\Delta Bare_{UQ}$) is the *ΔBare* for the option listings in the lower (upper) quartiles ranked by measures of asymmetric information. The table reports both the paired-sample sign test and the Wilcoxon signed-rank test applied to the change in the option relative bid-ask spread. The null hypothesis of no difference in *ΔBare* is tested against the one-sided alternative of a positive difference between $\Delta Bare_{UQ}$ and $\Delta Bare_{LQ}$. For instance, the first row shows that out of 152 pairs of matched option listings, 89 have higher *ΔBare* in the upper quartile than in the lower quartile of options ranked by *PIN* values in the year prior to the listing date. [a], [aa], and [a] denote significance at 1%, 5%, and 10%, respectively, for the paired-sample sign test. [bbb], [bb], and [b] indicate significance at 1%, 5%, and 10%, respectively, for the Wilcoxon signed-rank test.

$\Delta BAre = BAre_{OP,13M}/BAre_{OP,1M}$	Obs.	$\#(\Delta BAre_{LQ} < \Delta BAre_{UQ})$	$\%(\Delta BAre_{LQ} < \Delta BAre_{UQ})$	Median $\Delta BAre_{LQ}$	Median $\Delta BAre_{UQ}$	Median % Change ($\Delta BAre_{UQ}/\Delta BAre_{LQ}$-1)
	Panel A: Differences in Option Adoption (Year Following Opt. Listings) between the Groups in the Lower and Upper Quartiles by the PIN_{0Y} (Year Prior to Opt. Listings)					
Δ BAre	152	89	58.55%	1.32	1.49	19.32%[aa,bb]
	Panel B: Differences in Option Adoption (Year Following Opt. Listings) between the Groups in the Lower and Upper Quartiles by the $AdjPIN_{0Y}$ (Year Prior to Opt. Listings)					
Δ BAre	141	84	59.57%	1.22	1.43	23.02%[aa,bbb]
	Panel C: Differences in Option Adoption (Year Following Opt. Listings) between the Groups in the Lower and Upper Quartiles by the $InvAnlst_{0Y}$ (Year Prior to Opt. Listings)					
Δ BAre	146	86	58.90%	1.25	1.38	17.94%[aa,bb]

Table 7

Matched Sample Analysis of the Impact of Listings on the Change in Relative Bid-Ask Spreads under a Time-Window Constraint

The table reports a similar matched sample analysis as in Table 12, but in this case the matching reflects an additional constraint by which matched pairs must both belong to a time-window of 252 trading days from the baseline listing. For instance, in the case of the matching of a listing *i* with a listing *j*, we use the same matching criteria as in Table 12, but if the listing *i* has occurred on day *t*, the listing *j* must fall in the interval [t-252, t+252]. $BAre_{OP,1M}$ ($BAre_{OP,13M}$) is the average of the option relative bid-ask spread in the first (thirteenth) month after option introduction. The change in the option relative bid-ask spread is defined as $\Delta Bare = BAre_{OP,13M}/BAre_{OP,1M}$. PIN_{0Y}, $AdjPIN_{0Y}$, and $InvAnlst_{0Y}$ are defined in Table 1. In Panels A, B, and C the matched pairs consist of listings in the lower and upper quartiles built using *PIN*, A*djPIN*, and *InvAnlst*, respectively, calculated in the year prior to the listing date. The matching criteria to form pairs of option listings are the underlying stock industry, the underlying stock return volatility, and the underlying stock dollar-volume. $\Delta Bare_{LQ}$ ($\Delta Bare_{UQ}$) is the *ΔBare* for the option listings in the lower (upper) quartiles ranked by measures of asymmetric information. The table reports both the paired-sample sign test and the Wilcoxon signed-rank test applied to the change in the option relative bid-ask spread. The null hypothesis of no difference in *ΔBare* is tested against the one-sided alternative of a positive difference between $\Delta Bare_{UQ}$ and $\Delta Bare_{LQ}$. For instance, the first row shows that out of 41 pairs of matched option listings, 28 have higher *ΔBare* in the upper quartile than in the lower quartile of options ranked by *PIN* values in the year prior to the listing date. [a], [aa], and [a] denote significance at 1%, 5%, and 10%, respectively, for the paired-sample sign test. [bbb], [bb], and [b] indicate significance at 1%, 5%, and 10%, respectively, for the Wilcoxon signed-rank test.

$\Delta BAre = BAre_{OP,13M}/BAre_{OP,1M}$	Obs.	$\#(\Delta BAre_{LQ} < \Delta BAre_{UQ})$	$\%(\Delta BAre_{LQ} < \Delta BAre_{UQ})$	Median $\Delta BAre_{LQ}$	Median $\Delta BAre_{UQ}$	Median % Change ($\Delta BAre_{UQ}/\Delta BAre_{LQ}$-1)
	Panel A: Differences in Option Adoption (Year Following Opt. Listings) between the Groups in the Lower and Upper Quartiles by the PIN_{0Y} (Year Prior to Opt. Listings)					
$\Delta BAre$	41	28	68.29%	1.31	1.47	21.48%[aa,bb]
	Panel B: Differences in Option Adoption (Year Following Opt. Listings) between the Groups in the Lower and Upper Quartiles by the $AdjPIN_{0Y}$ (Year Prior to Opt. Listings)					
$\Delta BAre$	38	27	71.05%	1.20	1.46	24.79[aaa,bb]
	Panel C: Differences in Option Adoption (Year Following Opt. Listings) between the Groups in the Lower and Upper Quartiles by the $InvAnlst_{0Y}$ (Year Prior to Opt. Listings)					
$\Delta BAre$	37	25	67.57%	1.21	1.44	18.49%[aa,bb]

Table 8

Reduction in *PIN* After Option Listings

The table presents a matched sample analysis of the effects of option listings on changes in the *PIN* measure after the listing date. PIN_{0Y}, PIN_{1Y}, $DVlm_{OP,1Y}$, $Vlm_{OP,1Y}$, and $OInt_{OP,1Y}$ are defined in Table 1. The matched pairs contain *PIN* estimates from the year before and the year after option listings. The table reports results for both the paired-sample sign test and the Wilcoxon signed-rank test applied to measure the change from PIN_{0Y} to PIN_{1Y}. The null hypothesis of no change in *PIN* is tested against the one-sided alternative of PIN_{1Y} being inferior to PIN_{0Y}. Both tests are applied to alternative quartile sub-samples. For instance, the first row shows that out of 891 pairs of matched *PIN* values in the complete sample, 532 have smaller *PIN* after listings than in the year prior to the listing. [a], [aa], and [a] denote significance at 1%, 5%, and 10%, respectively, for the paired-sample sign test. [bbb], [bb], and [b] indicate significance at 1%, 5%, and 10%, respectively, for the Wilcoxon signed-rank test.

Differences in *PIN* between the Year Prior to and the Year Following Option Listings Using Multiple Sub-Samples

	Obs.	$\#(PIN_{0Y} > PIN_{1Y})$	$\%(PIN_{0Y} > PIN_{1Y})$	Median PIN_{0Y}	Median PIN_{1Y}	Median % Change $(PIN_{1Y}/PIN_{0Y} - 1)$
			Complete Sample			
PIN	891	532	59.71%	0.19	0.14	-22.47%[aaa,bbb]
			Lower Quartile by $DVlm_{OP,1Y}$			
PIN	222	125	56.31%	0.17	0.15	-10.61%[aa,bb]
			Upper Quartile by $DVlm_{OP,1Y}$			
PIN	222	144	64.86%	0.23	0.15	-36.35%[aaa,bbb]
			Lower Quartile by $Vlm_{OP,1Y}$			
PIN	222	124	55.86%	0.17	0.14	-10.82%[aa,bb]
			Upper Quartile by $Vlm_{OP,1Y}$			
PIN	222	142	63.96%	0.21	0.15	-34.70%[aaa,bbb]
			Lower Quartile by $OInt_{OP,1Y}$			
PIN	222	127	57.21%	0.17	0.14	-14.66%[aa,bb]
			Upper Quartile by $OInt_{OP,1Y}$			
PIN	222	147	66.22%	0.23	0.14	-35.97%[aaa,bbb]

Table 9

Reduction in *AdjPIN* After Option Listings

The table presents a matched sample analysis of the effects of option listings on changes in the *AdjPIN* measure after the listing date. The matched pairs contain *AdjPIN* estimates from the year before and the year after option listings. The table reports results for both the paired-sample sign test and the Wilcoxon signed-rank test applied to the change from $AdjPIN_{0Y}$ to $AdjPIN_{1Y}$. The null hypothesis of no change in *AdjPIN* is tested against the one-sided alternative of $AdjPIN_{1Y}$ being inferior to $AdjPIN_{0Y}$. Both tests are applied to alternative quartile sub-samples. For instance, the first row shows that out of 891 pairs of matched *PIN* values in the complete sample, 532 have smaller *AdjPIN* after listings than in the year prior to the listing. [a], [aa], and [a] denote significance at 1%, 5%, and 10%, respectively, for the paired-sample sign test. [bbb], [bb], and [b] indicate significance at 1%, 5%, and 10%, respectively, for the Wilcoxon signed-rank test.

Differences in *Adj PIN* between the Year Prior to and the Year Following Option Listings Using Multiple Sub-Samples						
	Obs.	#($AdjPIN_{0Y}$ > $AdjPIN_{1Y}$)	%($AdjPIN_{0Y}$ > $AdjPIN_{1Y}$)	Median $AdjPIN_{0Y}$	Median $AdjPIN_{1Y}$	Median % Change ($AdjPIN_{1Y}$/$AdjPIN_{0Y}$ - 1)
	Complete Sample					
AdjPIN	891	558	62.63%	0.16	0.13	-19.96%[aaa,bbb]
	Lower Quartile by $D\ Vlm_{OP,1Y}$					
AdjPIN	222	125	56.31%	0.15	0.13	-12.02%[aa,bb]
	Upper Quartile by $D\ Vlm_{OP,1Y}$					
AdjPIN	222	149	67.12%	0.18	0.12	-30.22%[aaa,bbb]
	Lower Quartile by $Vlm_{OP,1Y}$					
AdjPIN	222	129	58.11%	0.14	0.13	-14.78%[aaa,bb]
	Upper Quartile by $Vlm_{OP,1Y}$					
AdjPIN	222	152	68.47%	0.18	0.12	-32.17%[aaa,bbb]
	Lower Quartile by $OInt_{OP,1Y}$					
AdjPIN	222	134	60.36%	0.15	0.13	-14.91%[aaa,bbb]
	Upper Quartile by $OInt_{OP,1Y}$					
AdjPIN	222	150	67.57%	0.18	0.12	-30.64%[aaa,bbb]

Table 10

Reductions in *PIN* After the Listing Date in the Control Group

The table presents a matched sample analysis of the effects of option listings on changes in the *PIN* measure after the listing date for a control group of stock options. The control group is created by selecting a seasoned equity option (with at least three years of market activity subsequent to its listing) to match each listing in the original sample. The matching is performed using: the underlying stock industry, the underlying stock return volatility (annualized standard deviation of daily returns over the 252 trading days prior to listing), and underlying stock volume (mean of daily dollar-volume over the 252 trading days prior to listing). All the statistics in this table are calculated using data from the equity options in the control group. PIN_{0Y}, PIN_{1Y}, $DVlm_{OP,1Y}$, $Vlm_{OP,1Y}$, and $OInt_{OP,1Y}$ are defined in Table 1. The matched pairs consist of *PIN* estimates from different time periods for each matching seasoned stock option (in the year before and the year after the listing date). The table reports both the paired-sample sign test and the Wilcoxon signed-rank test applied to the change from PIN_{0Y} to PIN_{1Y}. The null hypothesis of no change in *PIN* is tested against the one-sided alternative of PIN_{1Y} being inferior to PIN_{0Y}. Both tests are applied to alternative quartile sub-samples. For instance, the first row shows that out of 891 pairs of matched *PIN* values in the complete sample, 458 have smaller *PIN* after the listing date than in the previous year. [a], [aa], and [a] denote significance at 1%, 5%, and 10%, respectively, for the paired-sample sign test. [bbb], [bb], and [b] indicate significance at 1%, 5%, and 10%, respectively, for the Wilcoxon signed-rank test.

Differences in *PIN* between the Year Prior to and the Year Following Option Listings Using Multiple Sub-Samples

	Obs.	#($PIN_{0Y} > PIN_{1Y}$)	%($PIN_{0Y} > PIN_{1Y}$)	Median PIN_{0Y}	Median PIN_{1Y}	Median % Change (PIN_{1Y}/PIN_{0Y} - 1)
			Complete Sample			
PIN	891	458	51.40%	0.14	0.13	-1.35%
			Lower Quartile by $D\,Vlm_{OP,1Y}$			
PIN	222	114	51.35%	0.14	0.13	-1.34%
			Upper Quartile by $D\,Vlm_{OP,1Y}$			
PIN	222	109	49.10%	0.14	0.14	1.58%
			Lower Quartile by $Vlm_{OP,1Y}$			
PIN	222	116	52.25%	0.14	0.14	-2.29%
			Upper Quartile by $Vlm_{OP,1Y}$			
PIN	222	107	48.20%	0.14	0.15	2.13%
			Lower Quartile by $OInt_{OP,1Y}$			
PIN	222	118	53.15%	0.13	0.13	-1.88%
			Upper Quartile by $OInt_{OP,1Y}$			
PIN	222	110	49.55%	0.15	0.15	2.06%

Table 11

Reductions in *AdjPIN* Levels after the Listing Date: Control Group

The table presents a matched sample analysis of the effects of option listings on changes in the *AdjPIN* measure after the listing date for a control group of stock options. The control group is created by selecting a seasoned equity option (with at least three years of market activity subsequent to its listing) to match each listing in the original sample. The matching criteria are defined in Table 7. All the statistics in this table are calculated using data from the equity options in the control group. $AdjPIN_{0Y}$, $AdjPIN_{1Y}$, $DVlm_{OP,1Y}$, $Vlm_{OP,1Y}$, and $OInt_{OP,1Y}$ are defined in Table 1. The matched pairs consist of *AdjPIN* estimates from different time periods for each matching seasoned stock option (in the year before and the year after the listing date). The table reports both the paired-sample sign test and the Wilcoxon signed-rank test applied to the change from $AdjPIN_{0Y}$ to $AdjPIN_{1Y}$. The null hypothesis of no change in *AdjPIN* is tested against the one-sided alternative of $AdjPIN_{1Y}$ being inferior to $AdjPIN_{0Y}$. Both tests are applied to alternative quartile sub-samples. For instance, the first row shows that out of 891 pairs of matched *AdjPIN* values in the complete sample, 458 have smaller *AdjPIN* after the listing date than in the previous year. [a], [aa], and [a] denote significance at 1%, 5%, and 10%, respectively, for the paired-sample sign test. [bbb], [bb], and [b] indicate significance at 1%, 5%, and 10%, respectively, for the Wilcoxon signed-rank test.

Differences in *Adj PIN* between the Year Prior to and the Year Following Option Listings Using Multiple Sub-Samples						
	Obs.	#($AdjPIN_{0Y} > AdjPIN_{1Y}$)	%($AdjPIN_{0Y} > AdjPIN_{1Y}$)	Median $AdjPIN_{0Y}$	Median $AdjPIN_{1Y}$	Median % Change ($AdjPIN_{1Y}/AdjPIN_{0Y}$ - 1)
			Complete Sample			
AdjPIN	891	463	51.96%	0.13	0.13	-1.59%
			Lower Quartile by $D\,Vlm_{OP,1Y}$			
AdjPIN	222	117	52.70%	0.13	0.13	-1.89%
			Upper Quartile by $D\,Vlm_{OP,1Y}$			
AdjPIN	222	107	48.20%	0.14	0.14	0.77%
			Lower Quartile by $Vlm_{OP,1Y}$			
AdjPIN	222	113	50.90%	0.13	0.12	-1.03%
			Upper Quartile by $Vlm_{OP,1Y}$			
AdjPIN	222	110	49.55%	0.14	0.14	0.46%
			Lower Quartile by $OInt_{OP,1Y}$			
AdjPIN	222	115	51.80%	0.13	0.12	-1.98%
			Upper Quartile by $OInt_{OP,1Y}$			
AdjPIN	222	108	48.65%	0.14	0.14	1.12%

Table 12

Increase in Analysts Following after Option Listings

The table presents a matched sample analysis of the effects of option listings on changes in the inverse of the average number of analysts following stocks after the listing date. $InvAnlst_{0Y}$, $InvAnlst_{1Y}$, $DVlm_{OP,1Y}$, $Vlm_{OP,1Y}$, and $OInt_{OP,1Y}$ are defined in Table 1. The matched pairs concern the inverse of the average number of analysts from the year before and the year after option listings. The table reports both the paired-sample sign test and the Wilcoxon signed-rank test applied to the change in $InvAnlst_{0Y}$ from $InvAnlst_{1Y}$ (i.e., a measure of the increase in the number of analysts after listing). The null hypothesis of no change in the inverse of the number of analysts is tested against the one-sided alternative of $InvAnlst_{1Y}$ being inferior to $InvAnlst_0$. Both tests are applied to alternative quartile sub-samples. For instance, the first row shows that out of 891 pairs of matched values of the inverse number of analysts in the complete sample, 610 display a lower *InvAnlst* after the option listing than in the previous year. [a], [aa], and [a] denote significance at 1%, 5%, and 10%, respectively, for the paired-sample sign test. [bbb], [bb], and [b] indicate significance at 1%, 5%, and 10%, respectively, for the Wilcoxon signed-rank test.

Differences in the *InvAnlst* between the Year Prior to and the Year Following Option Listings Using Multiple Sub-Samples						
	Obs.	#($InvAnlst_{0Y}$ > $InvAnlst_{1Y}$)	%($InvAnlst_{0Y}$ > $InvAnlst_{1Y}$)	Median $InvAnlst_{0Y}$	Median $InvAnlst_{1Y}$	Median % Change ($InvAnlst_{1Y}$/$InvAnlst_{0Y}$-1)
	Complete Sample					
InvAnlst	891	610	68.46%	0.27	0.20	-22.38%[aaa,bbb]
	Lower Quartile by $DVlm_{OP,1Y}$					
InvAnlst	222	137	61.71%	0.21	0.19	-13.48%[aaa,bbb]
	Upper Quartile by $DVlm_{OP,1Y}$					
InvAnlst	222	162	72.97%	0.32	0.20	-37.03%[aaa,bbb]
	Lower Quartile by $Vlm_{OP,1Y}$					
InvAnlst	222	138	62.16%	0.22	0.20	-12.34%[aaa,bbb]
	Upper Quartile by $Vlm_{OP,1Y}$					
InvAnlst	222	155	69.82%	0.30	0.19	-31.17%[aaa,bbb]
	Lower Quartile by $OInt_{OP,1Y}$					
InvAnlst	222	139	62.61%	0.23	0.20	-12.50%[aaa,bbb]
	Upper Quartile by $OInt_{OP,1Y}$					
InvAnlst	222	150	67.57%	0.28	0.18	-28.48%[aaa,bbb]

Table 13

Increase in Analysts Following after Option Listings: Control Group

The table presents a matched sample analysis of the effects of option listings on changes in the inverse of the average number of analysts following stocks after the listing date for a control group of stock options. The control group is created by selecting a seasoned equity option (with at least three years of market activity subsequent to its listing) to match each listing in the original sample. The matching criteria are defined in Table 7. All the statistics in this table are calculated using data from the equity options in the control group. $AdjPIN_{0Y}$, $AdjPIN_{1Y}$, $DVlm_{OP,1Y}$, $Vlm_{OP,1Y}$, and $OInt_{OP,1Y}$ are defined in Table 1. The matched pairs concern the inverse of the average number of analysts from the year before and the year after option listings. The table reports both the paired-sample sign test and the Wilcoxon signed-rank test applied to the change from $InvAnlst_{0Y}$ to $InvAnlst_{1Y}$ (i.e., a measure of the increase in the number of analysts after listing). The null hypothesis of no change in *InvAnlst* is tested against the one-sided alternative of $InvAnlst_{1Y}$ being inferior to $InvAnlst_{0Y}$. Both tests are applied to alternative quartile sub-samples. For instance, the first row shows that out of 891 pairs of matched values in the inverse of number of analysts in the complete sample, 461 have a lower *InvAnlst* levels after the listing date than in the previous year. [a], [aa], and [a] denote significance at 1%, 5%, and 10%, respectively, for the paired-sample sign test. [bbb], [bb], and [b] indicate significance at 1%, 5%, and 10%, respectively, for the Wilcoxon signed-rank test.

Differences in the *InvAnlst* between the Year Prior to and the Year Following Option Listings Using Multiple Sub-Samples

	Obs.	#($InvAnlst_{0Y}$ > $InvAnlst_{1Y}$)	%($InvAnlst_{0Y}$ > $InvAnlst_{1Y}$)	Median $InvAnlst_{0Y}$	Median $InvAnlst_{1Y}$	Median % Change ($InvAnlst_{1Y}$/$InvAnlst_{0Y}$-1)
			Complete Sample			
InvAnlst	891	461	51.74%	0.20	0.19	-1.77%
			Lower Quartile by $DVlm_{OP,1Y}$			
InvAnlst	222	118	53.15%	0.19	0.19	-1.49%
			Upper Quartile by $DVlm_{OP,1Y}$			
InvAnlst	222	115	51.80%	0.21	0.19	-2.49%
			Lower Quartile by $Vlm_{OP,1Y}$			
InvAnlst	222	122	54.95%	0.19	0.19	-1.45%
			Upper Quartile by $Vlm_{OP,1Y}$			
InvAnlst	222	117	52.70%	0.20	0.20	-1.92%
			Lower Quartile by $OInt_{OP,1Y}$			
InvAnlst	222	120	54.05%	0.20	0.19	-1.57%
			Upper Quartile by $OInt_{OP,1Y}$			
InvAnlst	222	115	51.80%	0.21	0.20	-2.54%

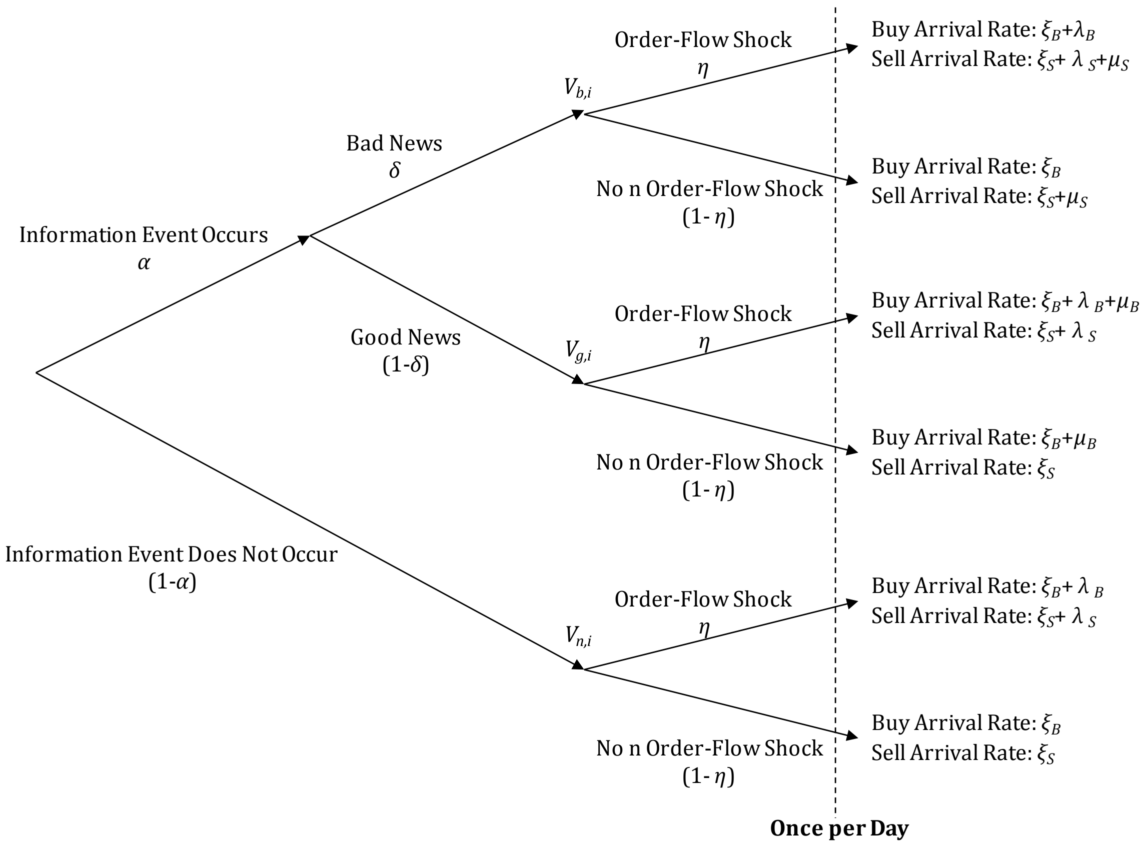

Figure A1. Tree diagram of the dynamic securities market model. This tree diagram reflects the trading process that is characterized in the microstructure model presented in Duarte and Young (2009), in which α is the probability that an informational event occurs, δ is the probability of bad news, η is the probability of a symmetric order-flow shock, ξ_B (ξ_S) is the rate of uninformed buyer- (seller-) initiated trades, μ_B (μ_S) is the rate of informed buy (sell) trades arrival, and in the event of a symmetric order-flow, the additional arrival rate of buys is λ_B and sells is λ_S.

Table BI

Summary Statistics of Estimated Parameters from the Microstructure Model to Estimate the Probability of Informed Trading (*PIN*)

The table presents the cross-sectional distribution of parameter estimates concerning *PIN* for the year prior to and the year following option listings. In the table, α is the probability that an informational event occurs, μ is the rate of arrival of informed trades (buys or sells), δ is the probability of bad news, and ξ_B (ξ_S) is the rate of uninformed buyer (seller) initiated trades. ***, **, and * denote significance at 1%, 5%, and 10%, respectively (*t*-statistics are in parentheses). Following Duarte and Young (2009), the *t*-statistics for the *PIN* estimates are calculated using the delta method based on the asymptotic covariance matrix for estimated model parameters.

	Upper Quartile	Median	Lower Quartile	Upper Quartile	Median	Lower Quartile
	Year Prior to Option Listings			Year Following Option Listings		
α	0.37	0.26	0.16	0.34	0.23	0.15
μ	46.17	15.35	5.89	32.95	11.59	4.65
δ	0.16	0.25	0.44	0.16	0.25	0.46
ξ_B	25.39	7.65	2.19	27.73	7.51	2.19
ξ_S	28.52	9.14	2.62	30.64	8.63	2.49
PIN	0.24	0.19	0.16	0.16	0.14	0.12
	(11.43)***	(9.47)***	(6.82)***	(12.47)***	(8.54)***	(7.42)***

Table BII

Summary Statistics of Estimated Parameters from the Microstructure Model to Estimate the Probability of Informed Trading (*AdjPIN*)

The table presents the cross-sectional distribution of parameter estimates concerning *AdjPIN* for the year prior to and the year following option listings. In the table, α is the probability that an informational event occurs, μ is the rate of arrival of informed trades (buys or sells), δ is the probability of bad news, and ξ_B (ξ_S) is the rate of uninformed buyer (seller) initiated trades, η is the probability of a symmetric order-flow shock, and in the event of symmetric order-flow the additional arrival rate of buys is λ_B and sells is λ_S. ***, **, and * denote significance at 1%, 5%, and 10%, respectively (*t*-statistics are in parentheses). Following Duarte and Young (2009), the *t*-statistics for the *PIN* estimates are calculated using the delta method based on the asymptotic covariance matrix for estimated model parameters.

	Upper Quartile	Median	Lower Quartile	Upper Quartile	Median	Lower Quartile
	Year Prior to Option Listings			Year Following Option Listings		
α	0.43	0.33	0.26	0.42	0.34	0.26
μ_B	35.98	11.90	4.12	27.03	8.08	3.02
μ_S	36.47	12.82	3.30	26.69	7.40	2.68
δ	0.14	0.41	0.70	0.11	0.47	0.70
ξ_B	20.63	6.94	1.93	21.28	5.75	1.86
ξ_S	22.81	8.07	2.01	22.37	7.02	1.94
η	0.39	0.23	0.19	0.35	0.23	0.15
λ_B	40.88	13.66	4.77	41.89	14.15	4.50
λ_S	33.68	10.79	4.61	31.25	9.66	4.45
AdjPIN	0.18	0.16	0.14	0.14	0.13	0.12
	(11.06)***	(8.49)***	(5.26)***	(12.15)***	(8.68)***	(6.01)***