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Derivatives, Information Transmission and Informed Trading

par

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Résumé

Cette thèse est constituée de deux essais en microstructure des marchés et d'un essai en finance corporative.

Les produits sur indices constituent une gamme de produits dérivés dont les premières transactions débutent en 1982 aux États-Unis. Dans un premier essai, nous nous intéressons à la manière dont ces produits altèrent les stratégies d'investisseurs sophistiqués. D'après la littérature théorique (Subrahmanyam, 1991 ; Yuan, 2005), l'introduction de produits dérivés sur indices (PDI) modifie le comportement d'investisseurs informés de deux manières. Premièrement, les investisseurs spécialisés dans le risque sectoriel préfèrent transiger le PDI plutôt que les actions pour limiter les coûts de transactions ainsi que leur exposition au risque idiosyncratique. Deuxièmement, les investisseurs spécialisés dans le risque spécifique à la firme peuvent utiliser le PDI comme instrument de couverture et neutraliser leur exposition au risque sectoriel. Ils peuvent alors transiger d'avantage les actions. Les tout premiers fonds cotés (ETF) sur secteurs ont été introduits en Décembre 1998 par State Street. En utilisant cet évènement comme laboratoire et en reprenant le modèle de Albuquerque et coll. (2008), nous mettons en évidence que l'effet migratoire est validé mais pas l'effet couverture.

Les options offrent un effet de levier très puissant, faisant de ces produits dérivés un terrain idéal pour la spéculation. Dans notre deuxième essai, nous étudions comment les investisseurs sophistiqués allouent leur ordre de transaction entre le marché des actions et celui des options. Pour cela, nous develloppons un modèle Bayésien appliqué aux marchés financiers où des teneurs de marchés transigent une action et une option avec des investisseurs informés ou non, tel que décrit dans Easley et coll. (1998). Nous innovons à deux égards. D'une part, nous utilisons quatre états de la nature plutôt que deux, ce qui permet d'avoir un a priori sur la valeur de l'option ("moneyness"). D'autre part, nous introduisons un système de marge, ce qui nous permet d'intégrer au modèle des investisseurs contraints budgétairement. Dans une première étape, nous dérivons des équilibres de Nash. Dans une seconde étape, nous calibrons le système de marge sur la régulation T et les exigences du CBOE et les paramètres du modèle sur de récentes études empiriques afin de dériver la proportion d'équilibre d'investisseurs informés négociant l'option. Dans le cas de base, cette proportion atteint 14% quand l'information privée sur l'action est bonne et 23% quand celle-ci est mauvaise. Cette étude confirme le rôle significatif du marché des options pour l'incorporation de l'information privée.

Les options d'achat d'actions ("stock-options") sont des produits dérivés utilisés pour rémunérer les gestionnaires. Depuis 2006, il est obligatoire de comptabiliser ces produits en tant que dépenses et de reporter les paramètres relatifs à la valoration. Dans notre troisième essai, nous examinons si un paramètre clé de la valorisation des options, le taux de dividende, est utilisé comme canal de transmission d'information des gestionnaires vers les investisseurs. Alternativement, ce taux peut-être manipulé par des manageurs cherchant à camoufler la valeur de leur rémunération à base d'option. Nous proposons une nouvelle méthodologie pour identifier manipulation à la baisse, maipulation à la hausse et absence de manipulation. En examinant la période 2006-2014, nous mettons en évidence que, pour les 344 entreprises qui manipulent, l'hypothèse de transmission d'information trouve un écho favorable alors que l'hypothèse de camouflage de rémunération n'est pas validée. Cette étude confirme l'utilisation des notes de pages comme canal d'information par les gestionnaires. Par ailleurs, la probabilité de reporter un taux de dividende biaisé augmente quand les commissions d'audit baissent. Ainsi, il semblerait que seul un processus d'audit coûteux soit garant d'une vérification de notes de bas de page.

Mots clés : Négociation informée, risque sectoriel, risque idiosyncratique, produits dérivés sur indices, options, système de marge, états financiers, taux de dividende.

Méthodes de recherche : Économétrie, analyse numérique, modélisation mathématique

Abstract

This thesis is made of two essays in market microstructure and one essay in corporate finance.

Tradable indices are financial derivatives introduced in 1982 on US financial markets. In our first essay, we study how these products modify the behavior of sophisticated investors. According to the theoretical literature (Subrahmanyam, 1991 ; Yuan, 2005), the introduction of tradable indices is expected to modify the behavior of sophisticated in two ways. First, investors specialized in trading the industry risk should prefer to negotiate a tradable index rather than a basket of stocks to limit their exposure to the idiosyncratic risk (the migration hypothesis). Second, investors specialized in trading the firm-specific risk can increase their trading activity because they can use the tradable index as an hedging instrument (the hedging hypothesis). The first sector-specific ETF were introduced in December 1998. By using this event as laboratory and adapting the model of Albuquerque et al. (2008), we find strong evidence in favor of the migration effect but no support for the hedging effect.

Options provide a lot of leverage, making these derivatives a natural ground for speculative bets. In our second essay, we develop, in the spirit of Easley et al. (1998), a Bayesian model where market-makers can trade a stock or an option with informed and non-informed traders. Our contribution to the theoretical literature is two-fold. For the option contract, we are able to define the option moneyness before the trading session starts. For market participants, a margin system is introduced, so that our model encompasses the presence of wealth-constrained investors. After deriving the Nash equilibrium, our parameters are calibrated regarding Regulation T and CBOE margin rates. We study the relative allocation of informed trading across markets and moneyness. We find that the asymmetry in margins between long and short option position conveys into difference in option informed trading (OIT) probability. In our benchmark case, OIT reaches 14% when signals are low and 23% when signal are high. In addition, OIT overcomes 50% for

some information set - moneyness combinations. This study confirms the important role of options for the incorporation of private information.

The stock-option is another derivative product widely used for executive and employee compensations. In our third essay, we study the report accuracy of the dividend yield reported in the 10-K financial statements and used to price executive stock options. This yield can be manipulated by managers in a attempt to convey superior information (information revelation hypothesis) to shareholders or in a attempt to hide the true value of their stock options (managerial opportunism hypothesis). However, the audit firm might impose the company to report a truthful dividend yield (discipline hypothesis). We propose a new methodology to identify underreport, fair report and overreport. By focusing firms that have biased their report over the period 2006-2014, we show that the information revelation hypothesis receives strong evidence while there is no evidence of managerial opportunism. Hence, our study brings new evidence that footnote information can be used by managers to convey information to market participants. In addition, the likelihood to report a fair dividend yield increases with audit commissions. It seems that only a costly audit process guarantees footnote information verification.

Keywords: Informed trading, sector-specific risk, firm-specific risk, ETFs, options, margin system, financial statements, dividend yield

Research methods: Econometrics, numerical analysis, mathematical modeling

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List of Acronyms

PIN	:	Probability of informed trading
ETF	:	Exchange-traded funds
OIT	:	Option informed trading
ESO	:	Executive stock option
FDY	:	10-K Footnote dividend yield

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Preface

The research idea developed in the first part of this thesis, which is also my job market paper, takes root when I was doing my master studies in 2011. In a theoretical paper published in 2005, Kathy Yuan from the London School of Business, shows how sophisticated traders modify their trading behavior when an index is introduced and tradable. In particular, she demonstrates how the traders informed about the systematic risk concentrate their trades in the index market while the traders informed on the idiosyncratic risk participate more in the component stock markets. Although tradable indices exist since 1982 and the literature on this topic is very developed, no research was able to bring an empirical verification of her claims. I find the appropriate statistical tool in 2013, during a course at Concordia and the appropriate event study in 2015. This first working paper was published in the SSRN library in 2016 and presented at the Bank of Canada in Ottawa.

My second research idea emerged in 2014. Informed trading in the option market and the competition between stocks and options for the incorporation of information have been the subject of an extensive literature. Although it was a hot topic, I noticed that only three theoretical studies was published within the last 15 years. It took me one year to understand the mathematics of the Bayesian model applied to financial markets, so that I could undertake an extension. It took me an additional year to clearly define my research path, to produce 100 pages of equations written by hand, and to find stable market equilibria. My model is the first one to characterize a multimarket trading session when investment on margins and option moneyness are taken into account. With this paper, I give predictions on how sophisticated traders split their trades between stock and options, and explain some empirical results.

My third essay started with an RA realized during 2012 for Professor Pierre Chaigneau and Julien le-Maux. My swift ability to prepare a clean dataset, produce results and suggest extensions led to me being invited to become a coauthor. I surely accepted and thank Pierre and Julien for this opportunity. An early draft of the paper was presented during IFM Days in 2013 and at the department of accounting of UQAM in 2015. Although the research question has not changed since 2013, we have widely improved our methodology to address the critics raised during the presentations.

1

Introduction

Despite more than twenty years of empirical researches on tradable indices, there is no evidence on how the introduction of these financial securities affects the behavior of sophisticated traders. This is quite intriguing as theories (Subrahmanyam, 1991; Yuan, 2005) explore the channels by which introducing tradable indices modifies the appetite of sophisticated investors for collecting private information. Understanding the behavior of these traders is crucial, as they are responsible for the incorporation of private information into stock prices, directly impacting market efficiency (Chordia et al., 2005). In the first essay of this thesis, we explore the effect of introducing tradable index on sophisticated investors. The behavior of these traders is analyzed under two angles. First, the introduction of tradable indices on financial markets should trigger a decline in sophisticated trading activity because investors specializing in trading the sector-specific risk have the opportunity to leave the stock markets for the index markets (Subrahmanyam, 1991; Yuan, 2005). This is the migration hypothesis. Second, the introduction of tradable indices should generate an increase in sophisticated trading because investors specializing in trading the firm-specific risk can use indices as hedging instruments (Yuan, 2005). This is the hedging hypothesis.

Our study is designed as follows. We develop a model that identifies three components of the trading activity: non-informed trades, trades on firm-specific information and trades on sector-specific information. This decomposition is based on Albuquerque et al. (2008). We focus on the introduction of the State Street SPDR Select-Sectors ETFs in December 1998 to analyze the pattern of informed trading around this event. The design of these ETFs is based on the assignment of the S&P 500 stocks into nine industries, so that investors were offered the possibility to obtain a specific exposure on industry risk for the first time. This makes this event a very appropriate laboratory for our research question. We find strong support for the migration hypothesis but no support for the hedging hypothesis The robustness of our findings is tested in two ways. First, we use two different algorithms in order to classify trades. Second, we perform tests on a sample that excludes firms belonging to the Information Technology industry. Doing so, we rule out the possibility that our results are driven by an industry whose stocks are characterized by an unusually high speculative activity (the Dot-Com bubble).

In the second essay, we develop a market microstructure model in the spirit of Glosten and Milgrom (1985), extended to multimarket trading, like in Easley et al. (1998), John et al. (2003) and Huh et al. (2015). There is one single asset but all investors are offered the possibility to trade a put on the stock or the stock itself. There is an exogenous amount of non-informed investors and an amount of informed traders whose trading activity across markets is endogenous. Moreover, there is a margin system so that wealth-constrained investors, informed or not, can participate. Under this framework, which takes root in John et al. (2003), informed traders seek to maximize expected returns. An additional feature of our market structure is the moneyness of the option contract: Out-the-money (OTM), near-the-money (NTM) or in-the-money option (ITM).

We derive the Nash equilibrium and obtain a probability of option informed trading (OIT). We analyze how OIT changes for different level of moneyness, relative liquidity, total informed trading and margin rates. In our benchmark case, OIT reaches 14% when signals are low and 23% when signal are high. In addition, we find that OIT exceeds 50% when the option/stock liquidity ratio is high and total informed trading is low. Asymmetry between long put and short put margin requirements is responsible for this difference in OIT magnitude. Traders can achieve larger returns by writing a put when signals are high than purchasing a put when signals are low.

In the third essay, we analyze the accuracy of the dividend yield reported in the financial statement footnotes, used as an input to price executive stock options. Two different mechanisms can explain the lack of accuracy: An objective of information revelation or pure opportunism by the team of managers. A third mechanism favors accuracy: the discipline imposed by the audit firm. To test the three mechanisms, we develop a new methodology to measure report accuracy. Our method is based on 10-K and 10-Q files that are publicly available, and can be replicated by analysts and auditors. A lot of studies have analyzed the accuracy of the reported dividend yield. However, these papers compare this yield to a single measure while the flexibility allowed by FASB guidance indicates that there is no clear specified method of measurement but rather a range of possible benchmarks. Using quarterly and annual Compustat files, we compute various dividend yields. The minimum (maximum) of these measures is selected as a low (high) bound to detect under- (over-) report. By doing so, our methodology is robust to the heterogeneity of methodologies across firms.

Among the three effects tested in this paper, we find strong evidence in support of the information revelation motive. Low Tobin's Q and low total Tobin's Q are strongly associated to the risk of underreporting while large decreases in the operating risk favor the overreporting risk. These results differ from Choudhary (2011) that rejects the information revelation hypothesis. The managerial opportunism hypothesis receives moderate evidence: Analyst's coverage is strongly associated with underreporting, suggesting that the companies the most exposed to analyst scrutiny are more likely to bias the dividend yield downwardly. However, we find no link between excessive compensation and overreporting risk. Third, higher audit fees are associated to less overreport. All together, our findings suggest that information revelation objectives and evidence of disciplinary mechanisms are both present in our data and influence the relative likelihood of underreporting over reporting fairly the footnote dividend yield.

2

Sector-specific ETFs and the Reallocation of Informed Trading

(JOB MARKET PAPER)

This paper identifies a component of the informed trading activity induced by sector-specific information (S-trading) and one induced by idiosyncratic information (I-trading). The introduction of tradable indices on financial markets should trigger a decline in S-trading because investors specializing in trading the sector-specific risk can migrate to index markets. The introduction of tradable indices should also generate an increase in I-trading because investors specializing in trading the firm-specific risk can use indices as hedging instruments. We find that the first effect dominates the second effect.[1]

JEL Classification: C58, G14

Keywords: ETF, informed trading, sector-specific risk, firm-specific risk

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2.1 Introduction

Despite more than twenty years of empirical researches on tradable indices[2], there is no evidence on how the introduction of these financial securities affects the behavior of sophisticated traders. This is quite intriguing as theories (Subrahmanyam, 1991; Yuan, 2005) explore the channels by which introducing tradable indices modifies the appetite of sophisticated investors for collecting private information. Understanding the behavior of these traders is crucial, as they are responsible for the incorporation of private information into stock prices, directly impacting market efficiency (Chordia et al., 2005). For instance, a migration of investors specializing in trading the sector-specific risk to index markets and away from stock markets should result in less incorporation of information into stock prices, leading to a greater uncertainty about stock fundamental values.

In this paper, we explore the effect of introducing tradable index on sophisticated investors. The behavior of these traders is analyzed under two angles. First, the introduction of tradable indices on financial markets should trigger a decline in sophisticated trading activity because investors specializing in trading the sector-specific risk have the opportunity to leave the stock markets for the index markets. Second, the introduction of tradable indices should generate an increase in sophisticated trading because investors specializing in trading the firm-specific risk can use indices as hedging instruments. We find strong support for the migration effect but weak support for the hedging effect.

Our study is designed as follows. We develop a model that identifies three components of the trading activity: non-informed trades, trades on firm-specific information and trades on sector-specific information. This decomposition is based on Albuquerque et al. (2008).[3]

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2 The effect of introducing tradable indices on underlying stocks has been analyzed under many angles. This includes, but is not limited, to: Edwards (1988; stock index futures as instruments, volatility as dependent variable), Harris (1989; stock index futures, volatility), Jegadeesh and Subrahmanyam (1993; stock index futures, volume) and Choi and Subrahmanyam (1994; stock index futures, volume) Kumar et al. (1995; index options, volatility, spread and trading volume). Rahman (2001; stock index futures, volatility), Hedge and McDermott (2004; stock index futures, spread and price impact). Madura and Ngo (2008; ETFs, trading volume) and Henker and Martens (2008; ETFs, Hasbrouck's (1995) information shares).

3 Their model is an extension on the PIN model developed by Easley et al. (1996). PIN is the acronym for Probability of Informed Trading. Like in Vega (2006), we posit that informed trading does not solely reflect private or confidential information held by some investors. It also designates traders that have talent to analyze and interpret the informational content of public releases. In our framework, informed and sophisticated are equivalent.

We focus on the introduction of the State Street SPDR Select-Sectors ETFs in December 1998 to analyze the pattern of informed trading around this event. The design of these ETFs is based on the assignment of the S&P 500 stocks into nine industries, so that investors were offered the possibility to obtain a specific exposure on industry risk for the first time. This makes this event a very appropriate laboratory for our research question.

The SPDR Select Sector ETFs are expected to modify the trading activity of sophisticated traders in two ways. First, the specialists of sector-specific risk (the S-informed traders) should migrate towards the ETF markets because these securities match their informational advantage better than stocks do (Subrahmanyam, 1991; Yuan, 2005). They are expected to trade less component stocks. This is the migration hypothesis. Second, the specialists of the firm-specific risk (the I-informed traders) have incentives to trade more component stocks, since they can now use ETFs as hedging instruments against industry-specific risk (Yuan, 2005). This is the hedging hypothesis. We find strong support for the migration hypothesis while we find only weak support for the hedging hypothesis.

These findings have interesting implications for the market microstructure of stocks. Prior the introduction of the financial products reflecting industry risk, the trading activity on sector-specific information is the dominant component of sophisticated trading on stocks. In our setting, prior to the introduction of the SPDR Select-sector ETFs, there are on average 0.91 units of weighted trading intensity[1] from the I-informed traders for one unit of weighted S-informed trading intensity. After the introduction of the ETFs , this proportion shifts to 1.12 units. It means that trades based on information related to the firm-specific risk becomes the dominant component of sophisticated trading on stocks after ETF introductions. Hence the growth in trading volume following the introduction of tradable indices hides a reallocation of informed trading. To the best of our knowledge, we are the first to document on this effect.

To address how the introduction of tradable indices impacts sophisticated trading, we rely on a decomposition of the sophisticated trading activity into a number of trades

[1] The trading activity is weighted by the probability of private information incorporation, because there are some days with no news.

driven by information on firm-specific risk and a number of trades driven by information on sector-specific news. This is a realistic assumption regarding the current practice in the financial industry. Many institutional investors have research teams specialized in the analysis of news and data on a particular industry. It is also possible that some investors have benefited from the leakage of confidential macroeconomic or sector-specific data generated by national statistical agency.[5] By contrast, an I-informed trader is an investor skilled in interpreting public news related to the firm fundamentals. The latter also refers to investors that have benefited from the leakage of confidential information on upcoming takeovers or earning announcements.[6]

Our distinction between sector-specific and firm-specific information finds some support in the literature. Tookes (2008) develop a model of informed trading where information event can be firm-specific or industry-wide. In Piotroski and Roulstone (2004), market participants possess three types of information: Firm-specific, sector-specific or marketwide. In Crawford et al. (2012), the financial analysts have skills in producing one of the three information type. Traders based on marketwide information, like macroeconomic news, are not present in our model for tractability purpose. Marketwide factors can be converted into sector-specific factors by analyzing the sensitivity of an industry to business cycle shocks, making the restriction acceptable. We assume that the S-informed trader is an investor that knows the impact of market-wide information on the industry she is the specialist of.

To capture the trading activity of the I-informed and S-informed traders separately, the PIN model by Easley et al. (1996) is extended in a very similar way to Albuquerque et al. (2008). Although the PIN model has received considerable attention[7], it assumes that

5 For a recent example of illegal insider trading based on macro-information, see Stewart, R., "Two Sentenced in Australia Insider-Trading Case", The Wall Street Journal, March 2015.

6 There is actually evidence that short-term institutional investors have access to private information, through communication with management team (Ke and Petroni, 2004; Yan and Zhang, 2007). Gao and Huang (2014) show that the lobbyist connections of hedge fund managers give them informational advantage that enables to outperform passive benchmark. Hendershott et al. (2015) find that significant price discovery related to news occurs through institutional trading prior to the official release of the news.

7 The popularity of this measure has widely transcended the microstructure literature. It has been connected to research questions in corporate finance (Duarte et al., 2008; Backed ad Whited, 2010) and asset pricing (Easley et al., 2010; Hwang et al., 2013). Several extensions have also been proposed. See Easley et al. (1997), Grammig et al. (2001), Lei and Wu (2005), Easley et al. (2008), Duarte and Young (2009), Tay et al. (2009).

the pool of informed traders represents a homogeneous group because they all negotiate in the same direction: They buy (sell) on "good news" ("bad news") days. In Albuquerque et al. (2008), traders are heterogeneously informed as they acquire either sector-specific signals or firm-specific ones. Accordingly, the total informed trading activity is split into two components. Because the market incorporates private information of nature sector-specific or firm-specific, the probability of private information arrival is also split into two components. With these distinctions, their model reflects a richer trading process. They show that trades based on market-wide private information is able to forecast industry stock returns and also currency returns. Their evidence provides good support on the ability of the structural model we propose to disentangle liquidity trades from trades on sector-specific risk and firm-specific risk.

There are three important technical points that makes our model different from this of Albuquerque et al. (2008). (i) Their model does not tolerate the arrival of days with both positive (negative) marketwide private information and negative (positive) firm-specific information. We do not enforce this restriction. Duarte and Young (2009) argue that shocks that occur simultaneously on the buy and sell side of the market must be added to the trading process because some days, market participants are enable to agree about information flow content. By lifting the restriction, our framework gives an explanation to the Duarte and Young (2009) claim: Some days, positive (negative) signals on the firm's industry are collected simultaneously to negative (positive) signals about the firm herself. As a consequence, the I-informed investors trade on the opposite side of the S-informed ones. (ii) Buyer-side and seller-side liquidity trades are captured by the same parameter. Quantifying aggregate liquidity trading is not the heart of this paper and this restriction avoids unnecessary complexity and liberates several degrees of freedoms. (iii) By applying the reformulation of the likelihood function following Lin and Ke (2011), structural parameters can be estimated for all stocks, regardless the trading volume level.

An additional feature of our model is the ability to produce cross-correlation in the order-flow. Without tradable indices, the S-informed traders must trade several stocks of the same industry simultaneously to obtain a profit free of idiosyncratic innovations. By trading, their information of the S-informed traders disseminates across stocks, which triggers co-movements in the order-flow cross-section. By performing simulations, we show that our model is able to generate this cross-correlation. This is a feature which is particularly appealing since the recent evidence of significant price impact cross-correlations at industry-level, documented by Pasquariello and Vega (2015).

Using a non-parametric test, we assess whether the two components of sophisticated trading activity (i.e. trades on sector-specific risk and trades on firm-specific risk) have experienced a significant shift after the introduction of the sector-specific ETFs. The downward shift of the S-informed trading activity (the migration hypothesis) finds strong support. An upward shift of the I-informed trading activity (the hedging hypothesis) is also detected, but this is not significant at the 5% conventional level. In addition, liquidity trading turns out to greater after the introduction of tradable indices, consistent with the findings of Choi and Subrahmanyam (1994) and Hedge and McDermott (2004). Using cross-listed stocks as a control sample, difference-in-difference estimates show economically large and significant shifts for the S-informed trading activity and the non-informed one.

The robustness of our findings is tested in two ways. Our main analysis is based on the use of the Lee-Ready algorithm (Lee and Ready, 1991) to classify trades. We redo the analysis by replacing this algorithm by the one proposed by Chakrabarty et al. (2007). In addition, we perform tests on a sample that excludes firms belonging to the Information Technology industry. This is justified by the existence of a Dot-Com bubble that goes through 1998. Doing so, we rule out the possibility that our results are driven by an industry whose stocks are characterized by an unusually high speculative activity.

The paper is organized as follows: Section 2 links tradable indices to sophisticated trading activity, section 3 introduces the model and section 4 presents the methodology. Section 5 shows the results. Section 6 concludes.

2.2 Tradable indices and informed trades

2.2.1 Foundations

Discretionary traders (or liquidity traders) trade on several assets simultaneously following clients' willing or for reasons exogenous to expected asset payoffs.[8] A discretionary trader experiences losses when the matching position is a trader more informed about the stock fundamental value. But it turns out that this adverse-selection problem is less detrimental for the uninformed in the index market (Subrahmanyam, 1991). Indeed, the value of the tradable index tends to reflect the systematic risk only since idiosyncratic (stock-specific) innovations tend to offset each other. So tradable indices offer the opportunity to limit adverse-selection costs compared to stocks whose prices are combination of systematic and idiosyncratic risk. They are superior investment vehicle for discretionary traders as it reduces the informational advantage of informed traders. Aware of this advantage, liquidity traders are expected to concentrate their trades on tradable indices, at the expense of the liquidity of the component stocks. This idea is also defended in Gorton and Pennacchi (1993) and has received strong support in Berkman et al. (2005).

Like liquidity traders, S-informed traders are exposed to idiosyncratic risk in a universe without a tradable index. To ensure that the payoffs strictly reflect the change in the systematic component, traders need to replicate their strategy on a wide range of stocks, which is very costly. Negotiating the index avoid the duplication of order costs and guarantees that the returns reflect only private signals of type S.[9] Expected profits increase with the extent of the diversification effect. Regarding the competitive advantage of tradable indices, Subrahmanyam (1991) and Yuan (2005) predict a migration of the S-informed traders toward tradable indices.

For the I-informed traders, the exposure to systematic risk makes payoffs uncertain. Yuan (2005) also argues that an I-informed trader can use the tradable index as a hedging

[8] Such liquidity needs encompass random wealth shocks, portfolio rebalancing, tax planning purpose and a desire of immediate consumption.

[9] "type S" ("type I") for information on the systematic (firm-specific) risk.

instrument. By initiating an offsetting position on the tradable index, she limits her exposure to the systematic risk. The literature dealing with the effects of index derivative introductions is abundant (Jegadeesh and Subrahmanyam, 1993; Choi and Subrahmanyam, 1994; Hedge and McDermott, 2004; Henker and Martens, 2008; Madura and Ngo, 2008). Volume and trading cost measures are widely used but trading intensities are never analyzed. By decomposing the total trading activity into a I-informed, S-informed and a non-informed component, we bridge the gap between theoretical works mentioned above and empirical support.

2.2.2 Hypotheses

If a sophisticated investor has expertise to analyze the information of one specific industry, he is willing to trade an index derivative that tracks the performance of this industry. Indeed, among all securities, this is the one that provides returns that are the most correlated to the unobservable sector risk, for which this investor is a specialist of. When a country-specific index derivative is introduced, an investor skilled in analyzing the country-specific risk might be interested to switch to the new market for the same reason: It is the "best" instrument to trade, given the signals that she observes.[10] This reasoning holds as soon as index are large enough to guarantee a negligible influence of the idiosyncratic risk from components stocks. This leads to our first hypothesis:

I. *Migration hypothesis*

With the introduction of a sector-specific tradable index on financial markets, the S-informed traders whose expertise is on this sector should migrate from stock markets to this new market because the expected payoffs from trading the index match their signals. We predict a decline of their trading activity on stock markets.

Traders specialized in firm-specific risk have incentives to collect information because they

[10] Likewise, an investor specialized in trading on volatility information might find more interesting to trade a volatility ETF than initiating costly straddles with options.

can use the index derivative as a viable hedging instrument against changes in systematic risk (Yuan, 2005). For instance, consider a situation where a sophisticated investor have some information indicating that the price of a particular stock will go up, so that she initiates a long position on this stock. Bad news on the sector are revealed to the market before she closes her position. Three outcomes are possible: She loses money if the pricing of the sector-specific risk is dominant over the firm-specific risk. She earns nothing if both risks are equally priced. She earns money if the firm-specific risk is dominant over the sector-specific risk. Now if she can short-sell the index, she will earn money on the index, as its price will go down. This offsets the loss on the stock position under the first scenario or is an additional gain under the third scenario. Under the second scenario, the trader earns money, too. As a consequence, I-informed traders are expected to collect more signals and intensify their participation to the stock market. This is our second hypothesis:

II. *Hedging hypothesis*

Given the possibility to use tradable index as hedging instruments, the uncertainty associated to payoffs declines substantially for any traders specialized in the firm-specific risk. Their appetite to acquire signals on the firm-specific risk is greater and we predict a soar of their trading activity on stocks.

It is important to mention that traders are likely to choose a highly liquid instrument among available index derivatives, even if it is not the most appropriate instrument to trade regarding their signal. Since informed investors need non-informed ones to trade with and make a profit, the overall level of liquidity matters. Consider a sophisticated investor that has private information specifically on the sub-industry Automobiles (GICS subcode 2510). If the index derivative that offers an exposure to this sub-industry is illiquid, the investor would prefer to trade a larger index derivative, for instance the one reflecting performance of the Consumer Discretionary Sector (GICS code 25). For an I-informed investor looking for the right index derivative to initiate an offsetting position, the transactions cost is also an important factor when selecting the security.

2.2.3 Index derivative data

Index Futures are today very popular investment vehicles. In April 1982, the first S&P 500 Futures contract was launched and attracted considerable attention from investors. The monthly dollar trading volume reached 6.89 billions of U.S. dollars in May, 14.37 in June, and 35.84 in November (Jegadeesh and Subrahmanyam, 1993). This success paved the way for the establishment of other stock index futures like MMI Futures (introduced in 1984) and the NASDAQ 100 Futures (1985).

Then, options on index were launched (S&P 500, NASDAQ, Russel). A major innovation in the universe of tradable indices occurs in 1993, with the arrival of the Standard and Poor's Depositary Receipts (SPDRs), the first American Exchange-Traded Funds (ETFs). ETFs are diversified, low fees and tax efficient negotiated funds. They are continuously traded during the trading day and ETF shares can be created or redeemed, usually by exchanging underlying stocks against 50,000 ETF units. Dividend payments are transferred to a separate interest-bearing account and distributed periodically to ETF shareholders, net of management fees. This new design has guaranteed a growing popularity through years and makes them a formidable competitor of conventional mutual funds.[11]

ETFs also bring innovations with respect to index futures in terms of risk exposure, attracting investors that have particular investment goals. In March 1996, BlackRock introduces 14 country-specific ETFs bringing a specific exposure over each of the most developed countries. In December 1998, State Street introduced simultaneously nine ETFs, called "Select Sector". These securities provide investment results that, before expenses, match the price and yield performance of the Select Sectors index. It was the first time that investors were offered the opportunity to obtain a sector-specific exposure.[12] Beyond

[11] For an analysis of this competition, see Agapova (2011).

[12] The definition of economic segment and stock classifications are based on the Global Industry Classification Standard (GICS). This classification is widely used as benchmark in the financial community. Bhojraj et al. (2003) put in evidence that this classification outperforms significantly SIC code, NAICS code and the Fama and French (1997) classification.

the uniqueness of risk exposure that provide the Select Sector ETFs, this event is a very good laboratory for three reasons. First, 1998 intraday data are reliable and centralized in the TAQ database. Second, this period precedes the decimalization (2001), so that bid/ask spread are wider and classifying trades is less difficult. Third, Electronic Communication Networks were at early stages of their existence in 1998, so that the NYSE and NASDAQ account for most of the trading volume this year. **Figure I** shows monthly volumes of the Select Sector ETFs during the first semester that follows their introduction (panel A). We also plot the average trading volume for the largest S&P 500 companies, by industry, around the event (panel B).

2.2.4 Related works

The effect of tradable indices on component stocks has been addressed in two ways. One stream puts the emphasis on the volatility impact while the other one focuses on changes in trading volume. Edwards (1988) studies the day-to-day price volatility around the S&P 500 Futures introduction in 1982 and find that the market-wide volatility is greater before the introduction of the S&P 500 Futures. Harris (1989) obtains a different result: Stock volatility has actually increased relative to this of a non-S&P control group, following the introduction of the S&P 500 Futures. Laatsch (1991) conducts a similar study around the launch of Major Market Index (MMI). It turns out that the volatility of MMI component stocks does not appear to be greater in the post-inception period, relative to the volatility of a control group. Using intraday data, Rahman (2001) finds that the introduction of index futures and futures options on the Dow Jones Industrial Average has produced no structural changes in the conditional volatility of component stocks.

Jegadeesh and Subrahmanyam (1993) document a significant increase in the monthly average volume after the introduction of the S&P 500 Futures. Choi and Subrahmanyam (1994) find a growth of trading volume upon the launch of MMI Futures. Hedge and

The Select Sector ETFs match the following nine industries (two-digit GICS code): Energy (10), Materials (15), Industrials (20), Consumer Discretionary (25), Consumer Staples (30), Health Care (35), Financials (40), Information Technology (45) and Utilities (55).

McDermott (2004) analyze standardized trading volume, spread and price impact and find evidence of an improvement of liquidity over the 50 trading days following the introduction of the Dow Jones Industrial Average Futures. Madura and Ngo (2008) analyze the impact of the introduction of 124 ETFs on the 1,041 component stocks and find a significant increase in the ratio of trading volume to the number of outstanding shares. Henker and Martens (2008) study the impact of AMEX and NYSE listing of the Holding Company Depositary Receipts ("HOLDRS" by Merryl Lynch) in 2002. They show that it did not reduce the consolidated trading volume of the underlying securities. Our study is closed to Henker and Martens (2008) as we both test the predictions of Subrahmanyam (1991) using sector-specific ETF as index derivative data. However, their hypotheses and conclusions are on trading activity at the aggregate level while ours are only about informed trading and the mechanisms underlying the allocation of trades across stocks and ETFs by this specific class of investors.

2.3 Identification of S- and I-informed trading activities

2.3.1 The probability of informed trading

Easley et al. (1996) propose an econometric model to quantify informed trading activity using order-flow data. The daily number of buyer-initiated trades and seller-initiated trades (BITs and SITs hereafter) are random variables following a Poisson distribution. Expected intensities combine the arrival rate of uninformed traders (sellers or buyers), denoted ε, with the arrival rate of informed traders, denoted μ. There is a probability $1-\alpha$ that informed traders do not participate, leaving the market to non-informed investors. There is no incorporation of private information during these days. A day with incorporation of "Bad news", occurs with a probability $P\{\text{"}bad\ news\text{"} \mid \alpha\} = \delta$. This day is recognized by an unusual trading activity on the sell side, due to the presence of informed traders on this side. Accordingly, the expected intensity for the random variable SIT is the sum of the non-informed part (ε) and the informed part (μ). On the other side, nothing changes and ε is the expected intensity for the random variable BIT. A "Good news" day happens with a probability $P\{\text{"}good\ news\text{"} \mid \alpha\} = 1 - \delta$. During this day, informed traders are present just on the buy side, and trade with an intensity μ while the trading activity on the sell side stands at its usual level ε. The sum of the two components defines the expected intensity for the random variable BIT.[13]

Figure II exhibits the trading process. The joint density function is a weighted sum of three Poisson distributions, where each weight is the probability of state occurrence:

$$\begin{aligned} f(\Omega \mid BIT, SIT) &= (1-\alpha) \times \exp(-\varepsilon) \times \frac{\varepsilon^{BIT}}{BIT!} \times \exp(-\varepsilon) \times \frac{\varepsilon^{SIT}}{SIT!} \\ &+ \alpha \times (1-\delta) \times \exp(-(\varepsilon+\mu)) \times \frac{(\varepsilon+\mu)^{BIT}}{BIT!} \times \exp(-\varepsilon) \times \frac{\varepsilon^{SIT}}{SIT!} \\ &+ \alpha \times \delta \times \exp(-\varepsilon) \times \frac{\varepsilon^{BIT}}{BIT!} \times \exp(-(\varepsilon+\mu)) \times \frac{(\varepsilon+\mu)^{SIT}}{SIT!} \end{aligned} \tag{1}$$

Ω defines the set of structural parameters. The probability of informed trading is defined as $\alpha \times \mu$ divided by the total trading activity $2 \times \varepsilon + \alpha \times \mu$. The PIN metric is well established in the literature as a proxy for private information incorporation. It turns out to be significantly correlated to size (Easley et al., 1996), analyst coverage (Easley et al., 1998), price impact (Chung et al., 2005) and investment decision (Bakke and Whited, 2010).

2.3.2 The proposed extension

Informed traders are assigned to two classes: Informed on the sector-specific or on the firm-specific risk. The private information set is split into two types of signals: sector-specific and purely idiosyncratic. The S-(I-)informed traders are responsible for the spillage of private information of type "S" ("I") through a trading intensity μ_S (μ_I). In a day, an event of type "S" occurs with a probability α_S while an event of type "I" happens with a probability α_I. Bad sector-specific (firm-specific) news occurs with a probability δ_S (δ_I). Once S-investors have acquired signals, they trade over a wide range of assets to limit their

[13] Easley et al. (2002) propose to split ε into ε_b (uninformed buyer-specific trading intensity) and ε_S (uninformed seller-specific trading intensity). Duarte and Yuang (2009) extend this approach by splitting μ into μ_b and μ_S too.

exposure to idiosyncratic risk. It is this identification strategy that allows us to disentangle private information arrival probabilities into $\{\alpha_S, \alpha_I\}$. We assume that the probability of the arrival of private information of type "S" (α_S) is the same for the whole cross-section of stocks. Given the incorporation of private information by the market, the probability that this is of type "bad" (δ_S) is also assumed to be fixed in the cross-section. However, there are as many $\{\alpha_I, \delta_I\}$ pairs as stocks in the cross-section.

Figure III exhibits the trading process. In our setting, the three states of nature about the incorporation of information of type "S" are coupled to the three states of nature concerning the incorporation of type "I" private information. It generates nine states of nature. The new likelihood function is:

$$f(\Omega \mid BIT, SIT) = \sum_{k=1}^{9} \pi_k(\alpha_S, \delta_S, \alpha_I, \delta_I) \times f(\varepsilon, \mu_S, \mu_I; BIT, SIT) \tag{2}$$

where Ω stands for the set of structural parameters $\{\alpha_S, \delta_S, \alpha_I, \delta_I, \varepsilon, \mu_S, \mu_I\}$, π_k is the probability associated to the state of the nature k and $f(\bullet)$ is the corresponding Poisson distribution. Intensities vary across states and the density function can be rewritten:

$$\begin{aligned} f(\Omega \mid BIT, SIT) = \quad & \sum_{k=1}^{9} \Bigg[\pi_k(\alpha_S, \delta_S, \alpha_I, \delta_I) \times \exp(-(\varepsilon + \lambda_{k,b})) \times \frac{(\varepsilon + \lambda_{k,b})^{BIT}}{BIT!} \\ & \times \exp(-(\varepsilon + \lambda_{k,s})) \times \frac{(\varepsilon + \lambda_{k,s})^{SIT}}{SIT!} \Bigg] \end{aligned} \tag{3}$$

The details of π_k and λ_k are given in **Appendix I**. Our model uses both time-series and cross-section to estimate the structural parameter while the Easley et al. (1996) likelihood (1) only uses information from individual stock time-series. $\alpha_S \times \mu_S$ captures the trading intensity of the S-informed traders. The migration hypothesis is validated if there is a significant downward shift of this metric in the cross-section of stocks, following the arrival of the Select-Sector ETFs. $\alpha_I \times \mu_I$ captures the trading intensity of the I-informed ones. The hedging hypothesis will find support if this quantity increases following ETF introductions.

With our model, our customized PIN is made with a sector-specific component $(\alpha_S \times \mu_S)/(2\times\varepsilon+\alpha_S\times\mu_S+\alpha_I\times\mu_I)$ (SPIN) and an idiosyncratic component $(\alpha_I\times\mu_I)/(2\times\varepsilon+\alpha_S\times\mu_S+\alpha_I\times\mu_I)$ (IPIN). To bring some support to our decomposition, we show later in this paper how these two measures correlate with popular proxies for private information incorporation, including the PIN. Finally, we define a relative trading intensity, the I/S-Ratio, as $(\alpha_I\times\mu_I)/(\alpha_S\times\mu_S)$. This measure will be used to provide some economic intuition behind our results.

Albuquerque et al. (2008) propose a similar extension of the Easley et al. (1996) model. In their framework, informed traders trade on marketwide private information or firm-specific private information. First, they show that their estimate of liquidity trades (ε in our model) correlates very well with the first principal component in order-flow proposed by Hasbrouck and Seppi (2001). Second, they show that information-driven trading is able to forecast industry stock returns and also currency returns. This evidence provides support to the ability of our econometric model to disentangle well liquidity from sector-specific and firm-specific trades.

There are three important technical points that make our model different from that of Albuquerque et al. (2008). First, their model allows liquidity trades from the buy side (ε_b) to differ from the amount on the sell side (ε_s). Setting the same decomposition of ε would lead to $2+6\times N$ parameters to estimate instead of $2+5\times N$, where N is the number of stocks. This means less degree of freedom while quantifying aggregate liquidity trading is not the heart of this paper. As a result, we avoid this additional complexity.

Second, their model does not tolerate the arrival of days with both positive (negative) marketwide private information and negative (positive) firm-specific information.[14] We do not enforce this restriction. Duarte and Young (2009) argue that shocks that occur simultaneously on the buy and sell side of the market must be added to the trading process because some days, market participants are enable to agree about information flow content.

[14] "*Whenever marketwide and firm-specific private information on any firm i are qualitatively contradictory, the firm-specific news dominates investors' behavior, which is consistent with the view that marketwide private information is generally composed on less precise information.*" (pp. 2301 of their paper).

By lifting the restriction, our framework gives an explanation to Duarte and Young (2009) statement: Some days, positive (negative) signals on the firm's business environment are collected simultaneously to negative (positive) signals about the firm herself. Under these scenarios, the I-informed investors trade on the opposite side of the S-informed ones on some days.

Third, our reformulation of the likelihood function following Lin and Ke (2011) allows to estimate our model on every stock, whatever the size of the underlying company. The raw likelihood function used by Albuquerque et al. (2008) forces the authors to adapt the sample length by industry for their analysis "*...for some months the number of buy and/or sell orders is so high that maximizing the log-likelihood function requires values higher than the largest positive floating point number in our personal computers. For this reason the sample length varies across industries*" (pp. 2316 of their paper).

Within a managed fund, it is possible that there are analysts dedicated to market-wide risk and analysts dedicated to firm-specific risk. The analyst teams generate reports suggesting two, perhaps opposite, trading strategies. If advises differ, the fund clears internally before sending orders to the market maker, in order to minimize transaction costs. We cannot observe market orders associated to each strategy, just the executed orders. Our assumption is that investors replicate systematic-based strategies over several stocks of, for instance, a single industry. With the daily aggregation of transactions, a tendency of type long or short emerges. Our model captures this trend. Cross-trading of S-informed traders should generate cross-correlation in the order-flow. Simulations show that α_S actually drives cross-correlation in the order-flow, and the magnitude of cross-correlation coefficients using real trade series influences estimates and precision of α_S.

The existence of cross-price impact, i.e. the impact of trading activity in one asset on the price of other, has been recently documented by Pasquariello and Vega (2015). In their setting, cross-price impact is likely to be attributable to the cross-trading activity of sophisticated speculators. Rational uninformed market makers, aware of this strategy, attempt to learn about the liquidation value of one asset from the order flow in other assets and set prices accordingly. The S-informed traders might fit the trader profile described by Pasquariello and Vega (2015). However, the motivation behind the trading strategy is different in our setting. In Pasquariello and Vega (2015), the trader attempts to attenuate the dissipation of their information advantage in one asset while trading a cross-section of assets limits the impact of idiosyncratic innovations on profits in our framework.

2.3.3 Estimation of parameters

Trades are defined as buyer-initiated and seller-initiated using a trade classification algorithm. The next subsection discusses the procedure. Once each trade is classified, we obtain the daily amounts of buyer-initiated trades and seller-initiated trades. These are the two inputs of the Poisson mixture. The set of structural parameters $\left\{\alpha_S, \delta_S, \alpha_I^1, \delta_I^1, \varepsilon^1, \mu_S^1, \mu_I^1, ..., \alpha_I^N, \delta_I^N, \varepsilon^N, \mu_S^N, \mu_I^N\right\}$ is estimated by maximum likelihood (ML hereafter), and N stands for the number of stocks. The "market" parameters set $\{\alpha_S, \delta_S\}$ is estimated from the time-series and the cross-section of observations. Without this constraint, we would be unable to distinguish the arrival of sector-specific news from the arrival of idiosyncratic news. Simultaneously to $\{\alpha_S, \delta_S\}$, each set $\left\{\alpha_I^i, \delta_I^i, \varepsilon^i, \mu_S^i, \mu_I^i\right\}$ for $i = 1, ..., N$ is estimated by using individual time series. For instance, a bucket of $N = 10$ companies leads to $2 + 5 \times 10 = 52$ parameters to estimate simultaneously, given a total number of $63 \times 10 = 630$ observations. Low (high) bounds of $\left\{\alpha_S, \delta_S, \alpha_I^i, \delta_I^i\right\}$ are set to 0.05 (0.95) while $\{\varepsilon^i, \mu_S^i, \mu_I^i\}$ are bounded by 1 and 10,000.

When maximum likelihood is running, large buys and sells that feed the Poisson distribution may generate a numerical value that exceeds the range of real values that software can handle. For instance, the exponent of 710 or higher numbers results in an overflow under MATLAB. This trouble is called the floating point exception (FPE). Lin and Kee (2011) reformulate the log-likelihood to overcome the floating-point exception. We extend their methodology to our framework. The steps of this reformulation are given in **Appendix II,** with specific information about the algorithm used. Yan and Zhang (2012) document a strong sensitivity of structural parameter estimates to the starting points. To avoid that a local maximum is reached instead of a global maximum, we adapt the procedure proposed by Yan and Zhang (2012) in order to derive a set of initial guesses. Hence, 500 sets of parameters are tested as initial values and the set of structural parameters returning the highest objective function is kept as the solution of the optimization task. The set is kept even if some parameters are boundary solutions. The adaptation of Yan and Zhang (2012) to our model is described **Appendix III**. Estimation are performed on MATLAB, over the HEC Montréal dedicated servers "Hermes". Parrallel processing is implemented to increase computational speed.

2.4 Methodology and data

2.4.1 Event study design

The official introduction date of the Select Sector ETFs, 12/18/1998, is used as the event. The pre-event period is the 63 trading days (one quarter) that ends 21 days before the event. The post-event period is the 63 trading days that starts 21 days after the event. Hence, the 40 trading days (two month) that surrounds the event are excluded. With Compustat, we gather information about GICS sector membership for the S&P 500 stocks. We create nine buckets of highly liquid stocks, one bucket per sector. Buckets are filled according to the following procedure. First, S&P 500 stocks are sorted regarding their liquidity level over the 250 trading days that precede our event study. To do so, we calculate the medians of the daily trading volumes recorded between August 1997 and August 1998. Volume data are from CRSP. The 10 most liquid stocks of an industry fill a bucket.

Three additional criteria drive the sample design. (i) The average trading activity must be at least 100 BITs and 100 SITs over the pre-event period and over the post-event period.[15] (ii) Companies must not experience corporate events like mergers, spin-offs or stock splits that induce trading discontinuities or jumps in the order-flow or stock prices.

[15] Our simulations show that at least this liquidity level is necessary to obtain reliable estimates of structural parameters.

(iii) A matching ticker from the Trades and Quotes (TAQ) dataset must be available since TAQ is our intraday data provider. A stock that does not respect any of the three criterion is replaced by next ones.[16]

Tickers, companies and median volume are reported **Table I**. The most traded stocks belong to the "Information Technology" industry, with a cross-sectional average of the median daily volume of $8,725,066$ shares. It is followed by "Consumer Staples" $(2,229,127)$ and Health Care $(1,794,386)$. The dominance of the Information Technology (IT) sector in terms of trading volume is related to the Dot-Com bubble that occurs between 1997 and 1999. To rule out the possibility that our results are driven by the influence of the IT sector, we re-run our analysis without the IT sector.

2.4.2 Microstructure and descriptive statistics

Trades (from TAQ Consolidated Trades file) and quotes (from TAQ Consolidated Quotes file) before 9.30 am and after 16 p.m. are deleted. Quotes with a null size or with incorrect mode $(4, 7, 9, 11, 13, 14, 15, 19, 20, 27, 28)$ are also removed from the sample. Following Duarte and Young (2009), if $SPREAD >$ \$5 or if \$5 $< MIDPOINT <$ \$50 with $SPREAD/(BID + ASK)$ >0.25 or if $MIDPOINT >$ \$50 with $SPREAD/(BID + ASK) > 0.1$, the observation is deleted. Trades with a non-null correction indicator or with a null price are removed. Once the dataset is clean of abnormal trades and quotes, we derive the national best bid and offer (NBBO) for each second, using the SAS script developed by Rabih Moussawi.

Trades and quotes are merging using the SAS "Dow Loop" created by researchers of Wharton University. We adopt a 1-second lag rule between trades and prevailing quotes, as suggested in Henker and Wang (2006).[17] If no quote is available at the delay, the trade

[16] Doing so, Exxon Corporation and Mobil Corporation (merge in 1999), Citicorp and Travelers Group (merge in 1998), First Chicago Bank and Bank One Corp. (merge in 1998) are excluded from the sample. Gillette and Chrysler are excluded because there is no matching TAQ ticker.

[17] Bessembinder (2003) recommends a zero delay in matching trades with quotes. However, Henker and Wang (2006) argue that the contemporaneous quote is most likely driven by the trade. Using a zero delay will result in quotes being wrongly used as prevailing quotes. They show that a 1-second quote delay should be used to match quotes with trades instead. Moreover, their study comprises all stocks in the S&P 500 index in 1999 with a primary listing on the NYSE and traded for at least 200 trading days. Our sample is a subsample of their sample.

is compared to the most recent quote available. Trades in the few seconds after 9.30 a.m. are compared to the most recent quotes between 9.00.01 and 9.29.59. Then, we follow Easley et al. (1996) by collapsing into one trade all trades occurring within 5 seconds of each other at the same price, with no intervening quote revisions. Descriptive statistics for August 1998 - November 1998 (pre-event period) are given in **Table II** and in **Table A.II** (**Appendix V**) at the stock level. Same table for January 1999 - April 1999 (post-event period) are available upon request.

There is a low heterogeneity of trade dispersions around quotes. First, more than two-third of trades are realized at quotes, on average. This is good news for the accuracy of estimated parameters, because the misclassification rate is the lowest for trades at quotes (Ellis et al., 2000). Second, between 16% and 18% of daily trades are realized at midpoint. Trades outside represent only a small proportion of the daily trade amount: Between 2.5% and 6.5% on average, depending on the industry. However, it soars to 6.8% for the Health Care sector and 13.8% for the IT sector. Trades realized inside quotes represent a proportion that lies between 8% and 14% on average, except for the IT sector (4.2%). This singular distribution of trades for the IT sector is an additional motivation to re-run our study on a subsample that excludes this sector. The largest end-of-day bid/ask spread, scaled by midpoint, holds for the Energy sector (cross-sectional average of 0.5%), following by Materials (0.4%) and Utilities (0.3%). Other industries return the same figure (0.2%).

2.4.3 Comparison with popular proxies for private information incorporation

To assess the reliability of our model, the sector-specific and idiosyncratic component of the PIN are compared to the original PIN by Easley et al. (1996), a refined version proposed by Duarte and Young (2009), bid/ask spread, absolute net order-flow, size, analysts coverage and idiosyncratic volatility. Correlation coefficients are reported **Table III**. It turns out that IPIN is better correlated than SPIN to proxies for private information incorporation. First, the correlation reaches 0.78 for IPIN versus PIN against 0.44 for SPIN versus PIN. This is large and significant at 0.5%. We observe the same pattern with the extended

PIN by Duarte and Young (2009) with a coefficient of 0.58 for IPIN versus DY_PIN and 0.32 for SPIN versus DY_PIN. Second, IPIN (SPIN) is correlated at 0.38 (0.29) and 0.56 (0.36) with bid/ask spread and absolute net order-flow, respectively. Third, SPIN is less correlated to analyst coverage than IPIN (−0.16 versus −0.22). This suggests that the private information holding by stock analysts is more firm-specific than sector-specific.

Idiosyncratic volatility quantifies the incorporation of private information into stock prices (Roll, 1988). It is defined as the standard error of residuals from a regression of daily stock return over daily market return (proxied by the S&P 500 total daily returns). We should obtain similar pattern with respect to proxies for private information incorporation: High correlation with IPIN and low correlation with SPIN. However, both coefficients turn out to be large and significant (0.39 and 0.35). The idiosyncratic volatility measure is obtained from a regression that controls for market-wide movements (S&P 500 returns) and not for sector-specific variations. Hence the latter is reflected in the residuals, and idiosyncratic volatility correlates significantly with SPIN.[18]

2.4.4 Order-flow cross-correlation, parameter estimates and precision

Our model is able to generate a cross-correlation in the order-flow, due to the arrival of information common to companies that belong to the same industry. In **Table IV**, we measure cross-correlation levels truly observed in data. A bucket is made with 10 stocks so that 45 correlation coefficients are computed per bucket. As expected, order-flow cross-correlation matrix is large and significant. Average cross-correlation lies within 22% and 55% for BIT, between 26% and 62% for SIT and between 19% and 31% for the net order-flow. For the the sectors Energy (GICS code 10), Finance (40) and Utilities (55), the average correlation is above 45% and at least 75% of the coefficients are significant.

Median estimates and median standard errors of SPIN, IPIN and I/S-Ratio are reported **Table V** for the pre-event period and **Table VI** for the post-event period. Standard errors

[18] These coefficients are obtained when IPIN and SPIN are derived using the Lee and Ready (1991) algorithm to sign trades. Modifying the algorithm could affect correlation level. In **Table III**, one can easily check that the coefficients are quite similar when the Chakrabarty et al. (2007) algorithm replaces the Lee and Ready one.

are computed using the delta method. See **Appendix II** for computational details. In addition stock-level estimates and standard errors are provided **Table A.II** (**Appendix V**). Duarte and Young (2009) provides estimates of PIN for a long period of time and a large cross-section (48,512 firm-year observations between 1983 and 2004). The 5th, 50th and 95th percentiles reported in the table 5, pp. 131 of their paper are 8%, 17% and 37%. With our sample, we obtain 11%, 18% and 26% under LR and 11%, 18% and 25% under CLNV for the 5th, 50th and 95th percentile, respectively. Except for the 95th percentile, this is fairly close. The absence of small capitalization in our sample explains this large difference.

Highest PINs can be found in the Energy industry, consistent with the high bid/ask spreads observed for this sector. In the pre-event period, IPIN and SPIN median estimates are 0.103 and 0.106 under the LR algorithm and 0.103 and 0.102 under the CLNV algorithm, respectively. The "IT" sector returns the lowest PINs, with a median IPIN of 0.075 and a median SPIN of 0.081, under the LR algorithm and a median IPIN of 0.081 and a median SPIN of 0.080 under the CLNV one. This is consistent with the unusual high trading volume that characterized this industry in the middle of the Dot-Com bubble.

The lowest median I/S-Ratio is observed for the industry Financials. This is 0.79 under LR and 0.80 under CLNV. The I/S-Ratio can be interpreted as follows: For one unit of S-informed trades, there is 0.79 unit of I-informed trades. Hence, the specialist of the sector-specific information constitutes the large majority of the pool of sophisticated traders. In the industry Energy, this is the opposite pattern: there is more I-informed trades than S-informed trades. The I/S-Ratio is 1.09 under LR and 1.15 under CLNV.

Overall, estimations are precise under the LR algorithm. Median standard errors lie within 0.4% and 4.0% for both IPIN and SPIN. Only three cases return a median standard error above the median parameter estimate: Consumer Staples and IT, in the post-event period and Financials in the pre-event period. However, this occurs only under the CLNV algorithm. Although we have run the optimization package (fmincon) several times for these cases, these solutions turn out to return the highest objective functions. So these estimates are kept, despite the lack of precision.

2.5 Results

2.5.1 A modification in S- and I-informed trading activity

To test the migration and the hedging hypothesis, a series of Wilcoxon signed-rank tests are performed. Results are provided **Table VII**. There is evidence of a significant decline in the amount of trades based on sector-specific risk information. For the full sample and under the LR algorithm, $\alpha_S \times \mu_S$ moves from 81.56 to 68.75 from the pre-event to the post-event period. This represents a drop by 15.7%. This result is strongly significant, returning a *z-value* of 2.88. To be sure that this result is not driven by the unusual high trading activity on the IT sector, tests are performed again without this industry. We obtain that $\alpha_S \times \mu_S$ shifts from 73.70 to 60.70 under LR and from 70.77 to 61.52 under CLNV. Both result are significant at 0.5% (*z-value* = 2.99) and 5% (*z-value* = 2.10), respectively. There is no evidence of more trades related to firm-specific risk information. For the full sample and under the LR algorithm, $\alpha_I \times \mu_I$ moves from 67.41 to 75.44 from the pre-event to the post-event period. This increases by 11.9% is consistent with the predicted direction of the I-informed trading activity. However, this result is not significant, returning a *z-value* of -0.80. It remains non-significant under CLNV and when the IT sector is excluded of the sample.

I/S-Ratio gives some economic intuition of what happened. In the benchmark test (full sample, LR algorithm), the median I/S-Ratio is 0.91 in the pre-event period and 1.12 in the post-event period. For one unit of expected S-informed trades, there is 0.91 unit of expected I-informed trades before the introduction of the ETFs. After the introduction, there is 1.12 units of expected I-informed trades for one unit of expected S-informed trades. It means that the traders specializing in trading the sector-specific risk (firm-specific risk) were a majority (minority) of sophisticated investors and became a minority (majority) after the ETF introductions in December 1998. This finding is robust to IT sector exclusion and to a change of the classification algorithm.

The panel of plots provided **Figure IV** summarizes our findings. In addition, shifts at industry-level are exhibited **Figure V.** For $\alpha_S \times \mu_S$, there is a downward shift observed for all industries except for "Information Technology" and "Utilities" for which there is no change. The largest shift is observed for the industry Industrials (-31%). $\alpha_I \times \mu_I$ goes up for four industries, goes down for four industries and does not move for one. These differences across sectors generates non-significant results at the aggregate level. The largest upward shift of the I/S-Ratio is observed for the Health Care sector: From 0.77 to 1.28 under LR.[19]

2.5.2 Evidence of the migration effect

In this subsection, we show that the migration of the S-informed traders toward ETF markets is responsible for the significant decline in the incorporation of sector-specific information. In **Table VIII**, we show that the PINs observed for the Select Sector ETFs in the 3-month post-inception is unusually high with respect to PINs of other well-known ETFs. Under LR, Select Sector ETF PINs lie within [24%;34%] and reach 44% for "XLP" and 46% for "XLV". For the SPDR S&P 500 ETF ("SPY", introduced the 01/22/1993), the SPDR Dow Jones Industrial Average ETF ("DIA", 01/13/1998) and the PowerShares QQQ ETF ("QQQ" 03/10/1999), the PIN values over the first 3-month of their existence are 18%, 11% and 5% respectively. This is far below Select Sector ETF PINs. One can observe that results are quite similar with the CLNV algorithm. We claim that the migration of S-informed traders is responsible for the unusual level of sophisticated trading for the Select Sector ETFs compared to other popular ETFs.

To rule out the possibility that the PIN reflects more illiquidity than informational asymmetry between market participants, we reestimate parameters using the adjusted PIN by Duarte and Young (2009). For the sector-specific ETFs, the adjusted PINs vary between 24% and 34%, except for "XLP" (45.2%) and "XLV" (46.5%). For "SPY", "DIA"

[19] At stock-level, the largest shift has been observed for the company PG&E (Utilities industry) for which the I/S-Ratio has moved from 1.09 to 3.32, under LR.

and "QQQ", values are 19%, 9% and 3%, respectively, which is very inferior. Hence, the Select Sector ETFs seem to have experienced an abnormal amount of sophisticated trading over the three months following their introduction. In the analysis of Duarte and Young (2009) over 48,512 firm-year observations, the PIN (adjusted PIN) equals to 28% (23%) at the 75th percentile and 51% (37%) at the 95th percentile (Table II, pp. 124 and Table V, pp. 131). Select Sector ETF PINs are hence abnormally large, not only with respect other ETFs, but also regarding the results of Duarte and Young (2009). We attribute this phenomenon to the presence of the S-informed traders, that just migrate from underlying stocks to the ETF markets.

If our claim, i.e. the migration of the S-informed traders toward the ETF market, is correct, one could expect a relationship between the loss in S-informed trading activity in a bucket, measured by $[\alpha_S \times \mu_S]_{pre}^{stock} - [\alpha_S \times \mu_S]_{post}^{stock}$ and the magnitude of sophisticated trading on the corresponding ETF $[\log(\alpha \times \mu)]^{ETF}$, where α and μ are estimated with the original model of Easley et al. (1996). On the **Figure VI**, one can observe that a positive relationship seems to emerge. However, because the scatter plot is made with nine dots (for the nine ETFs), this result cannot be supported with statistical tests. With the LR algorithm used to classify trades, the correlation between $[\alpha_S \times \mu_S]_{pre}^{stock} - [\alpha_S \times \mu_S]_{post}^{stock}$ and $[\log(\alpha \times \mu)]^{ETF}$ reaches 66.5% while this is 42.9% with the CLNV algorithm.

2.5.3 Control sample

To rule out the possibility that something different of ETF introductions drives the significant changes in informed-based trading activity, we (i) re-run tests over a control sample (ii) produce difference-in-differences (DD hereafter) figures. The control sample is made from two sources. A first bucket of 10 stocks from the largest and most liquid companies belonging to the Telecommunications sector (GICS code 50) is created. Stock are selected in the same way as in the treatment sample. "Telecommunications" is the only one industry for which a corresponding Select Sector ETF has not been introduced in December 1998. The second group is a sample of 15 cross-listed stocks (ADRs level II and III or regular stock if Canada is the home-market).[20] From the whole cross-listing universe, there are 15 stocks, traded on NYSE or NASDAQ, level II or III, respecting an average level of 100 trades per day.

Consistent with the bucketing procedure for the treatment group, stocks of the control group are bucketed by sector too. Five buckets of three stocks each are hence created, the industries are Materials (GICS code 15), Consumer Discretionary (25), Consumer Staples (30), Information technology (45) and Telecommunications (50). Pooling the 25 five defines our control sample. Company names, countries and main cross-listing details are provided in **Table IX**. Results of the Wilcoxon Ranksum tests are displayed in **Table X**.[21] Regarding the size of the control sample (25 observations), we report the exact statistic instead of the approximate one, only valid for large samples. Under LR (CLNV), the medians of $\alpha_S \times \mu_S$ and $\alpha_I \times \mu_I$ shifts by -1.15 (-3.66) and -5.42 (-0.38), respectively. None of these variations are nonsignificant. The I/S-Ratio shifts upward under LR (-0.03) but downward under CLNV (0.12). Hence, the pattern is very different in the control sample, compared to what is observed in the treatment sample.

To convince that no variation is observed on the control sample, we also produce difference-in-difference measures. Since very few stock - matched stock pairs can be generated, we set up a bootstrapping-like procedure, working as follows: The twelve cross-listed stocks from four buckets (GICS code 15, 25, 30 and 45, bucket code 50 is excluded given the absence of matches) are randomly matched with the US stocks from a similar industry, with replacement. Then, we compute the following statistic:

$$v_j = \frac{1}{12} \times \sum_{i=1}^{12} \left(\left[\left(\frac{\alpha_I \mu_I}{\alpha_S \mu_S} \right)_{post} - \left(\frac{\alpha_I \mu_I}{\alpha_S \mu_S} \right)_{pre} \right]^T - \left[\left(\frac{\alpha_I \mu_I}{\alpha_S \mu_S} \right)_{post} - \left(\frac{\alpha_I \mu_I}{\alpha_S \mu_S} \right)_{pre} \right]^C \right) \quad (4)$$

[20] ADRs is the most popular way for a company to have its share cross-listed in US. Sponsored Level I shares have minimal reporting requirements, and they are only traded over-the-counter. Sponsored Level II shares must file a registration statement with the SEC and are required to file a Form 20-F annually. The share can be traded on a U.S. Stock Exchange among NYSE, NASDAQ and AMEX. Sponsored Level III companies must file Form F-1, Form 20-F and Form 6K. The upgrade with respect to Level II allows to raise capital.

[21] To save space, we do not report SPIN and IPIN for the control sample, results are available upon request.

where $j = 1, ..., 1000$ stands for sampling index, T for treatment sample and C for control sample. We obtain an average ($\bar{\upsilon}$) of 0.27 with a standard deviation of 0.13. A t-test on the υ_j time series produces a t-stat of 60.51, showing that we strongly reject the null hypothesis that $\bar{\upsilon} = 0$. Hence, there are evidence that the informed-based component of the trading activity for the treatment group (the US sample) has been really affected by the introduction of the Select Sector ETFs while no significant change has been observed for stocks not spanned by the ETFs, that is US stocks from the Telecommunications industry and ADRs.

2.5.4 International evidence

The introduction of the SPDR Select Sector ETFs is not the only one laboratory that exists to analyze the reallocation of informed-based trading activity between stocks and tradable indices. Cross-listed stocks are interesting investment vehicles for sophisticated investors actually.[22] S-informed traders might see shares of some liquid and diversified foreign companies as a way to obtain a specific exposure to the home-market country. When a country-specific index derivative is introduced, the investor specialized in the country-specific risk might be very interested into switching to the new instrument because the payoff on this security is more correlated to the unobservable country risk . For the I-informed traders, country-specific ETF can be used as an hedging instrument since the country risk is an important factor driving stock returns in international markets. Country factors have a dominant role in stock return co-movements (Heston and Rouwenhorst, 1994) and this is even stronger for emerging markets (Serra, 2000).

We gather tick-by-tick data for a sample of American Depositary Receipts (ADRs) from emerging countries around the introduction of country-specific ETFs.[23] Putting together,

[22] The extent of private information is even wider with respect to US stocks since additional source of risk exist, like the exchange rate or the political risk. Moreover, some news provided in local tongue are not necessarily reflected in the host-market stock prices. Visaltachoti and Yang (2010) confirm that cross-listed stocks have higher informational asymmetry than US stocks, with an average PIN of 13% for foreign stocks against 7% for US stocks.

[23] Unlike the Select Sector ETFs, they are not introduced simultaneously but dispersed between 2006 and 2011, and with different ETF sponsorship. In alphabetic order: Argentina ("Global X MSCI Argentina ETF, introduced the 03/03/2011, 6 liquid ADRs with intraday data available), Brazil ("iShares MSCI Brazil Capped ETF", 07/10/2000, 2 ADRs), Chile ("iShares MSCI Chile Capped ETF", 11/12/2007, 5 ADRs), China ("iShares China Large-cap", 10/05/2004, 8 ADRs), India ("MSCI India Index ETN", 12/19/2006, 8 ADRs), Mexico ("iShares MSCI Mexico Capped

this represents a sample of 46 stock-quarter observations. We follow a methodology similar to the one used for the analysis of the US sample. We perform the same event study methodology: The 40 trading days centered on the ETF introductions are excluded and the parameters are estimated with a quarter of trading days before and after. ADR list, parameter estimations and standard errors are available upon request. Results are exhibited in **Table XI**. The null hypothesis that sample medians are equals for $\alpha_S \times \mu_S$ and $\alpha_I \times \mu_I$ cannot be rejected. Under LR, we obtain a difference of 7.65 (*z-value* $= 0.14$) for $\alpha_S \times \mu_S$ and a difference of -9.40 (*z-value* $= 0.97$) for $\alpha_I \times \mu_I$. Under CLNV, results do not widely differ and p-values are all above 5%. One cannot conclude that the S-informed traders have migrated toward the country-specific ETF markets and the hypothesis that the hedging hypothesis does not find support either.

2.6 Conclusion

This paper is the first to present a model that attempts to disentangle the informed-based trading activity into a sector-specific (type S) and a firm-specific (type I) components. This specification is based on an underlying structure in which some agents acquire signals on the sector-specific risk while others acquire purely firm-specific private information. The arrival of tradable indices is supposed to modify the behavior of these two types of traders (Subrahmanyam, 1991; Yuan, 2005). Because tradable indices are more correlated to the unobservable sector-specific risk than a single stock, the specialists of this information should migrate toward markets for index (*migration hypothesis*). Investors that trade on firm-specific information are expected to increase their trading activity: By using tradable indices as an hedging instrument, they limit their exposure to the sector-specific risk and achieve higher returns (*hedging hypothesis*).

The introduction of the State Street SPDR Select Sectors ETFs in December 1998 is the ideal laboratory to study how the informed-based trading activity evolves. The specialists

ETF, 12/03/1996, 2 ADRs), Russia ("RSX Market Vector", 04/24/2007, 3 ADRs), South Africa ("iShares MSCI South Africa ETF", 02/03/2003, 3 ADRs), Taiwan ("iShares MSCI Taiwan ETF", 03/26/2008, 7 ADRs). At inception, All ETFs provide a country exposure above 95% except Argentina (around 50%).

of the industry risk are expected to migrate to the ETF markets while the specialists of the firm-specific risk can use these ETFs as an hedging instrument against sector-specific innovations. To conduct our empirical analysis, we create nine buckets of 10 stocks, each bucket reflecting a two-digit GICS sector and containing the largest, most liquid companies of their respective sectors. This aims at reflecting the presumed underlying holdings of the ETF sponsorship. We follow Albuquerque et al. (2008) by assuming the arrival of private information of type S or type I, separately or the two simultaneously. We estimate structural parameters by maximum likelihood over the stock-quarter panel of intraday data, before and after ETF introductions.

By performing non-parametric tests over the trading activity related to sector-specific information and firm-specific information separately, we find strong evidence in favor of the migration hypothesis. This finding is robust to the choice of the trade classification algorithm and to the exclusion of stocks from the IT sector (exclusion justified by the Dot-Com bubble). However, there is clearly no evidence in favor of the hedging hypothesis. An increase in the trading activity of type I is actually observed but this is small and non-significant at 5%. Trading costs (expense ratios, short-sell costs) may play a role to explain why the I-informed traders do not use the ETFs as hedging instrument.

To rule out the possibility that something different than ETF inception is responsible for our findings, we conduct the same event study on a control sample. We find no significant change in the S-informed and the I-informed trading intensity around the event. In the 3 months post-introduction the Select Sector ETFs are characterized by a highly level of sophisticated trading compared to what experienced other popular ETFs in the aftermath of their launch. In addition, it seems that there is a positive relationship between the loss if S-informed traders on an industry and the magnitude of sophisticated trading on the corresponding ETF. This provides additional evidence in favor of a migration effect.

2.7 References

[1] Agapova, A., 2011, "Conventional mutual index funds versus exchange-traded funds", Journal of Financial markets, Vol. 14, pp. 323-343

[2] Aitken, M., Frino, A., 1996, "The accuracy of the tick test: Evidence from Australian stock exchange", Journal of Banking and Finance, Vol. 20, pp. 1715-1729

[3] Akbas, F., Meschke, F., Wintoki, B., 2016, "Director networks and informed trades", Journal of Accounting and Economics, Vol. 62, pp. 1-23

[4] Albuquerque, R., de Francisco, E., B. Marques, L., 2008, "Marketwide private information in stocks: Forecasting currency returns", Vol. 63, pp. 2297-2343

[5] Bakke, T-E., Whited, T., 2010, "Which firms follow the market? An analysis of corporate investment decisions", Review of Financial Studies, Vol. 23, pp. 1941-1980

[6] Barigozzi, M., Brownlees, C., Gallo, G., Veredas, D., 2010, "Disentangling systematic and idiosyncratic risk for large panels of assets", Working Paper

[7] Berkman, H., Brailsford, T., Frino, A., 2005, "A note on execution for stock index futures: Information versus liquidity effects", Journal of Banking and Finance, Vol. 29, pp. 565-577

[8] Bessembinder, H., 2003, "Issues in assessing trade execution costs", Journal of Financial Markets, Vol. 6, pp. 233-257

[9] Bhojraj, S., Lee, C., Oler, D., 2003, "What's my line? A comparison of industry classification schemes for capital market research", Journal of Accounting Research, Vol. 41, pp. 745-774

[10] Boehmer, E., Grammig, J., Theissen, E., 2007, "Estimating the probability of informed trading, does trade misclassification matter ?", Journal of Financial Markets, Vol. 10, pp. 26-47

[11] Bollerslev, T., Todorov, V., Zhengzi Li, S., 2013, "Jump tails, extreme dependencies, and the distribution of stock returns", Journal of Econometrics, Vol. 172, pp. 307-324

[12] Cao, H., 1999, "The effect of derivative assets on information acquisition and price behavior in a rational expectations equilibrium", Review of Financial Studies, Vol. 12, pp. 131-163

[13] Chakrabarty, B., Li, B., Nguyen, V., Van Ness, R.A., 2007, "Trade classification algorithms for electronic communications network trades", Journal of Banking and Finance, Vol. 31, pp. 3806-3821.

[14] Choi, H., Subrahmanyam, A., 1994, "Using intraday data to test for effects of index futures on the underlying stock markets", Journal of Futures Markets, Vol. 14, pp. 293-322

[15] Chordia, T., Roll, R., Subrahmanyam, A., 2005, "Evidence on the speed of convergence to market efficiency", Journal of Financial Economics, Vol. 76, pp. 271-292

[16] Chung, K., Mingsheng, L., McInish, T., 2005, "Information-based trading, price impact of trades, and trade autocorrelation", Journal of Financial markets, Vol. 29, pp. 1645-1669

[17] Cooch, E., White, G., 2014, "Program MARK: a gentle introduction", Appendix B: The 'delta' method, pp. B.1-B.30

[18] Crawford, S., Roulstone, D., So, E., 2012, "Analyst initiations of coverage and stock return synchronicity", Accounting Review, Vol. 87, pp. 1527-1533

[19] Duarte, J., Han, X., Harford, J., Young, L., 2008, "Information asymmetry, information dissemination and the effect of regulation FD on the cost of capital", Journal of Financial Economics, Vol. 87, pp. 24-44

[20] Duarte, J., Young, L., 2009, "Why is PIN priced?", Journal of Financial Economics, Vol. 91, pp. 119-138

[21] Easley, D., O'Hara, M., 1987, "Price, trade size and information in securities markets", Journal of Financial Economics, Vol. 19, pp. 69-90

[22] Easley, D., Kiefer, N., O'Hara, M., Paperman, J., 1996, "Liquidity, information, and infrequently traded stocks", Journal of Finance, Vol. 51, pp. 1405-1436

[23] Easley, D., Kiefer, N., O'Hara, M., 1997, "The information content of the trading process", Journal of Empirical Finance, Vol. 4, pp. 159-186

[24] Easley, D., O'Hara, M., Saar, G., 2001, "How stock splits affect trading: A microstructure approach", Journal of Financial and Quantitative Analysis, Vol. 36, pp. 25-51

[25] Easley, D., O'Hara, M., Paperman, J., 1998, "Financial analysts and information-based trade", Journal of Financial markets, Vol. 1, pp. 175-201

[26] Easley, D., Engle, R., O'Hara, M., Wu, L., 2008, "Time-varying arrival rates of informed and uninformed trades", Journal of Financial Econometrics, Vol. 6, pp. 171-207

[27] Easley, D., Hvidkjaer, S., O'Hara, M., 2010, "Factoring information into returns", Journal of Financial and Quantitative Analysis, Vol. 45, pp. 293-309

[28] Edwards, F., 1988, "Does futures trading increase stock market volatility", Financial Analysts Journal, Vol. 44, pp. 63-69

[29] Ellis K., Michaely, R., O'Hara, M., 2000, "The accuracy of trade classification rules: Evidence from Nasdaq", Journal of Financial and Quantitative Analysis, Vol. 35, pp. 529-551

[30] Fama, E., French, K., 1997, "Industry costs of equity", Journal of Financial Economics, Vol. 43, pp. 153-193

[31] Feldhütter, P., Nielsen, M., 2012, "Systematic and idiosyncratic default risk in synthetic credit markets", Journal of Financial Econometrics, Vol. 10, pp. 292-324

[32] Finucane, T., 2000, "A direct test of methods for inferring trade direction from intraday data", Journal of Financial and Quantitative Analysis, Vol. 4, pp. 553-576

[33] Gao, M., Huang, J., 2014, "Capitalizing on Capitol Hill: Informed trading by hedge fund managers", SSRN Working Paper

[34] Glosten, L., Milgrom, P., 1985, "Bid, ask and transaction prices in a specialist market with heterogeneously informed traders", Journal of Financial Markets, Vol. 14, pp. 71-100

[35] Gorton, G., Pennacchi, G., 1993, "Security baskets and index-linked securities", Journal of Business, Vol. 66, pp. 1-27

[36] Grammig J., Schiereck, D., Theissen, E., 2001, "Knowing me, knowing you: Trader anonymity and informed trading in parallel markets", Journal of Financial Markets, Vol. 4, pp. 385-412

[37] Harris, L., 1989, "S&P 500 cash stock price volatilities", Journal of Finance, Vol. 44, pp. 1155-1175.

[38] Hasbrouck, J., 1995, "One security, many markets: Determining the contributions to price discovery", Journal of Finance, Vol. 50, pp. 1175-1199

[39] Hasbrouck, J., Seppi, D., 2001, "Common factors in prices, order flows, and liquidity", Journal of Financial Economics, Vol. 59, pp. 383-411

[40] Hasbrouck, J., 2003, "Intraday price formation in U.S. equity index markets", Journal of Finance, Vol. 58, pp. 2375-2400

[41] Hendershott, T., Livdan, D., Schürhoff, N., 2015, "Are institutions informed about news?", Journal of Financial Economics, Vol. 117, pp. 249-287

[42] Hedge, S., McDermott, J., 2004, "The market liquidity of Diamonds, Q's, and their underlying stocks", Journal of Banking and Finance, Vol. 28, pp. 1043-1067

[43] Henker, T., Martens, M., 2008, "Price discovery and liquidity in basket securities", Financial Review, Vol. 43, pp. 219-239

[44] Henker, T., Wang, J-X., 2006, "On the importance of timing specifications in market microstructure research", Journal of Financial Markets, Vol. 9, pp. 162-179

[45] Heston, S., Rouwenhorst, K., 1994, "Does industrial structure explain the benefits of international diversification", Journal of Financial Economics, Vol. 36, pp. 3-27

[46] Hwang, L-S., Lee, W-J., Lim, S-Y., Park, K-H., 2013, "Does information risk affect the implied cost of equity capital? An analysis of PIN and adjusted PIN", Journal of Accounting and Economics, Vol. 55, pp. 148-167

[47] Jegadeesh, N., Subrahmanyam, A., 1993, "Liquidity effects of the introduction of the S&P 500 index futures contract on the underlying stocks", Journal of Futures Markets, Vol. 66, pp. 171-187

[48] Ke, B., Petroni, K., 2004, "How informed are actively trading institutional investors? Evidence from their trading behavior before a break in a string of consecutive earnings increases", Journal of Accounting Research, Vol. 5, pp. 895-927

[49] Laatsch, F., 1991, "A note on the effects of the initiation of MMI futures on the daily returns of the component stocks", Journal of Futures Markets, Vol. 11, pp. 313-317.

[50] Lee, C., Radhakrisna, B., 2000, "Inferring investor behavior: Evidence from TORQ data", Journal of Financial Markets, Vol. 3, pp. 183-204

[51] Lee, C., Ready, M., 1991, "Inferring trade direction from intraday data", Journal of Finance, Vol. 46, pp. 733-746

[52] Lei, Q., Wu, G., 2005, "Time-varying informed and uninformed trading activities", Journal of Financial Markets, Vol. 8, pp. 153-181

[53] Lin, H-W., Ke, W-C., 2011,"A computing bias in estimating the probability of informed trading", Journal of Financial Markets, Vol. 14, pp. 625-640

[54] Madura, J., Ngo, T., 2008, "Impact of ETF inception on the valuation of component stocks", Applied Financial Economics, Vol. 18, pp. 995-1007

[55] Odders-White, E., 2000, "On the occurrence and consequences of inaccurate trade classification", Journal of Financial Markets, Vol. 3, pp. 259-286

[56] Pasquariello, P., Vega, C., 2015, "Strategic cross-trading in the U.S. stock market", Review of Finance, Vol. 19, pp. 229-282

[57] Piotroski, J., Roulstone, D., 2004, "The influence of analysts, institutional investors and insiders on the incorporation of market, industry, and firm–specific information into stock prices", Accounting Review, Vol. 79, pp. 1119–1151

[58] Rahman, S., 2001, "The introduction of derivatives on the Dow Jones Industrial Average", Journal of Futures Markets, Vol. 21, pp. 633-653

[59] Roll, R., 1988, "R^2", Journal of Finance, Vol. 25, pp. 541-566

[60] Serra, A., 2000, "Country and industry factors in returns: Evidence from emerging markets' stocks", Emerging Markets Review, Vol. 1, pp. 127-151

[61] Subrahmanyam, A., 1991, "A theory of trading in stock index futures", Review of Financial Studies, Vol. 4, pp. 17-51

[62] Tay, A., Ting, C., Tse, Y., Warachka, M., 2009, "Using high-frequency transaction data to estimate the probability of informed trading", Journal of Financial Econometrics, Vol. 7, pp. 288-311

[63] Theissen, E., 2001, "A test of the accuracy of the Lee/Ready trade classification algorithm", Journal of International Financial Markets, Institutions and Money, Vol. 11, pp. 147-165

[64] Tookes, H., 2008, "Information, trading, and product market interactions: Cross-sectional implications of informed trading", Journal of Finance, Vol. 63, pp. 379-413

[65] Vega, C., 2006, "Stock price reaction to public and private information", Journal of Financial Economics, Vol. 82, pp. 103-133

[66] Visaltanachoti N., Yang T., 2010, "Speed of convergence to market efficiency for NYSE-listed foreign stocks", Journal of Banking and Finance, Vol. 34, pp. 594-605

[67] Yan, Y., Zhang, S., 2012, "An improved estimation method and empirical properties of the probability of informed trading", Journal of Banking and Finance, Vol. 36, pp. 454-467

[68] Yan, X., Zhang, Z., 2007, "Institutional investors and equity returns: Are short-term institutions better informed?", Review of Financial Studies, Vol. 22, pp. 893-924

[69] Yuan, K., 2005, "The liquidity service of benchmark securities", Journal of the European Economic Association, Vol. 3., pp. 1156-1180

[70] Zhao, X., Chung, K., 2006, "Decimal pricing and information-based trading: Tick size and informational efficiency of asset price", Journal of Business Finance and Accounting, Vol. 33, pp. 753-766

2.8 Figures

Figure I Panel A: SPDR Select Sector ETFs

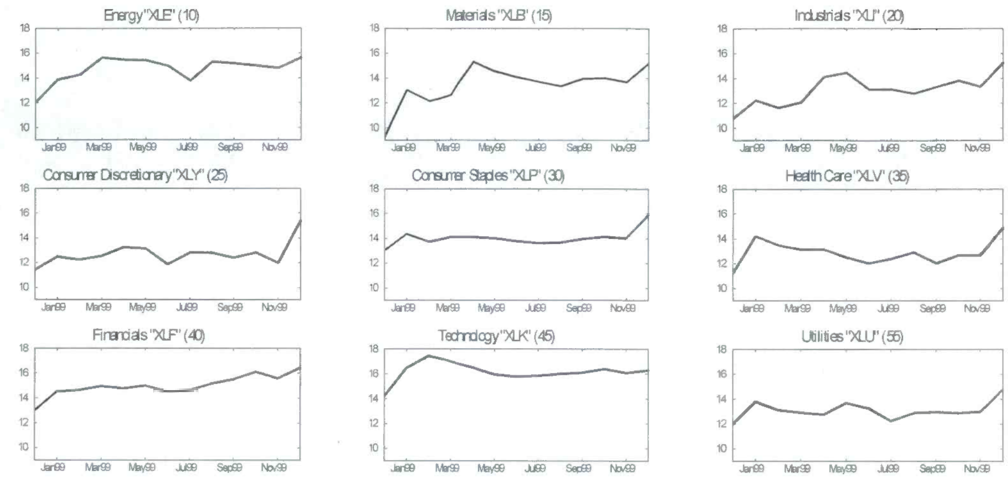


Figure I Panel B: Underlying stock volumes

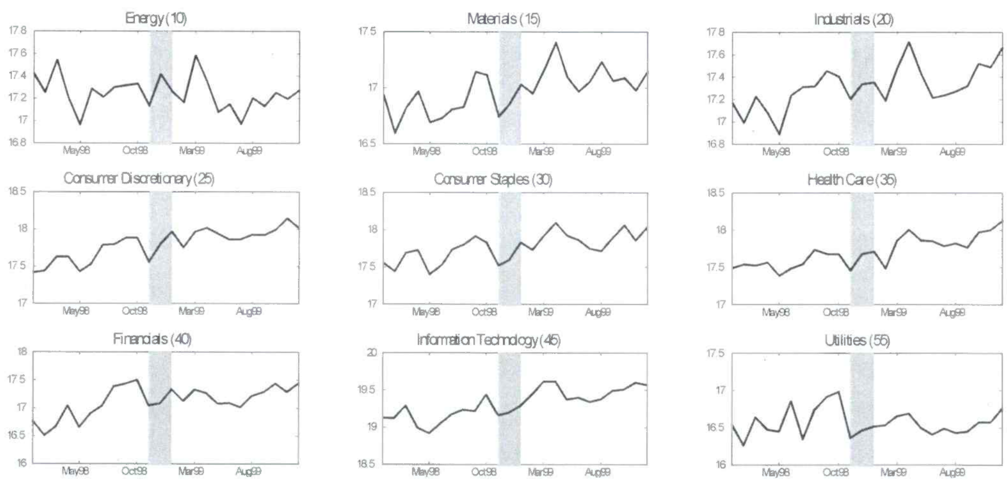
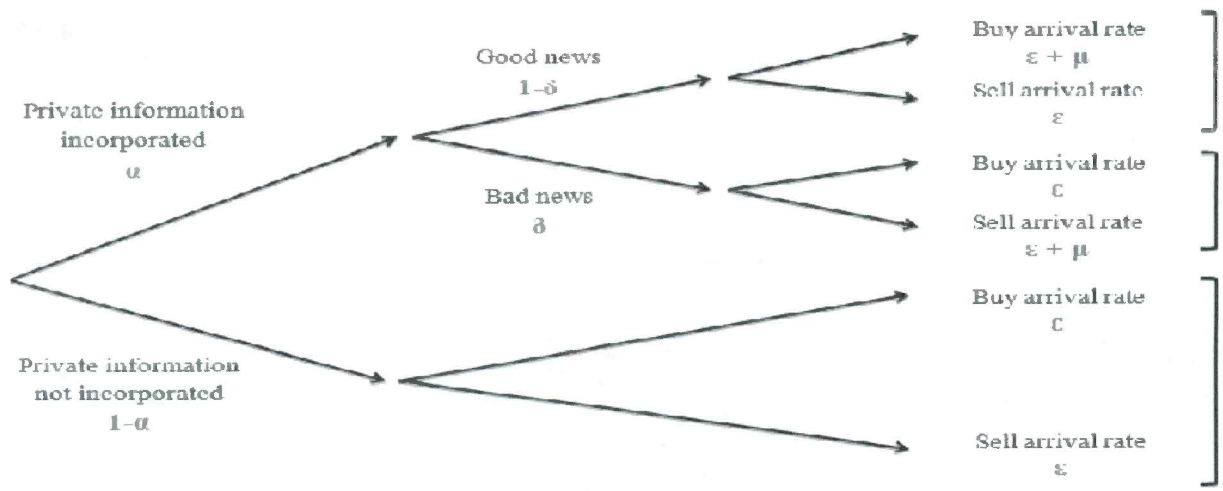


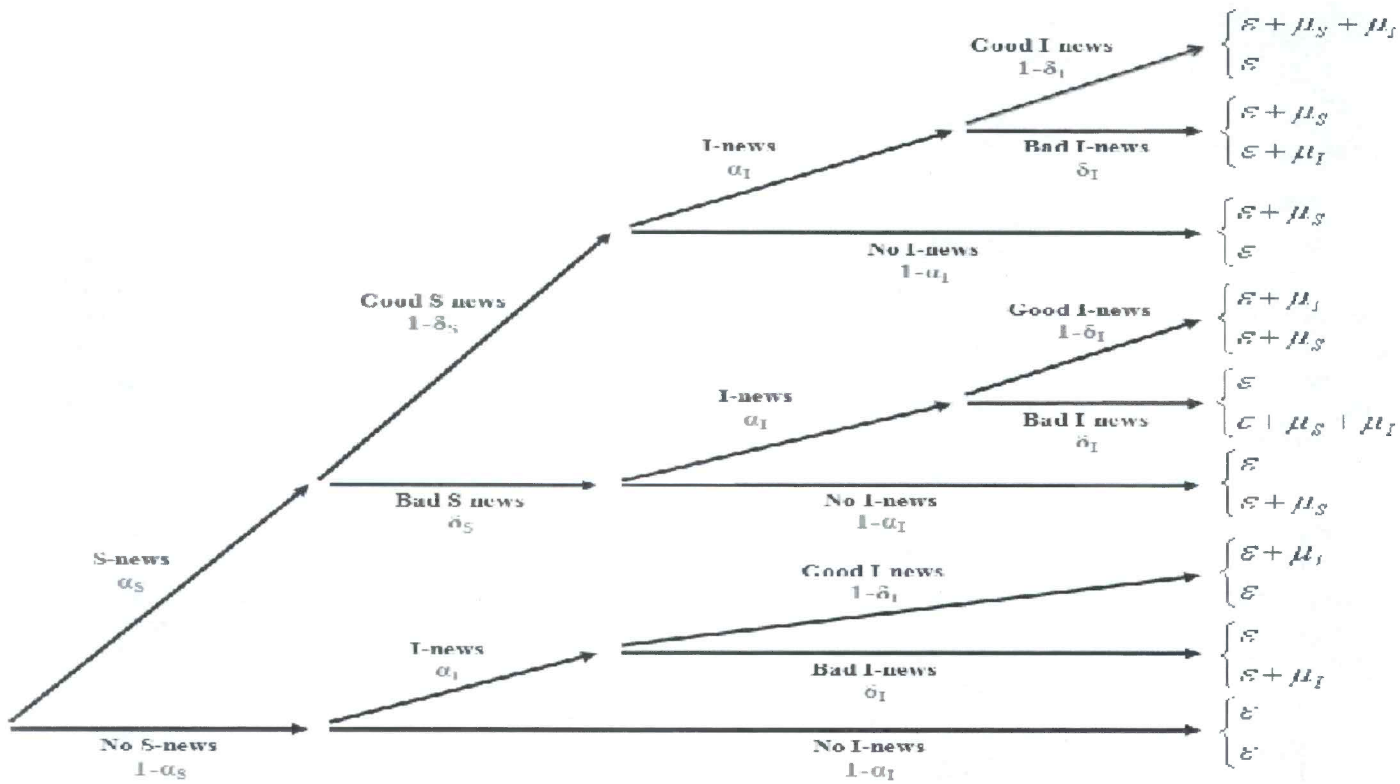
Figure I.A shows the total volume for ETFs and our stock sample. To make figures comparable, daily volumes (from CRSP) are summed over a month and displayed under a logarithmic transformation. Panel A shows volume time series of the nine State Street SPDR Select Sector ETFs, introduced simultaneously on 12/16/1998. The selected time period is December 1998 - December 1999. Plot subtitles are underlying sector names with CRSP tickers and two-digit GICS codes. Each of the SPDR ETF provides an exposure on a particular GICS sector. "GICS" stands for Gobal Industry Classification Standard. This classification has been jointly developed by Standard & Poor's and Morgan Stanley Capital International (MSCI). Definition of sectors can be found in https://www.msci.com/gics. Panel B shows volumes for our stock sample (90 stocks), split by industry. Company names and tickers and given in **Table X**. The stocks have been selected according to three criteria: (i) They are the most liquid stocks of their industry, where liquidity is proxied by the median volume over August 1997 - August 1998, and industry classification is derived from the two-digit GICS code, (iii) No significant corporate event (mergers, spin-offs or stock-splits) occurs during the analysis period August 1998 - April 1999. (iii) Intraday data availability is required over the analysis period. The plots are cross-sectional averages of stock-level time series.

Figure II: The original trading process



This scheme illustrates the way private information is incorporated into the market in Easley et al. (1996). A flow of private information is incorporated with a probability α. The private information have negative ("Bad news") informational content with a probability δ, while it has positive ("Good news") informational content with a probability $(1-\delta)$. ε represents trading intensity associated to the activity of discretionary traders while μ reflects the activity of informed investors. Three states of nature are possible: 1. There is no flow of informed-based trades and the expected trading intensity solely reflects non-informed trader activities (i.e. ε). 2. Bad news are incorporated in the market and the expected trading intensity on the sell side is $\varepsilon + \mu$, while this stands at ε on the buy side. 3. Informed traders observe high signal and trade on the buy side and the expected trading intensity just on this side becomes $\varepsilon + \mu$.

Figure III: The new trading process



The flow of systematic private information flow is incorporated in the market with a probability α_S. On these days, the informational content is "bad" ("good") with a probability δ_S $(1-\delta_S)$. Firm-specific information arrives on the market with a probability α_I. Private signals are of nature "bad" ("good") with a probability δ_I $(1-\delta_I)$. ε represents the the trading intensity associated to the activity of discretionary traders while μ_S (μ_I) reflects the activity of S-informed (I-informed) investors. There are three states of nature for the S-informed trader activities (No, sell side only, buy side only) combined to three states for the I-informed trader activities (No activity, sell side only, buy side only), which generate a total of nine states.

Figure IV Panel A: Structural parameter shifts - Full sample -

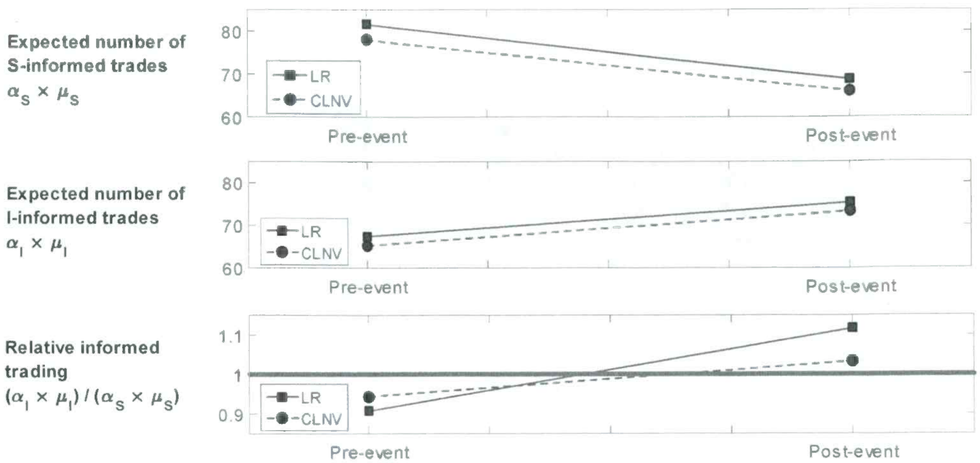
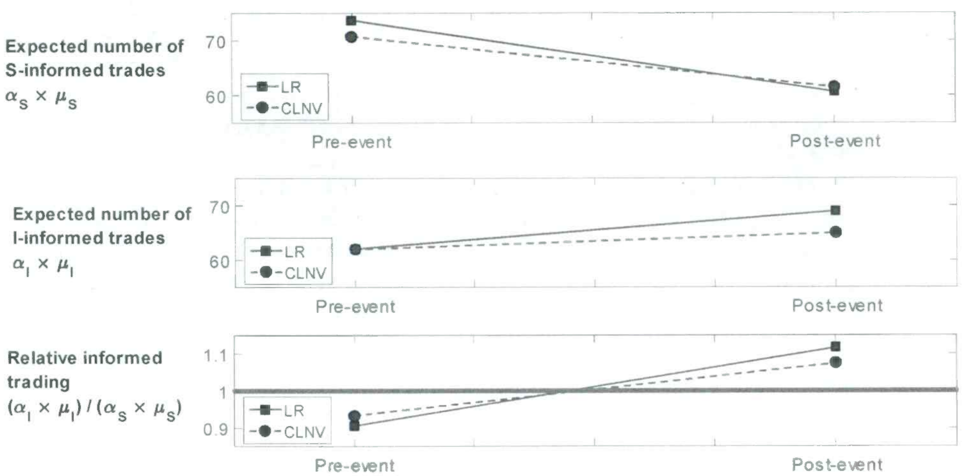
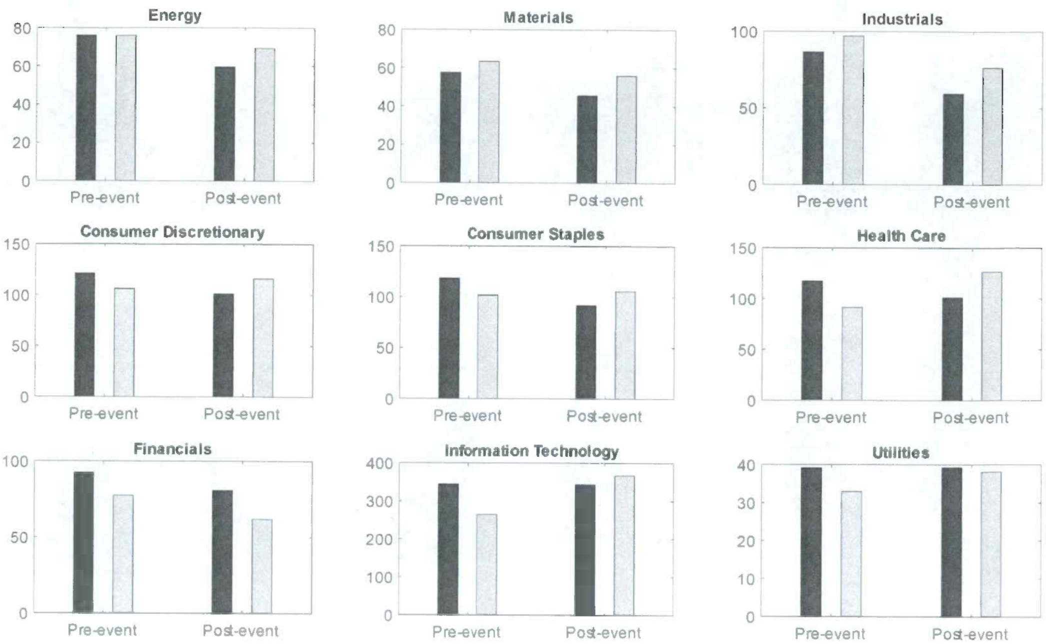


Figure IV Panel B: Structural parameter shifts - Information Technology excluded -



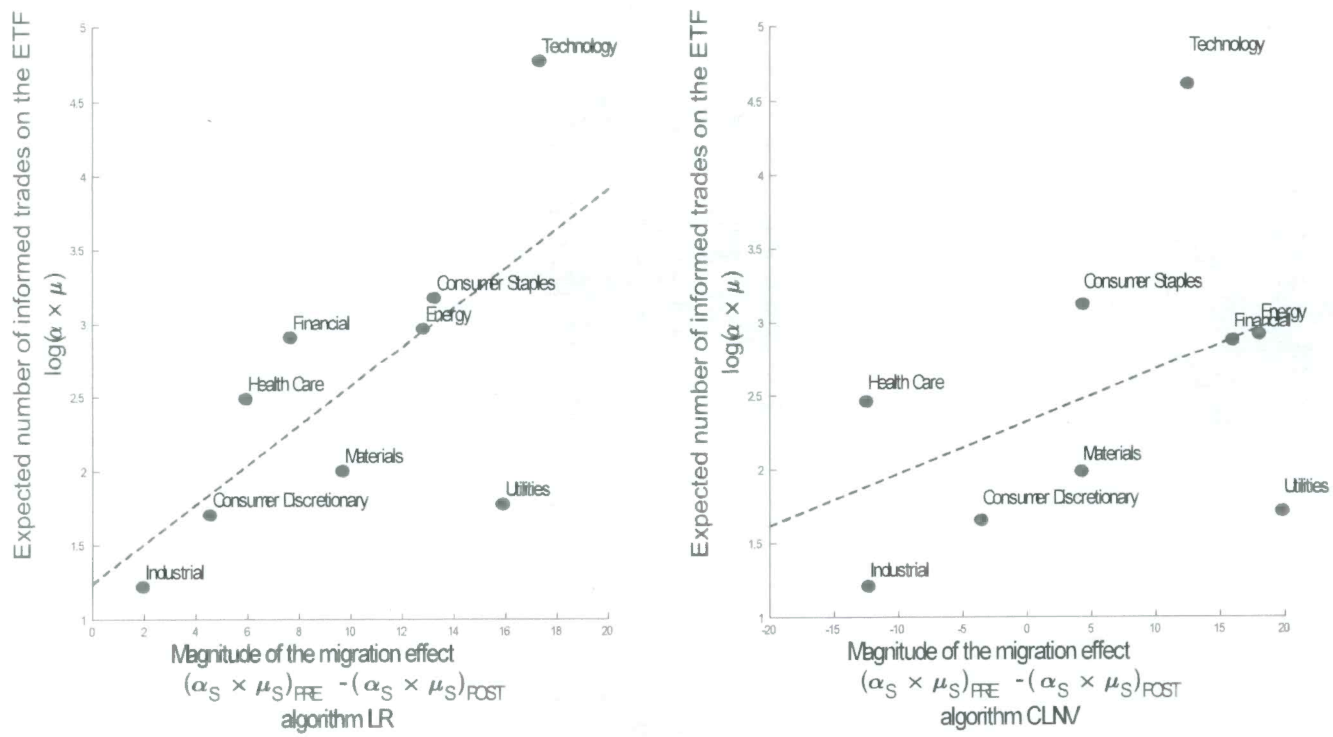
The sophisticated trading activity on the stock markets is decomposed in two components: $\alpha_S \times \mu_S + \alpha_I \times \mu_I$. α_S (α_I) is the probability of incorporation of private information of type sector-specific (idiosyncratic). μ_S (μ_I) is the expected trading intensity of the S-informed (I-informed) investors. $\alpha_S \times \mu_S$ reflects the expected number of trades from sophisticated investors specializing in trading the sector-specific risk. $\alpha_I \times \mu_I$ reflects the expected number of trades from sophisticated investors specializing in trading the idiosyncratic risk. This panel shows the median values of $\alpha_S \times \mu_S$ (left side) and $\alpha_I \times \mu_I$ (middle) before ("Pre-event") and after ("Post-event") the introduction of the State Street Select Sector ETFs in December 1998. The ratio of the two components is also displayed (right side). Panel A stands for the full sample (90 stock-quarter observations) while Panel B stands for a subsample that excludes stocks of the sector "Information Technology". Trades must be classified before parameter estimations. For robustness purpose, two different algorithms are used. Trades are classified according to the Lee and Ready (1991) algorithm first ("LR"), then trades are classified following an alternative rule proposed by Chakrabarty et al. (2007) ("CLNV").

Figure V: Industry-level shifts



The sophisticated trading activity on the stock markets is decomposed in two components: $\alpha_S \times \mu_S + \alpha_I \times \mu_I$. α_S (α_I) is the probability of incorporation of private information of type sector-specific (idiosyncratic). μ_S (μ_I) is the expected trading intensity of the S-informed (I-informed) investors. $\alpha_S \times \mu_S$ reflects the expected number of trades from sophisticated investors specializing in trading the sector-specific risk. $\alpha_I \times \mu_I$ reflects the expected number of trades from sophisticated investors specializing in trading the idiosyncratic risk. This panel shows the median values of $\alpha_S \times \mu_S$ (dark bar) and $\alpha_I \times \mu_I$ (light bar) before ("Pre-event") and after ("Post-event") the introduction of the State Street Select Sector ETFs in December 1998, at industry-level. Each industry name reflects a two-digit GICS sector.

Figure VI: Trader migration and sophisticated trading on ETF markets



$\alpha_S \times \mu_S$ reflects the expected number of trades from sophisticated investors specializing in trading the sector-specific risk. The x-axis measures the loss of S-informed traders for each industry, following the introduction of the Select Sector ETFs in December 1998. "PRE" ("POST") stands for the 3 month prior (after) ETF introductions. The Y-axis gives the logarithm of informed trades on the ETFs. We use a logarithm transformation because the IT sector stocks, due to the dotcom bubble, experiences far more trades than other industries. To estimate the parameter of the structural models, trades need to be classified. "algorithm LR" means that the Lee and Ready (1991) algorithm is used to classify trades while "algorithm CLNV" stands for the Chakrabarty et al. (2007) algorithm. Each industry reflects a two-digit GICS code. The correlation between dots reaches 66.5% on the first scatter and 42.9% on the second scatter.

2.9 Tables

Table I: List of stocks

Ticker	Company name	Daily volume	Ticker	Company name	Daily volume
		GICS 10: Energy			
BHI	Baker Hughes	1,632,600	NBR	Nabors Industries	873,500
CHV	Chevron	1,262,300	OXY	Occidental Petroleum	976,850
DO	Diamond Offshore	1,083,300	RDC	Rowan Drilling	898,000
ESV	Ensco	1,266,100	SLB	Schlumberger	2,417,850
HAL	Halliburton	1,875,450	WMB	William Cos	913,850
		GICS 15: Materials			
AA	Alcoa	767,550	IP	International Paper	1,179,900
BS	Bethelem Steel	1,025,400	NEM	Newmont Mining	957,900
DD	Du Pont de Nemours	2,545,600	UK	Union Carbide	588,250
DOW	Dow Chemical	578,950	SHW	Sherwin Williams	396,100
HM	Homestake Mining	891,950	X	United States Steel	524,500
		GICS 20: Industrials			
BA	Boing	3,651,600	LUV	Southwest Airlines	822,350
CAT	Caterpillar	1,226,400	MMM	Minnesota Mining	907,850
DE	Deere & Co.	816,100	UNP	Union Pacific	837,950
EMR	Emerson Electric	681,550	TYC	Tyco International	1,212,900
GE	General Electric	4,208,650	UTX	United technologies	700,500
		GICS 25: Consumer Discretionary			
CBS	CBS Corp.	2,029,400	MAT	Mattel Inc.	974,150
DIS	Walt Disney	1,433,200	MCD	McDonald's	1,932,600
F	Ford Motor	2,726,700	NKE	Nike Inc.	1,264,600
GM	General Motors	2,435,700	SPLS	Staples Inc.	1,598,228
HD	Home Depot	1,825,900	TWX	Time Warner	1,364,900
		GICS 30: Consumer Staples			
CAG	Conagra Foods	939,150	PEP	Pepsico	3,314,700
COST	Costco Wholeale	1,592,516	PG	Procter and Gamble	1,823,450
KMB	Kymberly-Clark	1,431,700	SLE	Sarah Lee Corp.	954,850
KO	Coca-Cola	3,034,200	SWY	Safeway Inc.	796,000
MO	Altria	5,594,601	WMT	Wal-Mart Stores	2,810,100

This table presents tickers and company names of our stock sample, in column (1) and (2) respectively. Each bucket has ten stocks and matches a particular GICS sector. "GICS" stands for Gobal Industry Classification Standard. This classification has been jointly developed by Standard & Poor's and Morgan Stanley Capital International (MSCI). Definition of sectors can be found in https://www.msci.com/gics. The stocks have been selected according to three criteria: (i) They are the most liquid stocks of their industry, where liquidity is proxied by the median volume over August 1997 - August 1998 and industry classification is derived from the two-digit GICS code, (ii) No significant corporate event (mergers, spin-offs or stock-splits) occurs during the analysis period August 1998 - April 1999. (iii) Intraday data availability is required over the analysis period. Column 3 gives the daily number of shares traded (median).

Table I: Continued

Ticker	Company name	Daily volume	Ticker	Company name	Daily volume
		GICS 35: Health Care			
ABT	Abbot Laboratories	1,275,400	LLY	Lilly and Co.	2,453,300
AMGN	Amgen Inc.	2,459,153	MDT	Medtronic Inc.	1,265,000
BMY	Bristo-Meyers	1,872,800	MRK	Merck and Co.	2,624,250
CNTO	Centocor Inc.	1,341,859	SGP	Schering-Plough	1,539,150
JNJ	Johnson and Johnson	2,243,700	UNH	United Healthcare	869,250
		GICS 40: Financials			
ALL	AllState Corp.	957,450	FNM	Fannie Mae	2,090,800
AIG	American International	945,050	JP	JP Morgan and Co.	754,800
AXP	American Express	1,158,650	MEL	Mellon Bank	902,750
BK	Bank of New York Inc.	795,300	PNC	PNC Bank	539,200
CNC	Conseco Inc.	971,000	STI	Suntrust Banks Inc.	239,850
		GICS 45: Information Technology			
AMAT	Applied Materials	7,346,347	INTC	Intel Corp.	15,627,592
COMS	3com Corp.	6,829,319	MSFT	Microsoft	9,548,057
CPQ	Compaq Computer	12,170,950	MU	Micron Technologies	3,773,900
CSCO	Cisco Systems	8,540,194	ORCL	Oracle Corp.	7,309,035
DELL	Dell	10,884,782	SUNW	Sun Microsystems	5,220,491
		GICS 55: Utilities			
AES	AES Corp.	400,550	PCG	PG&E	796,800
D	Dominion Resources	386,950	PEG	Public Service Enterprise	404,950
DUK	Duke Energy Corp.	584,900	SO	Southern Corp.	1,066,850
ED	Consolidated Edison	410,850	UCM	Unicom Corp.	608,500
ETR	Entergy Corp.	694,150	TXU	Texas Utilities	652,650

Table II: Descriptive statistics

Statistics	Share price ($)	B/A spread	BITs	SITs	Outside quotes (%)	At quotes (%)	Inside quotes (%)	At midpoint (%)
				GICS 10: Energy				
Mean	30.0	0.005	413	343	0.040	0.711	0.081	0.181
Median	22.6	0.004	350	300	0.033	0.714	0.078	0.181
Min	9.2	0.000	103	69	0.000	0.476	0.000	0.071
Max	88.9	0.023	1408	1011	0.300	0.915	0.231	0.313
				GICS 15: Materials				
Mean	39.3	0.004	328	295	0.033	0.703	0.107	0.167
Median	33.5	0.003	269	235	0.027	0.686	0.112	0.167
Min	7.1	0.000	73	81	0.000	0.506	0.000	0.060
Max	100.8	0.032	1228	1049	0.320	0.934	0.317	0.308
				GICS 20: Industrials				
Mean	54.1	0.002	550	491	0.045	0.663	0.127	0.178
Median	49.0	0.002	372	326	0.032	0.653	0.112	0.176
Min	16.4	0.000	130	125	0.002	0.395	0.000	0.066
Max	100.6	0.011	2755	2489	0.357	0.903	0.425	0.325
				GICS 25: Consumer Discretionary				
Mean	45.9	0.002	657	574	0.049	0.702	0.088	0.172
Median	40.4	0.002	526	494	0.037	0.707	0.073	0.176
Min	20.4	0.000	132	111	0.000	0.468	0.000	0.067
Max	98.8	0.009	2524	2092	0.429	0.912	0.327	0.310
				GICS 30: Consumer Staples				
Mean	51.5	0.002	656	613	0.059	0.693	0.086	0.175
Median	49.7	0.002	662	626	0.046	0.701	0.089	0.173
Min	23.3	0.000	157	143	0.005	0.492	0.000	0.067
Max	91.4	0.008	2154	1619	0.375	0.881	0.312	0.312

This table shows the descriptive statistics of the sample, aggregated at industry level, over 08/19/1998 - 11/16/1998. Industries are defined according to the two-digit GICS sector. "GICS" stands for Gobal Industry Classification Standard. This classification, jointly developed by Standard & Poor's and Morgan Stanley Capital International (MSCI), has been widely recognized as a benchmark by market participants and its superiority over other methods is documented in Bhojraj et al. (2003). Definition of sectors can be found in https://www.msci.com/gics. There are 10 stocks per bucket, see **Table II**. Sample design is detailed section IV, subsection I. Median, mean, maximum and minimum are derived from the 630 stock-day observations per bucket, i.e. 63 trading days over the period 08/19/1998 - 11/16/1998, times 10 stocks. Share price and B/A spread are observed at the end of the trading day. BITs and SITs stands for buyer-initiated trades and seller-initiated trades, respectively. The initiation is determined by the Lee and Ready (1991) algorithm. For these variables, statistics are rounded. The last four columns report statistics about the proportion of transactions realized outside of quotes, at the quotes, inside the quotes and at midpoint, respectively. These figures are averaged over days and then averaged over the cross-section so the sum of the four statistics differs slightly from one.

Table II: Continued

Statistics	Share price ($)	B/A spread	BITs	SITs	Outside quotes (%)	At quotes (%)	Inside quotes (%)	At midpoint (%)
				GICS 35: Health Care				
Mean	74.9	0.002	623	602	0.068	0.635	0.143	0.164
Median	74.9	0.002	618	563	0.057	0.643	0.131	0.168
Min	32.3	0.000	102	101	0.000	0.389	0.000	0.036
Max	147.1	0.008	1938	1915	0.409	0.964	0.327	0.287
				GICS 40: Financials				
Mean	59.8	0.002	496	408	0.052	0.660	0.133	0.168
Median	59.5	0.002	471	388	0.041	0.661	0.131	0.166
Min	23.5	0.000	126	89	0.004	0.407	0.019	0.071
Max	126.2	0.011	1362	1029	0.456	0.875	0.289	0.313
				GICS 45: Information Technology				
Mean	53.4	0.002	1748	1805	0.138	0.708	0.042	0.115
Median	42.4	0.002	1522	1590	0.112	0.734	0.040	0.114
Min	19.1	0.000	300	339	0.022	0.137	0.000	0.045
Max	128.7	0.007	9412	8529	0.753	0.916	0.132	0.219
				GICS 55: Utilities				
Mean	40.3	0.003	182	180	0.025	0.697	0.101	0.186
Median	38.3	0.003	170	170	0.020	0.699	0.095	0.180
Min	24.3	0.000	61	65	0.000	0.446	0.000	0.064
Max	70.7	0.010	451	405	0.303	0.918	0.317	0.431

Table III: Correlation matrix

	SPIN	EKOP_PIN	DY_PIN	B/A SPREAD	Abs(OFI)	SIZE	ANA. COV.	IDIO. VOL.
				A. Lee-Ready (1991) algorithm				
IPIN	0.475***	0.784***	0.577***	0.383***	0.559***	-0.343***	-0.216*	0.386***
SPIN		0.440***	0.323***	0.290**	0.260*	-0.255*	-0.157	0.354***
EKOP_PIN			0.814***	0.420***	0.827***	-0.424***	-0.265*	0.349***
DY_PIN				0.313***	0.945***	-0.424***	-0.184	0.228*
B/A SPREAD					0.368***	-0.483***	-0.235*	0.605***
Abs(OFI)						-0.486***	-0.246*	0.178
SIZE							0.339***	-0.366***
ANA. COV.								-0.025

In this table, we measure the correlation between two variables produced by our structural model and some proxies for the magnitude of private information incorporation popular in the literature. The coefficients are cross-sectional ones, computed over a sample of 90 stocks, for the period 08/19/1998 - 11/16/1998. SPIN, IPIN, EKOP_PIN and DY_PIN are computed as:

$$IPIN = \frac{\alpha_I \times \mu_I}{2\times\varepsilon+\alpha_I\times\mu_I+\alpha_S\times\mu_S} \quad ; \quad SPIN = \frac{\alpha_I \times \mu_I}{2\times\varepsilon+\alpha_I\times\mu_I+\alpha_S\times\mu_S} \quad ; \quad EKOP\_PIN = \frac{\alpha\times\mu}{2\times\varepsilon+\alpha\times\mu} \quad ; \quad DY\_PIN = \frac{\alpha\times\mu}{2\times\varepsilon+\alpha\times\mu+2\times\theta\times\Delta}$$

The first three measures are presented Section III. DY_PIN is an extension by Duarte and Young (2009). Especially, this version accommodates the arrival of a symmetric order-flow shock with probability θ and magnitude Δ. This feature matches the observed covariance between buyer and seller-initiated trades. Bid-ask spread refers to the end-of-day difference between the ask and the bid, scaled by the midpoint. Abs(OFI) refers to the absolute order-flow imbalance. It is computed as $|B-S|/(B+S)$. "Size" is proxied by the logarithm of total market capitalization. "ANA. COV." refers to the total number of analysts producing EPS forecasts for a given company. Analysts' ID are extracted from the I/B/E/S detail history files. Finally, "IDIO. VOL." is defined as the standard deviation of residuals, extracted from the regression of daily stock return over daily market return. The latter is proxied by the return on the S&P 500 index. Test outcomes are summarized with the following notation: *, **, *** indicates significance at the 5%, 1%, and 0.5%, respectively.

Table III: Continued

	SPIN	EKOP_PIN	DY_PIN	B/A SPREAD	Abs(OFI)	SIZE	ANA. COV.	IDIO. VOL.
				B. Chakrabarty et al. (2007) algorithm				
IPIN	0.483***	0.700***	0.481***	0.416***	0.470***	-0.358***	-0.223*	0.440***
SPIN		0.449***	0.323***	0.366***	0.206	-0.272**	-0.192	0.379***
EKOP PIN			0.779***	0.462***	0.801***	-0.430***	-0.264*	0.379***
DY PIN				0.381***	0.932***	-0.465***	-0.210*	0.239*
B/A SPREAD					0.439***	-0.483***	-0.235*	0.605***
Abs(OFI)						-0.532***	-0.271*	0.193
SIZE							0.339***	-0.366***
ANA. COV.								-0.025

Table IV: Cross-correlation of order-flow

GICS Code	BIT mean	BIT %	SIT mean	SIT %	OFI mean	OFI %
10	0.46	0.78	0.45	0.73	0.29	0.58
15	0.22	0.53	0.26	0.51	0.20	0.42
20	0.34	0.73	0.39	0.80	0.25	0.53
25	0.31	0.60	0.50	0.91	0.21	0.42
30	0.33	0.62	0.46	0.82	0.21	0.40
35	0.37	0.71	0.41	0.69	0.31	0.62
40	0.49	0.84	0.52	0.96	0.30	0.69
45	0.46	0.76	0.35	0.64	0.19	0.40
55	0.55	0.89	0.62	0.98	0.24	0.53

This table exhibits two statistics about the cross-correlation of stock-level time series. Entries in column (2), (4) and (6) are average cross-correlation coefficients. Column (3), (5) and (7) are the proportion of coefficients that are significant at the 5% level. There are 10 stocks per industry (two-digit GICS code), producing 45 correlation coefficients per industry. "BIT" stands for buyer-initiated trades (we calculate BIT_i vs BIT_j with $i \neq j$), "SIT" stands for seller-initiated trades (SIT_i vs SIT_j with $i \neq j$) and "OFI" stands for order-flow imbalance ($[(BIT_i - BIT_i)/(BIT_i + BIT_i)]$ vs $[(BIT_j - BIT_j)/(BIT_j + BIT_j)]$ with $i \neq j$). The time series spanned the period 08/19/1998 - 11/16/1998 and companies i and j that belongs to the same industry.

Table V: Pre-event parameter estimates

TCA	Lee and Ready (1991)			Chakrabarty et al. (2007)		
Industry	IPIN	SPIN	I/S-Ratio	IPIN	SPIN	I/S-Ratio
Energy	0.103	0.106	1.090	0.103	0.102	1.148
(10)	(0.010)	(0.007)	(0.127)	(0.007)	(0.008)	(0.120)
Materials	0.106	0.099	1.138	0.086	0.110	0.906
(15)	(0.008)	(0.005)	(0.112)	(0.034)	(0.007)	(0.273)
Industrials	0.092	0.082	1.076	0.077	0.096	0.909
(20)	(0.006)	(0.004)	(0.108)	(0.036)	(0.010)	(0.407)
Consumer	0.076	0.087	0.820	0.092	0.082	1.081
Discretionary (25)	(0.011)	(0.006)	(0.152)	(0.006)	(0.004)	(0.115)
Consumer	0.066	0.092	0.848	0.076	0.090	0.915
Staples (30)	(0.021)	(0.012)	(0.316)	(0.015)	(0.022)	(0.327)
Health Care	0.077	0.091	0.805	0.078	0.081	0.896
(35)	(0.014)	(0.006)	(0.149)	(0.009)	(0.004)	(0.126)
Financials	0.090	0.101	0.793	0.083	0.100	0.799
(40)	(0.035)	(0.013)	(0.419)	(0.076)	(0.075)	(0.882)
IT	0.075	0.081	0.945	0.081	0.080	1.030
(45)	(0.026)	(0.005)	(0.252)	(0.005)	(0.004)	(0.082)
Utilities	0.090	0.103	0.867	0.100	0.101	0.999
(55)	(0.012)	(0.006)	(0.150)	(0.009)	(0.006)	(0.123)

Structural parameter estimations are performed over a sample of 90 stocks. Sample design is detailed Section IV, subsection I. Stocks are bucketed according to the two-digit GICS sector (Column 1) and structural parameters are estimated by time series cross-sectional maximum likelihood, for the time window 08/19/1998 - 11/16/1998. The objective function, a mixture of Poisson distribution, is given equation (3). The daily records of buyer-initiated trades (BITs) and seller-initiated trades (SITs) are used as inputs of this density function. IPIN, SPIN and I/S-Ratio are derived for each stock-quarter observation. Entries are median values, while median standard errors are reported below. Standard errors of parameters are calculated with the delta method (See **Appendix II**). To classify trades as BITs or SITs, we use two different trade classification algorithms (TCA). Results under the Lee and Ready (1991) algorithm are reported column (2), (3) and (4) while results under the Chakrabarty et al. (2007) are reported column (5), (6) and (7). Testing different classification algorithms aim at making our results robust to the presence of the misclassification rate. To match trades with prevailing quotes, we select a lag of one second, following Henker and Wang (2003).

Table VI: Post-event parameter estimates

TCA	Lee and Ready (1991)			Chakravarty et al. (2007)		
Industry	IPIN	SPIN	I/S-Ratio	IPIN	SPIN	I/S-Ratio
Energy	0.090	0.083	1.194	0.086	0.084	1.095
(10)	(0.010)	(0.005)	(0.146)	(0.007)	(0.006)	(0.127)
Materials	0.086	0.074	1.160	0.085	0.073	1.144
(15)	(0.009)	(0.005)	(0.245)	(0.006)	(0.005)	(0.153)
Industrials	0.073	0.057	1.456	0.065	0.054	1.198
(20)	(0.008)	(0.005)	(0.222)	(0.010)	(0.015)	(0.370)
Consumer	0.089	0.078	1.248	0.086	0.079	1.252
Discretionary (25)	(0.005)	(0.004)	(0.098)	(0.010)	(0.008)	(0.338)
Consumer	0.070	0.061	1.212	0.069	0.074	0.868
Staples (30)	(0.006)	(0.005)	(0.152)	(0.403)	(0.105)	(5.353)
Health Care	0.086	0.069	1.286	0.081	0.066	1.332
(35)	(0.004)	(0.004)	(0.089)	(0.005)	(0.004)	(0.108)
Financials	0.070	0.080	0.856	0.067	0.063	0.957
(40)	(0.024)	(0.009)	(0.339)	(0.030)	(0.012)	(0.437)
IT	0.076	0.065	1.176	0.067	0.069	0.908
(45)	(0.003)	(0.002)	(0.073)	(0.066)	(0.081)	(1.383)
Utilities	0.084	0.088	0.998	0.088	0.094	0.991
(55)	(0.015)	(0.008)	(0.295)	(0.040)	(0.014)	(0.427)

Structural parameter estimations are performed over a sample of 90 stocks. Sample design is detailed Section IV, subsection I. Stocks are bucketed according to the two-digit GICS sector (Column 1) and structural parameters are estimated by time series cross-sectional maximum likelihood, for the time window 01/19/1999 - 04/19/1999. The objective function, a mixture of Poisson distribution, is given equation (3). The daily records of buyer-initiated trades (BITs) and seller-initiated trades (SITs) are used as inputs of this density function. IPIN, SPIN and I/S-Ratio are derived for each stock-quarter observation. Entries are median values, while median standard errors are reported below. Standard errors of parameters are calculated with the delta method (See **Appendix II**). To classify trades as BITs or SITs, we use two different trade classification algorithms (TCA). Results under the Lee and Ready (1991) algorithm are reported column (2), (3) and (4) while results under the Chakrabarty et al. (2007) are reported column (5), (6) and (7). Testing different classification algorithms aim at making our results robust to the presence of the misclassification rate. To match trades with prevailing quotes, we select a lag of one second, following Henker and Wang (2003).

Table VII: Non-parametric tests for the treatment sample

Variable	Sample	Algorithm	Pre-event	Post-event	Diff.	Signed Rank test (*z-value*)
Expected number of	All obs.	LR	81.564	68.753	-7.646	2.875***
S-informed trades	$(N = 90)$	CLNV	77.948	66.068	-5.926	1.603
$\alpha_S \times \mu_S$						
	IT exc.	LR	73.699	60.697	-7.646	2.998***
	$(N = 80)$	CLNV	70.770	61.525	-6.738	2.101*
Expected number of	All obs.	LR	67.411	75.438	0.890	-0.803
I-informed trades	$(N = 90)$	CLNV	65.250	73.401	-0.438	0.058
$\alpha_I \times \mu_I$						
	IT exc.	LR	62.061	68.984	0.262	0.038
	$(N = 80)$	CLNV	61.978	64.965	-0.438	0.312
I/S-Ratio	All obs.	LR	0.908	1.117	0.316	-4.690***
$(\alpha_I \times \mu_I)/(\alpha_S \times \mu_S)$	$(N = 90)$	CLNV	0.944	1.034	0.118	-2.597**
	IT exc.	LR	0.906	1.117	0.316	-4.350***
	$(N = 80)$	CLNV	0.933	1.075	0.133	-2.969***

The sophisticated trading activity on the stock markets is decomposed in two components: $\alpha_S \times \mu_S + \alpha_I \times \mu_I$. α_S (α_I) is the probability of incorporation of private information of type sector-specific (idiosyncratic). μ_S (μ_I) is the expected trading intensity of the S-informed (I-informed) investors. $\alpha_S \times \mu_S$ reflects the expected number of trades from sophisticated investors specializing in trading the sector-specific risk. $\alpha_I \times \mu_I$ reflects the expected number of trades from sophisticated investors specializing in trading the idiosyncratic risk. In this table, we report the median values of $\alpha_S \times \mu_S$ and $\alpha_I \times \mu_I$ before and after the introduction of the State Street Select Sector ETFs in December 1998. In addition, we run nonparametric tests in order to assess if medians are significantly different. The Wilcoxon signed rank test is well designed for detect shifts in a paired sample (i.e. before versus after a treatment) and it does not require assumptions on the underlying distribution of the variable. Our sample is made with nine buckets of ten stocks, one bucket per GICS sector. The cross-section time-series of trades (daily amount of buyer- and seller-initiated trades) are used as inputs of the density function (3) and all parameters are estimated by maximum likelihood. "All obs." refers to the whole sample (90 observations). "IT exc." refers to a subsample (80 observations) that excludes observations from the IT industry. Tests are performed on this subsample to rule out the issue that results are driven by the unusual high trading volume that characterized this industry during the Dot-Com bubble (1997-2000). Trades are classified according to the Lee and Ready ("LR", 1991) algorithm. For robustness purpose, we also classify trades following the Chakrabarty et al. ("CLNV", 2007) methodology, and tests are performed again. The pre-event period is defined as 08/19/1998 - 11/16/1998 and represents a 63 trading days (a quarter) ending 21 days before the official date of introduction of the nine Select Sector ETFs (12/16/1998). The post-event period is defined as 01/16/1999 - 04/19/1999 and represents 63 trading days (a quarter) beginning 21 days after the official date of introduction of the nine Select Sectors ETFs respectively. Test outcomes are summarized with the following notation: *, **, *** indicates significance at the 5%, 1%, and 0.5%, respectively.

Table VIII: Informed trading in ETF markets

Model	Easley et al. (1996)							
Algorithm	LR				CLNV			
XLB	7.44	14.16	0.34	(0.11)	7.32	13.98	0.34	(0.11)
XLE	19.44	50.72	0.28	(0.05)	18.57	51.28	0.27	(0.04)
XLF	18.36	54.64	0.25	(0.03)	17.81	54.73	0.25	(0.03)
XLI	3.39	10.49	0.24	(0.10)	3.36	10.33	0.25	(0.11)
XLK	118.96	341.82	0.26	(0.01)	101.28	358.77	0.22	(0.01)
XLP	24.03	30.93	0.44	(0.02)	22.72	31.76	0.42	(0.04)
XLU	5.94	14.22	0.29	(0.04)	5.57	14.54	0.28	(0.03)
XLV	12.08	14.06	0.46	(0.06)	11.72	14.04	0.46	(0.09)
XLY	5.53	11.46	0.33	(0.04)	5.24	11.54	0.31	(0.05)
SPY	6.74	31.34	0.18	(0.03)	6.87	31.20	0.18	(0.04)
DIA	28.80	225.14	0.11	(0.02)	27.79	225.83	0.11	(0.02)
QQQ	66.84	1232.24	0.05	(0.02)	50.71	1247.91	0.04	(0.01)

The probability of informed trading is computed for the nine Select Sector ETFs and for the window 01/16/1999 - 04/19/1999. These ETFs have been introduced on 12/16/1998 but we exclude the first 20 days of trading because there are usually very few sell orders in the weeks that immediately follow the inception of a new security. The standard PIN model of Easley et al. ("EKOP_PIN", 1996) and an extension proposed by Duarte and Young ("DY_PIN", 2009) are estimated by maximum likelihood. $\alpha \times \mu$, displayed column 2, 6, 10 and 14 stands for the informed-based trading intensity weighted by the probability of private information incorporation by the stock market and $2 \times \varepsilon$, displayed column 3, 7, 11, and 15, represents the total non-informed trading intensities. PIN formulas are:

$$EKOP\_PIN = (\alpha \times \mu)/(2 \times \varepsilon + \alpha \times \mu) \quad ; \quad DY\_PIN = (\alpha \times \mu)/(2 \times \varepsilon + \alpha \times \mu + 2 \times \theta \times \Delta)$$

"EKOP_PIN" is reported column 4 and 8 while "DY_PIN" is reported column 12 and 16. The extension of Duarte and Young (2009) accommodates the arrival of a symmetric order-flow shock with probability θ and magnitude Δ. This feature matches the observed covariance between buyer and seller-initiated trades. Aside PIN estimates, we provide the standard errors obtained by using the delta method. The derivation of standard errors is presented **Appendix II.** Trades are classified according to the Lee and Ready ("LR", 1991) algorithm. For robustness purpose, we also classify trades following the Chakrabarty et al. ("CLNV", 2007) methodology, and estimations are re-done. For space purpose, CRSP tickers are used as rows names. For "XLU", there is very few trading volume, making impossible to obtain precise estimate under the Duarte and Young (2009) model. For comparison, we also provide estimates for three famous ETFs. "SPY", "DIA" and "QQQ" stands for SPDR S&P 500 ETF (introduced 01/22/1993), SPDR Dow Jones Industrial Average ETF (01/13/1998) and PowerShares QQQ ETF (03/10/1999), respectively. Like Select Sector ETFs, we estimate PINs for the three months following their introduction (first 20 trading days excluded).

Table VIII: Continued

Model	Duarte and Young (2009)							
Algorithm	LR				CLNV			
XLB	5.60	12.43	0.24	(0.09)	6.74	11.74	0.28	(0.15)
XLE	22.87	39.19	0.33	(0.04)	21.81	37.30	0.31	(0.03)
XLF	20.93	35.74	0.29	(0.02)	20.22	35.59	0.28	(0.04)
XLI	3.14	8.77	0.23	(0.10)	5.87	9.04	0.33	(0.31)
XLK	108.77	291.45	0.24	(0.06)	83.99	295.95	0.18	(0.30)
XLP	24.87	21.66	0.45	(0.02)	23.82	22.61	0.44	(0.02)
XLU	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
XLV	12.15	10.02	0.46	(0.03)	11.87	9.50	0.46	(0.09)
XLY	5.70	9.76	0.34	(0.05)	5.43	9.76	0.32	(0.16)
SPY	7.09	24.25	0.19	(0.03)	7.09	24.36	0.19	(0.07)
DIA	23.04	198.32	0.09	(0.03)	27.29	198.75	0.11	(0.02)
QQQ	40.57	1108.14	0.03	(0.03)	29.05	1101.94	0.02	(0.02)

Table IX: Control sample

industry	ticker	company name	Country	Host-market	Level
		Cross-section I. US stocks			
50	BLS	BellSouth	US		
50	CTL	Centurylink	US		
50	GTE	GTE	US		
50	LVLT	Level 3 Communications	US		
50	NXTL	Nextel Communications	US		
50	S	Sprint Nextel	US		
50	SBC	Southwestern Bell	US		
50	USW	US West	US		
50	T	AT&T	US		
50	TLAB	Tellabs	US		
		Cross-section II. Cross-listed stocks			
15	ABX	Barrick Gold	Canada	NASDAQ	Ordinary share
15	PKX	Posco	South Korea	NYSE	3
15	POT	Potash Corporation of Saskatchewan	Canada	NYSE	Ordinary share
25	SNE	Sony Group	Japan	NYSE	2
25	PHG	Koninklyke Philips	Netherlands	NYSE	3
25	TV	Grupo Televisa	Mexico	NYSE	3
30	CCU	Compania Cervecerias	Chile	NYSE	3
30	DEO	Diageo	United Kingdom	NYSE	2
30	UN	Unilever	Netherlands	NYSE	2
45	SAP	SAP AG	Germany	NYSE	2
45	STM	ST Microelectronics	Netherlands	NYSE	3
45	TSM	Taiwan Semiconductor	Taiwan	NYSE	3
50	BT	BT Group	United Kingdom	NYSE	3
50	TMX	Telmex	Mexico	NYSE	3
50	VOD	Vodafone	United Kingdom	NASDAQ	2

This table introduces the control sample. It is designed by pooling two groups. The first one is a bucket of the ten largest and most liquid US companies belonging to the Telecommunications sector (GICS code 50). This is the only one industry for which a corresponding SPDR Select Sector ETF has not been introduced. To select stocks, companies of the S&P 500 of this industry are ranked according to the median daily trading volume for the period August 1997 - August 1998. Companies that have experienced spin-offs, stock splits or mergers during the analysis period (September 1998 - April 1999) are excluded. Companies that cannot be matched with a TAQ ticker are excluded too. The second part is a sample of 15 cross-listed stocks (ADRs level II and III or regular stock if Canada is the home-market). Consistent with the bucketing procedure for the treatment group, cross-listed stocks of the control group are bucketed by sector. The industries are Materials (GICS code 15), Consumer Discretionary (25), Consumer Staples (30), Information technology (45) and Telecommunications (50). Five buckets of three stocks each are hence created. Pooling the 25 five stocks lead to our control sample. Two-digit GICS codes, tickers and company names and countries displayed first, second third and fourth column, respectively. For American Depositary Receipts, we report host-market (stock exchange) and level column sixth and seventh, respectively.

Table X: Non-parametric tests for the control sample

Variable	Algorithm	Pre-event	Post-event	Difference	Sum of signed ranks
Expected number of S-informed trades $\alpha_S \times \mu_S$	LR	49.276	40.437	-1.147	152.000
	CLNV	48.286	37.591	-3.659	164.000
Expected number of I-informed trades $\alpha_I \times \mu_I$	LR	59.334	48.882	-5.415	172.000
	CLNV	53.370	50.935	-0.384	146.000
I/S-Ratio $(\alpha_I \times \mu_I)/(\alpha_S \times \mu_S)$	LR	1.166	0.969	-0.030	186.000
	CLNV	1.040	1.174	0.120	98.000

The sophisticated trading activity on the stock markets is decomposed in two components: $\alpha_S \times \mu_S + \alpha_I \times \mu_I$. α_S (α_I) is the probability of incorporation of private information of type sector-specific (idiosyncratic). μ_S (μ_I) is the expected trading intensity of the S-informed (I-informed) investors. $\alpha_S \times \mu_S$ reflects the expected number of trades from sophisticated investors specializing in trading the sector-specific risk. $\alpha_I \times \mu_I$ reflects the expected number of trades from sophisticated investors specializing in trading the idiosyncratic risk. In this table, we report the median values of $\alpha_S \times \mu_S$ and $\alpha_I \times \mu_I$ before and after the introduction of the State Street Select Sector ETFs in December 1998. In addition, we run nonparametric tests in order to assess if medians are significantly different. Our sample is made with 10 stocks of the Telecommunications sector (GICS=50) and 15 American Depositary Receipts, level II and III. Regarding our sample size, we report the exact statistic of the Wilcoxon tests. None result is significant at the conventional 5% level. The cross-section time-series of trades (daily amount of buyer- and seller-initiated trades) are used as inputs of the density function (3) and all parameters are estimated by maximum likelihood. Trades are classified according to the Lee and Ready ("LR", 1991) algorithm. For robustness purpose, we also classify trades following the Chakrabarty et al. ("CLNV", 2007) methodology, and tests are performed again. The pre-event period is defined as 08/19/1998 - 11/16/1998 and represents a 63 trading days (a quarter) ending 21 days before the official date of introduction of the nine Select Sector ETFs (12/16/1998). The post-event period is defined as 01/16/1999 - 04/19/1999 and represents 63 trading days (a quarter) beginning 21 days after the official date of introduction of the nine Select Sectors ETFs respectively.

Table XI: Non-parametric tests for the emerging market stocks

Variable	Algorithm	Pre-event	Post-event	Difference	Signed Rank test (*z-value*)
Expected number of S-informed trades $\alpha_S \times \mu_S$	LR	151.052	158.703	7.651	0.137
	CLNV	148.544	152.942	4.398	0.169
Expected number of I-informed trades $\alpha_I \times \mu_I$	LR	155.837	146.438	-9.399	0.967
	CLNV	154.725	145.397	-9.328	0.901
I/S-Ratio $(\alpha_I \times \mu_I)/(\alpha_S \times \mu_S)$	LR	1.122	1.017	-0.105	1.950
	CLNV	1.091	0.989	-0.103	1.928

The sophisticated trading activity on the stock markets is decomposed in two components: $\alpha_S \times \mu_S + \alpha_I \times \mu_I$. α_S (α_I) is the probability of incorporation of private information of type sector-specific (idiosyncratic). μ_S (μ_I) is the expected trading intensity of the S-informed (I-informed) investors. $\alpha_S \times \mu_S$ reflects the expected number of trades from sophisticated investors specializing in trading the sector-specific risk. $\alpha_I \times \mu_I$ reflects the expected number of trades from sophisticated investors specializing in trading the idiosyncratic risk. In this table, we report the median values of $\alpha_S \times \mu_S$ and $\alpha_I \times \mu_I$ before and after the introduction of country-specific ETFs. Unlike the Select Sector ETFs, they are not introduced simultaneously but dispersed between 2006 and 2011, and with different ETF sponsorship. In alphabetic order: Argentina ("Global X MSCI Argentina ETF, introduced the 03/03/2011, 6 ADRs), Brazil ("iShares MSCI Brazil Capped ETF", 07/10/2000, 2 ADRs), Chile ("iShares MSCI Chile Capped ETF", 11/12/2007, 5 ADRs), China ("iShares China Large-cap", 10/05/2004, 8 ADRs), India ("MSCI India Index ETN", 12/19/2006, 8 ADRs), Mexico ("iShares MSCI Mexico Capped ETF, 12/03/1996, 2 ADRs), Russia ("RSX Market Vector", 04/24/2007, 3 ADRs), South Africa ("iShares MSCI South Africa ETF", 02/03/2003, 3 ADRs), Taiwan ("iShares MSCI Taiwan ETF", 03/26/2008, 7 ADRs). At inception, All ETFs provide a country exposure above 95% except Argentina (around 50%). Total sample size is 46. Nonparametric tests are run in order to assess if medians of the pre- and post ETF introduction are significantly different. The Wilcoxon signed rank test is well designed for detect shifts in a paired sample (i.e. before versus after a treatment) and it does not require assumptions on the underlying distribution of the variable. The cross-section time-series of trades (daily amount of buyer- and seller-initiated trades) are used as inputs of the density function (3) and all parameters are estimated by maximum likelihood. Trades are classified according to the Lee and Ready ("LR", 1991) algorithm. For robustness purpose, we also classify trades following the Chakrabarty et al. ("CLNV", 2007) methodology, and tests are performed again. The pre-event period is defined as 08/19/1998 - 11/16/1998 and represents a 63 trading days (a quarter) ending 21 days before the official date of introduction of the nine Select Sector ETFs (12/16/1998). The post-event period is defined as 01/16/1999 - 04/19/1999 and represents 63 trading days (a quarter) beginning 21 days after the official date of introduction of the nine Select Sectors ETFs respectively. In this table, none result is significant at the conventional 5% level.

2.10 Appendix

2.10.1 Appendix I: Density function and I/S-Ratio

Below are the details of the density function in equation (3):

$$\begin{cases} \pi_1 &= (1-\alpha_S)\times(1-\alpha_I) \\ \lambda_{1,b} &= 0 \\ \lambda_{1,s} &= 0 \end{cases}$$

$$\begin{cases} \pi_2 &= (1-\alpha_S)\times\alpha_I\times\delta_I \\ \lambda_{2,b} &= 0 \\ \lambda_{2,s} &= \mu_I \end{cases}$$

$$\begin{cases} \pi_3 &= (1-\alpha_S)\times\alpha_I\times(1-\delta_I) \\ \lambda_{3,b} &= \mu_I \\ \lambda_{3,s} &= 0 \end{cases}$$

$$\begin{cases} \pi_4 &= \alpha_S\times\delta_S\times(1-\alpha_I) \\ \lambda_{4,b} &= 0 \\ \lambda_{4,s} &= \mu_S \end{cases}$$

$$\begin{cases} \pi_5 &= \alpha_S\times\delta_S\times\alpha_I\times\delta_I \\ \lambda_{5,b} &= 0 \\ \lambda_{5,s} &= \mu_S+\mu_I \end{cases}$$

$$\begin{cases} \pi_6 &= \alpha_S\times\delta_S\times\alpha_I\times(1-\delta_I) \\ \lambda_{6,b} &= \mu_I \\ \lambda_{6,s} &= \mu_S \end{cases}$$

$$\begin{cases} \pi_7 &= \alpha_S\times(1-\delta_S)\times(1-\alpha_I) \\ \lambda_{7,b} &= \mu_S \\ \lambda_{7,s} &= 0 \end{cases}$$

$$\begin{cases} \pi_8 &= \alpha_S\times(1-\delta_S)\times\alpha_I\times\delta_I \\ \lambda_{8,b} &= \mu_S \\ \lambda_{8,s} &= \mu_I \end{cases}$$

$$\begin{cases} \pi_9 &= \alpha_S\times(1-\delta_S)\times\alpha_I\times(1-\delta_I) \\ \lambda_{9,b} &= \mu_S+\mu_I \\ \lambda_{9,s} &= 0 \end{cases}$$

The PIN is constructed as the ratio of informed-based trading intensity to total trading intensity. To derive the numerator, informed trading intensities from buy and sell sides of the market are summed and multiplied by probabilities of state occurring. Products are summed over all states of nature:

$$\begin{aligned}
&NUM = (1-\alpha_S) \times (1-\alpha_I) \times 0 \\
&+(1-\alpha_S) \times \alpha_I \times \delta_I \times \mu_I \\
&+(1-\alpha_S) \times \alpha_I \times (1-\delta_I) \times \mu_I \\
&+\alpha_S \times \delta_S \times (1-\alpha_I) \times \mu_S \\
&+\alpha_S \times \delta_S \times \delta_I \times \alpha_I \times (\mu_S + \mu_I) \\
&+\alpha_S \times \delta_S \times \alpha_I \times (1-\delta_I) \times (\mu_S + \mu_I) \\
&+\alpha_S \times (1-\delta_S) \times (1-\alpha_I) \times (\mu_S) \\
&+\alpha_S \times (1-\delta_S) \times \alpha_I \times \delta_I \times (\mu_S + \mu_I) \\
&+\alpha_S \times (1-\delta_S) \times \alpha_I \times (1-\delta_I) \times (\mu_S + \mu_I)
\end{aligned}$$

This expression reduces to:

$$NUM = \alpha_S \times \mu_S + \alpha_I \times \mu_I$$

For the denominator, we extract the total trading intensity from buy and sell sides of the market, weighted by probabilities of state occurring:

$$\begin{aligned}
&DEN = (1-\alpha_S) \times (1-\alpha_I) \times (\varepsilon + \varepsilon) \\
&+(1-\alpha_S) \times \alpha_I \times \delta_I \times (\varepsilon + \varepsilon + \mu_I) \\
&+(1-\alpha_S) \times \alpha_I \times (1-\delta_I) \times (\varepsilon + \mu_I + \varepsilon) \\
&+\alpha_S \times \delta_S \times (1-\alpha_I) \times (\varepsilon + \varepsilon + \mu_S) \\
&+\alpha_S \times \delta_S \times \delta_I \times \alpha_I \times (\varepsilon + \varepsilon + \mu_S + \mu_I) \\
&+\alpha_S \times \delta_S \times \alpha_I \times (1-\delta_I) \times (\varepsilon + \mu_I + \varepsilon + \mu_S) \\
&+\alpha_S \times (1-\delta_S) \times (1-\alpha_I) \times (\varepsilon + \mu_S + \varepsilon) \\
&+\alpha_S \times (1-\delta_S) \times \alpha_I \times \delta_I \times (\varepsilon + \mu_S + \varepsilon + \mu_I) \\
&+\alpha_S \times (1-\delta_S) \times \alpha_I \times (1-\delta_I) \times (\varepsilon + \mu_S + \mu_I + \varepsilon)
\end{aligned}$$

This expression reduces to:

$$DEN = 2 \times \varepsilon + \alpha_S \times \mu_S + \alpha_I \times \mu_I$$

And our two-component PIN follows.

2.10.2 Appendix II: Likelihood function, standard errors and delta method

More than three thousands daily BIT or SIT are recorded on some days are the most liquid stocks. When an optimization algorithm is running, large buys or sells embedded in the Poisson distribution might generate numerical values that exceed the range of real values that the software can handle. This phenomenon is called the floating point exception (FPE hereafter). Lin and Kee (2011) re-formulate the likelihood function in order to this trouble. Their correction is applied to the original PIN model of Easley et al. (1996). We extend their methodology to reformulate our likelihood function. By replacing $\frac{x_y^Y}{Y!}$ by

$\exp(Y \times \log(x_y) - \log(Y!))$ in each expression, equation (3) can be factored:

$$f(\theta|B,S) = \\ \exp(-2 \times \varepsilon - \log(B! \times S!)) \times \\ \begin{pmatrix} (1-\alpha_S) \times (1-\alpha_I) \\ \times \exp\left(B \times \log(\varepsilon) + S \times \log(\varepsilon)\right) \\ +(1-\alpha_S) \times \alpha_I \times \delta_I \\ \times \exp\left(-\mu_I + B \times \log(\varepsilon) + S \times \log(\varepsilon + \mu_I)\right) \\ +(1-\alpha_S) \times \alpha_I \times (1-\delta_I) \\ \times \exp\left(-\mu_S + B \times \log(\varepsilon + \mu_I) + S \times \log(\varepsilon)\right) \\ +\alpha_S \times \delta_S \times (1-\alpha_I) \\ \times \exp(-\mu_S + B \times \log(\varepsilon) + S \times \log(\varepsilon + \mu_S)) \\ +\alpha_S \times \delta_S \times \alpha_I \times \delta_I \\ \times \exp(-\mu_S - \mu_I + B \times \log(\varepsilon) + S \times \log(\varepsilon + \mu_S + \mu_I)) \\ +\alpha_S \times \delta_S \times \alpha_I \times (1-\delta_I) \\ \times \exp(-\mu_S - \mu_I + B \times \log(\varepsilon + \mu_I) + S \times \log(\varepsilon + \mu_S)) \\ +\alpha_S \times (1-\delta_S) \times (1-\alpha_I) \\ \times \exp\left(-\mu_S + B \times \log(\varepsilon + \mu_S) + S \times \log(\varepsilon)\right) \\ +\alpha_S \times (1-\delta_S) \times \alpha_I \times \delta_I \\ \times \exp(-\mu_S - \mu_I + B \times \log(\varepsilon + \mu_S) + S \times \log(\varepsilon + \mu_I)) \\ +\alpha_S \times (1-\delta_S) \times \alpha_I \times (1-\delta_I) \\ \times \exp(-\mu_S - \mu_I + B \times \log(\varepsilon + \mu_S + \mu_I) + S \times \log(\varepsilon)) \end{pmatrix} \quad (1)$$

We define $\xi = \varepsilon + \mu_S + \mu_I$ for convenience. Then equation (1) can be rewritten as:

$$f(\theta|B,S) = \\ \exp(-2 \times \varepsilon + (B+S) \times \log(\xi) - \log(B! \times S!)) \times \\ \begin{pmatrix} (1-\alpha_S) \times (1-\alpha_I) \\ \times \exp\left(-(B+S) \times \log(\frac{\xi}{\varepsilon})\right) \\ +(1-\alpha_S) \times \alpha_I \times \delta_I \\ \times \exp\left(-\mu_I - B \times \log(\frac{\xi}{\varepsilon}) - S \times \log(\frac{\xi}{\varepsilon + \mu_I})\right) \\ +(1-\alpha_S) \times \alpha_I \times (1-\delta_I) \\ \times \exp\left(-\mu_I - B \times \log(\frac{\xi}{\varepsilon + \mu_I}) - S \times \log(\frac{\xi}{\varepsilon})\right) \\ +\alpha_S \times \delta_S \times (1-\alpha_I) \\ \times \exp\left(-\mu_S - B \times \log(\frac{\xi}{\varepsilon}) - S \times \log(\frac{\xi}{\varepsilon + \mu_S})\right) \\ +\alpha_S \times \delta_S \times \alpha_I \times \delta_I \\ \times \exp\left(-\mu_S - \mu_I - B \times \log(\frac{\xi}{\varepsilon}) - S \times \log(\frac{\xi}{\varepsilon + \mu_S + \mu_I})\right) \\ +\alpha_S \times \delta_S \times \alpha_I \times (1-\delta_I) \\ \times \exp\left(-\mu_S - \mu_I - B \times \log(\frac{\xi}{\varepsilon + \mu_I}) - S \times \log(\frac{\xi}{\varepsilon + \mu_S})\right) \\ +\alpha_S \times (1-\delta_S) \times (1-\alpha_I) \\ \times \exp\left(-\mu_S - B \times \log(\frac{\xi}{\varepsilon + \mu_S}) - S \times \log(\frac{\xi}{\varepsilon})\right) \\ +\alpha_S \times (1-\delta_S) \times \alpha_I \times \delta_I \\ \times \exp\left(-\mu_S - \mu_I - B \times \log(\frac{\xi}{\varepsilon + \mu_S}) - S \times \log(\frac{\xi}{\varepsilon + \mu_I})\right) \\ +\alpha_S \times (1-\delta_S) \times \alpha_I \times (1-\delta_I) \\ \times \exp\left(-\mu_S - \mu_I - B \times \log(\frac{\xi}{\varepsilon + \mu_S + \mu_I}) - S \times \log(\frac{\xi}{\varepsilon})\right) \end{pmatrix}$$

Lin and Ke (2011) show that the logarithm of a linear combination of exponential terms can be defined in a more convenient way:

$$
\begin{aligned}
\log \sum (\pi_i \times \exp(X_i)) &= \log \left(\sum \pi_i \times \exp(X_i) \times \exp(-Z) \times \exp(Z) \right) \\
&= \log \left(\sum \pi_i \times \exp(X_i - Z) \times \exp(Z) \right) \\
&= Z + \log \left(\sum \pi_i \times \exp(X_i - Z) \right)
\end{aligned}
$$

Lin and Ke (2011) choose $Z = \max(X_i)$. We apply this change and obtain finally:

$$
\log(f(\theta|B,S)) = -2 \times \varepsilon + (B+S) \times \log(\xi) + e_{\max}
+ \log \begin{pmatrix}
(1-\alpha_S) \times (1-\alpha_I) \times \exp(e_1 - e_{\max}) \\
+(1-\alpha_S) \times \alpha_I \times \delta_I \times \exp(e_2 - e_{\max}) \\
+(1-\alpha_S) \times \alpha_I \times (1-\delta_I) \times \exp(e_3 - e_{\max}) \\
+\alpha_S \times \delta_S \times (1-\alpha_I) \times \exp(e_4 - e_{\max}) \\
+\alpha_S \times \delta_S \times \alpha_I \times \delta_I \times \exp(e_5 - e_{\max}) \\
+\alpha_S \times \delta_S \times \alpha_I \times (1-\delta_I) \times \exp(e_6 - e_{\max}) \\
+\alpha_S \times (1-\delta_S) \times (1-\alpha_I) \times \exp(e_7 - e_{\max}) \\
+\alpha_S \times (1-\delta_S) \times \alpha_I \times \delta_I \times \exp(e_8 - e_{\max}) \\
+\alpha_S \times (1-\delta_S) \times \alpha_I \times (1-\delta_I) \times \exp(e_9 - e_{\max})
\end{pmatrix} \tag{2}
$$

with

$$
\begin{aligned}
e_1 &= -(B+S) \times \log\left(1 + \frac{\mu_S + \mu_I}{\varepsilon}\right) \\
e_2 &= -\eta - B \times \log\left(1 + \frac{\mu_S + \mu_I}{\varepsilon}\right) - S \times \log\left(1 + \frac{\mu_S}{\varepsilon + \mu_I}\right) \\
e_3 &= -\eta - B \times \log\left(1 + \frac{\mu_S}{\varepsilon + \mu_I}\right) - S \times \log\left(1 + \frac{\mu_S + \mu_I}{\varepsilon}\right) \\
e_4 &= -\mu - B \times \log\left(1 + \frac{\mu_S + \mu_I}{\varepsilon}\right) - S \times \log\left(1 + \frac{\mu_I}{\varepsilon + \mu_S}\right) \\
e_5 &= -\mu - \eta - B \times \log\left(1 + \frac{\mu_S + \mu_I}{\varepsilon}\right) \\
e_6 &= -\mu - \eta - B \times \log\left(1 + \frac{\mu_S}{\varepsilon + \mu_I}\right) - S \times \log\left(1 + \frac{\mu_I}{\varepsilon + \mu_S}\right) \\
e_7 &= -\mu - B \times \log\left(1 + \frac{\mu_I}{\varepsilon + \mu_S}\right) - S \times \log\left(1 + \frac{\mu_S + \mu_I}{\varepsilon}\right) \\
e_8 &= -\mu - \eta - B \times \log\left(1 + \frac{\mu_I}{\varepsilon + \mu_S}\right) - S \times \log\left(1 + \frac{\mu_S}{\varepsilon + \mu_I}\right) \\
e_9 &= -\mu - \eta - S \times \log\left(1 + \frac{\mu_S + \mu_I}{\varepsilon}\right)
\end{aligned}
$$

and

$$
e_{\max} = \max(e_1, e_2, e_3, e_4, e_5, e_6, e_7, e_8, e_9).
$$

The constant term $\log(B! \times S!)$ can be dropped. $\{\varepsilon^k, \mu_S^k, \mu_I^k\}$ with $k = b, s$ take values in $[0; \infty)$. The logarithms return positive values and the e_j's are therefore negative. Assuming $\alpha_S = 0$, (no distinction of the type of private information, no symmetric order-flow shock), our model collapses to the Easley et al. (1996) model, and equation (2) collapses to the likelihood expression of Lin and Ke (2011, pp. 628-629).

The amount that must be minimized is:

$$\mathcal{L} = -\sum_{n=1}^{N}\sum_{i=1}^{T} \log\left(f(\theta_n | B_i, S_i)\right)$$

with

$$\theta_n' = \left[\begin{array}{cc:ccccc} \alpha_S & \delta_S & \alpha_{I,n} & \delta_{I,n} & \varepsilon_n & \mu_{S,n} & \mu_{I,n} \end{array}\right]$$

An optimum is reached at:

$$\mathcal{L}(\theta^*) = min\{\mathcal{L}\}$$

with

$$\theta^{*\prime} = \left[\begin{array}{cc:ccccccccccc} \alpha_S & \delta_S & \alpha_{I,1} & \delta_{I,1} & \varepsilon_1 & \mu_{S,1} & \mu_{I,1} & \cdots & \alpha_{I,N} & \delta_{I,N} & \varepsilon_N & \mu_{S,N} & \mu_{I,N} \end{array}\right]$$

We use the MATLAB function FMINCON that takes the Nelder-Mead simplex direct search as algorithm. For $\{\alpha_S, \delta_S, \alpha_I, \delta_I,\}$ we set the lower bound at 0.05, the upper bound at 0.95. For the trading intensity measures $\{\varepsilon, \mu_S, \mu_I\}$, we set the lower bound at 0.1, the upper bound at 10,000. The maximum number of iterations is 100,000 while tolerance is set at 1e-15. The parallel processing toolbox of MATLAB is used to enhance calculation speed. The pseudo variance-covariance matrix is obtained by inverting the Hessian matrix, where the Hessian (Π) is returned as follows:

$$\begin{bmatrix} S & Q_1' & Q_2' & \cdots & Q_N' \\ Q_1 & M_1 & Z_{2,1}' & \cdots & Z_{N,1}' \\ Q_2 & Z_{2,1} & M_2 & & \vdots \\ \vdots & \vdots & & \ddots & Z_{N,N-1}' \\ Q_N & Z_{N,1} & \cdots & Z_{N,N-1} & M_N \end{bmatrix}$$

with:

$$S = \begin{bmatrix} \frac{\partial f^2}{\partial \alpha_S^2} & \frac{\partial f^2}{\partial \alpha_S \partial \delta_S} \\ \frac{\partial f^2}{\partial \delta_S \partial \alpha_S} & \frac{\partial f^2}{\partial \delta_S^2} \end{bmatrix}$$

$$M_i = \begin{bmatrix} \frac{\partial f^2}{\partial \alpha_{i,1}^2} & \frac{\partial f^2}{\partial \alpha_{i,1}\partial \delta_{i,1}} & \frac{\partial f^2}{\partial \alpha_{i,1}\partial \varepsilon_1} & \frac{\partial f^2}{\partial \alpha_{i,1}\partial \mu_{S,1}} & \frac{\partial f^2}{\partial \alpha_{i,1}\partial \mu_{i,1}} \\ \frac{\partial f^2}{\partial \delta_{i,1}\partial \alpha_{i,1}} & \frac{\partial f^2}{\partial \delta_{i,1}^2} & \frac{\partial f^2}{\partial \delta_{i,1}\partial \varepsilon_1} & \frac{\partial f^2}{\partial \delta_{i,1}\partial \mu_{S,1}} & \frac{\partial f^2}{\partial \delta_S \partial \mu_{i,1}} \\ \frac{\partial f^2}{\partial \varepsilon_1 \partial \alpha_{i,1}} & \frac{\partial f^2}{\partial \varepsilon_1 \partial \delta_{i,1}} & \frac{\partial f^2}{\partial \varepsilon_{i,1}^2} & \frac{\partial f^2}{\partial \varepsilon_1 \partial \mu_{S,1}} & \frac{\partial f^2}{\partial \varepsilon_1 \partial \mu_{i,1}} \\ \frac{\partial f^2}{\partial \mu_{S,1}\partial \alpha_{i,1}} & \frac{\partial f^2}{\partial \mu_{S,1}\partial \delta_{i,1}} & \frac{\partial f^2}{\partial \mu_{S,1}\partial \varepsilon_1} & \frac{\partial f^2}{\partial \mu_{S,1}^2} & \frac{\partial f^2}{\partial \mu_{S,1}\partial \mu_{i,1}} \\ \frac{\partial f^2}{\partial \mu_{i,1}\partial \alpha_{i,1}} & \frac{\partial f^2}{\partial \mu_{i,1}\partial \delta_{i,1}} & \frac{\partial f^2}{\partial \mu_{i,1}\partial \varepsilon_1} & \frac{\partial f^2}{\partial \mu_{i,1}\partial \mu_{S,1}} & \frac{\partial f^2}{\partial \mu_{i,1}^2} \end{bmatrix}$$

$$
Q_i = \begin{bmatrix}
\frac{\partial f^2}{\partial \alpha_{I,i} \partial \alpha_S} & \frac{\partial f^2}{\partial \alpha_{I,i} \partial \delta_S} \\
\frac{\partial f^2}{\partial \delta_{I,i} \partial \alpha_S} & \frac{\partial f^2}{\partial \delta_{I,i} \partial \delta_S} \\
\frac{\partial f^2}{\partial \varepsilon_i \partial \alpha_S} & \frac{\partial f^2}{\partial \varepsilon_i \partial \delta_S} \\
\frac{\partial f^2}{\partial \mu_{S,i} \partial \alpha_S} & \frac{\partial f^2}{\partial \mu_{S,i} \partial \delta_S} \\
\frac{\partial f^2}{\partial \mu_{I,i} \partial \alpha_S} & \frac{\partial f^2}{\partial \mu_{I,i} \partial \delta_S}
\end{bmatrix}
$$

$$
Z_{i,j} = \begin{bmatrix}
\frac{\partial f^2}{\partial \alpha_{I,i} \partial \alpha_{I,j}} & \frac{\partial f^2}{\partial \alpha_{I,i} \partial \delta_{I,j}} & \frac{\partial f^2}{\partial \alpha_{I,i} \partial \varepsilon_i} & \frac{\partial f^2}{\partial \alpha_{I,i} \partial \mu_{S,j}} & \frac{\partial f^2}{\partial \alpha_{I,i} \partial \mu_{I,j}} \\
\frac{\partial f^2}{\partial \delta_{I,i} \partial \alpha_{I,j}} & \frac{\partial f^2}{\partial \delta_{I,i} \partial \delta_{I,j}} & \frac{\partial f^2}{\partial \delta_{I,i} \partial \varepsilon_j} & \frac{\partial f^2}{\partial \delta_{I,i} \partial \mu_{S,j}} & \frac{\partial f^2}{\partial \delta_{I,i} \partial \mu_{I,j}} \\
\frac{\partial f^2}{\partial \varepsilon_i \partial \alpha_{I,j}} & \frac{\partial f^2}{\partial \varepsilon_i \partial \delta_{I,j}} & \frac{\partial f^2}{\partial \varepsilon_i \partial \varepsilon_j} & \frac{\partial f^2}{\partial \varepsilon_i \partial \mu_{S,j}} & \frac{\partial f^2}{\partial \varepsilon_i \partial \mu_{I,j}} \\
\frac{\partial f^2}{\partial \mu_{S,i} \partial \alpha_{I,j}} & \frac{\partial f^2}{\partial \mu_{S,i} \partial \delta_{I,j}} & \frac{\partial f^2}{\partial \mu_{S,i} \partial \varepsilon_j} & \frac{\partial f^2}{\partial \mu_{S,i} \partial \mu_{S,j}} & \frac{\partial f^2}{\partial \mu_{S,i} \partial \mu_{I,j}} \\
\frac{\partial f^2}{\partial \mu_{I,i} \partial \alpha_{I,j}} & \frac{\partial f^2}{\partial \mu_{I,i} \partial \delta_{I,j}} & \frac{\partial f^2}{\partial \mu_{I,i} \partial \varepsilon_j} & \frac{\partial f^2}{\partial \mu_{S,i} \partial \mu_{S,j}} & \frac{\partial f^2}{\partial \mu_{I,i} \partial \mu_{I,j}}
\end{bmatrix}
$$

The size of Π is $(2+5N) \times (2+5N)$. Standard errors of structural parameters are given by $\sqrt{diag(\Pi^{-1})}$. Stock-level pseudo variance-covariance matrix are extracted from Π:

$$
\Sigma_n(f) = \\
\left(\begin{bmatrix}
\frac{\partial f^2}{\partial \alpha_S^2} & \frac{\partial f^2}{\partial \alpha_S \partial \delta_S} & \frac{\partial f^2}{\partial \alpha_S \partial \alpha_{I,n}} & \frac{\partial f^2}{\partial \alpha_S \partial \delta_{I,n}} & \frac{\partial f^2}{\partial \alpha_S \partial \varepsilon_n} & \frac{\partial f^2}{\partial \alpha_S \partial \mu_{S,n}} & \frac{\partial f^2}{\partial \alpha_S \partial \mu_{I,n}} \\
\frac{\partial f^2}{\partial \delta_S \partial \alpha_S} & \frac{\partial f^2}{\partial \delta_S^2} & \frac{\partial f^2}{\partial \delta_S \partial \alpha_{I,n}} & \frac{\partial f^2}{\partial \delta_S \partial \delta_{I,n}} & \frac{\partial f^2}{\partial \delta_S \partial \varepsilon_n} & \frac{\partial f^2}{\partial \delta_S \partial \mu_{S,n}} & \frac{\partial f^2}{\partial \delta_S \partial \mu_{I,n}} \\
\frac{\partial f^2}{\partial \alpha_{I,n} \partial \alpha_S} & \frac{\partial f^2}{\partial \alpha_{I,n} \partial \delta_S} & \frac{\partial f^2}{\partial \alpha_{I,n}^2} & \frac{\partial f^2}{\partial \alpha_{I,n} \partial \delta_{I,n}} & \frac{\partial f^2}{\partial \alpha_{I,n} \partial \varepsilon_N} & \frac{\partial f^2}{\partial \alpha_{I,n} \partial \mu_{S,n}} & \frac{\partial f^2}{\partial \alpha_{I,n} \partial \mu_{I,n}} \\
\frac{\partial f^2}{\partial \delta_{I,n} \partial \alpha_S} & \frac{\partial f^2}{\partial \delta_{I,n} \partial \delta_S} & \frac{\partial f^2}{\partial \delta_{I,n} \partial \alpha_{I,n}} & \frac{\partial f^2}{\partial \delta_{I,n}^2} & \frac{\partial f^2}{\partial \delta_{I,n} \partial \varepsilon_N} & \frac{\partial f^2}{\partial \delta_{I,n} \partial \mu_{S,n}} & \frac{\partial f^2}{\partial \delta_S \partial \mu_{I,n}} \\
\frac{\partial f^2}{\partial \varepsilon_N \partial \alpha_S} & \frac{\partial f^2}{\partial \varepsilon_N \partial \delta_S} & \frac{\partial f^2}{\partial \varepsilon_N \partial \alpha_I} & \frac{\partial f^2}{\partial \varepsilon_N \partial \delta_{I,n}} & \frac{\partial f^2}{\partial \varepsilon_{I,n}^2} & \frac{\partial f^2}{\partial \varepsilon_N \partial \mu_{S,n}} & \frac{\partial f^2}{\partial \varepsilon_N \partial \mu_{I,n}} \\
\frac{\partial f^2}{\partial \mu_{S,n} \partial \alpha_S} & \frac{\partial f^2}{\partial \mu_{S,n} \partial \delta_S} & \frac{\partial f^2}{\partial \mu_{S,n} \partial \alpha_I} & \frac{\partial f^2}{\partial \mu_{S,n} \partial \delta_{I,n}} & \frac{\partial f^2}{\partial \mu_{S,n} \partial \varepsilon_N} & \frac{\partial f^2}{\partial \mu_{S,n}^2} & \frac{\partial f^2}{\partial \mu_{S,n} \partial \mu_{I,n}} \\
\frac{\partial f^2}{\partial \mu_{I,n} \partial \alpha_S} & \frac{\partial f^2}{\partial \mu_{I,n} \partial \delta_S} & \frac{\partial f^2}{\partial \mu_{I,n} \partial \alpha_I} & \frac{\partial f^2}{\partial \mu_{I,n} \partial \delta_{I,n}} & \frac{\partial f^2}{\partial \mu_{I,n} \partial \varepsilon_N} & \frac{\partial f^2}{\partial \mu_{I,n} \partial \mu_{S,n}} & \frac{\partial f^2}{\partial \mu_{I,n}^2}
\end{bmatrix} \right)^{-1}
$$

$$
\text{for } n = 1, ..., N
$$

Then standards errors of IPIN, SPIN and I/S-Ratio are obtained with the delta method. A clear presentation of the delta method is given by Cooch and White (2014, Appendix B). Consider θ^* as the large-sample maximum likelihood estimate of the k-dimensional parameter θ with approximate variance-covariance matrix Σ_θ, where $k = 2 + 5 \times N$ in our case. If $\Theta = g(\theta)$ is a scalar function, then the MLE of Θ_0 is given by $\Theta^* = g(\theta^*)$ and $\Theta^* \backsim N(\Theta_0, \Lambda)$ where $\Lambda = \Gamma \times \Sigma_\theta \times \Gamma'$ and $\Gamma = [\frac{\partial \Theta}{\partial \theta_1}, ..., \frac{\partial \Theta}{\partial \theta_k}]$ evaluated at θ^*. In our case, $\Gamma = [\frac{\partial \Theta}{\partial \alpha_S}, \frac{\partial \Theta}{\partial \delta_S}, \frac{\partial \Theta}{\partial \alpha_I}, \frac{\partial \Theta}{\partial \delta_I}, \frac{\partial \Theta}{\partial \varepsilon}, \frac{\partial \Theta}{\partial \mu_S}, \frac{\partial \Theta}{\partial \mu_I}]$. Defining ψ as the total trading intensity,

$\psi = 2 \times \varepsilon + \alpha_S \times \mu_S + \alpha_I \times \mu_I$, the derivatives are:

$$\Gamma_{SPIN} = [\frac{\mu_S}{\psi} \times (1 - SPIN); 0; -\frac{\mu_I}{\psi} \times SPIN; 0; -\frac{2}{\psi} \times SPIN; \frac{\alpha_S}{\psi} \times (1 - SPIN); -\frac{\alpha_I}{\psi} \times SPIN]$$

$$\Gamma_{IPIN} = [-\frac{\mu_S}{\psi} \times IPIN; 0; \frac{\mu_I}{\psi} \times (1 - IPIN); 0; -\frac{2}{\psi} \times IPIN; -\frac{\alpha_S}{\psi} \times IPIN; \frac{\alpha_I}{\psi} \times (1 - IPIN)]$$

$$\Gamma_{I/S-Ratio} = [\frac{\alpha_I \times \mu_I}{\alpha_S^2 \times \mu_S}; 0; \frac{\mu_I}{\alpha_S \times \mu_S}; 0; 0; -\frac{\alpha_I \times \mu_I}{\alpha_S \times \mu_S^2}; \frac{\alpha_I}{\alpha_S \times \mu_S}]$$

2.10.3 Appendix III: Initial values

We rely on the approach of Yan and Zhang (2012). First, we set $\varepsilon = \gamma \times E(B)$. Then, we derive the expectations of of buyer-initiated trades (B) and seller-initiated trades (S). Calculation steps are described in Yan and Zhang (2012, Appendix A). The three equations are:

$$\begin{aligned}
\varepsilon &= \gamma \times E(B) \\
E(B) &= \varepsilon + \alpha_S \times \mu_S \times (1 - \delta_S) + \alpha_I \times \mu_I \times (1 - \delta_I) \\
E(S) &= \varepsilon + \alpha_S \times \delta_S \times \mu_S + \alpha_I \times \delta_I \times \mu_I
\end{aligned}$$

Expectations are replaced by their empirical counterpart, the matrix of the system is:

$$\begin{bmatrix} \frac{1}{\gamma} & 0 & 0 \\ 1 & \alpha_S^0 \times (1 - \delta_S^0) & \alpha_I^0 \times (1 - \delta_I^0) \\ 1 & \alpha_S^0 \times \delta_S^0 & \alpha_I^0 \times \delta_I^0 \end{bmatrix} \begin{bmatrix} \varepsilon^0 \\ \mu_S^0 \\ \mu_I^0 \end{bmatrix} = \begin{bmatrix} \bar{B} \\ \bar{B} \\ \bar{S} \end{bmatrix}$$

The solutions are:

$$\begin{aligned}
\varepsilon^0 &= \gamma^0 \times \bar{B} \\
\mu_S^0 &= \frac{1}{\alpha_S^0 \times (\delta_I^0 - \delta_S^0)} \times (\bar{B} \times (\gamma^0 + \delta_I^0 - 2 \times \gamma^0 \times \delta_I^0) - \bar{S} \times (1 - \delta_I^0)) \\
\mu_I^0 &= \frac{1}{\alpha_I^0 \times (\delta_S^0 - \delta_I^0)} \times (\bar{B} \times (\gamma^0 + \delta_S^0 - 2 \times \gamma^0 \times \delta_S^0) - \bar{S} \times (1 - \delta_S^0))
\end{aligned}$$

We generate 500 set of $\{\alpha_S^0, \alpha_I^0, \delta_S^0, \delta_I^0, \gamma^0\}$, from which we derive $\{\varepsilon^0, \mu_S^0, \mu_I^0\}$. These values are plugged into the likelihood function as initial guess. To reduce the search area, we set $\gamma^0 = 0.9$. $\{\alpha_S^0, \alpha_I^0\}$ are randomly drawn for an uniform distribution between 0 and 0.5, while $\{\delta_S^0, \delta_I^0\}$are randomly drawn from an uniform distribution between 0 and 1. Sometimes, solving equations leads to negative intensity parameters, in which cases, these values are re-set to one (i.e. the lower bound). To assess the impact of initial values over final estimates, the 500 output set $\{\alpha_S^*, \alpha_I^*, \delta_S^*, \delta_I^*, \gamma^*\}$ are sorted by objective functions and parameters are sorted based on objective function ranks. **Figure A.II** shows how parameters converge to their final values as we move from the 500th "worst" IV set (returning the lowest objective function) to the 1th "best" IV set (returning the highest objective function). One can observe that a convergence starts around the 400th set and stability stands until the 500th one. To estimate the PIN model of Easley et al. (1996), we also follow Yan and Zhang by setting $\varepsilon^0 = \gamma^0 \bar{B}$ and deriving $\mu^0 = [\bar{B} \times (1 - \gamma^0)] / [\alpha^0 \times (1 - \delta^0)]$. We generate 125 combinations of $\{\alpha^0, \delta^0, \gamma^0\}$ with the values $\{0.1; 0.3; 0.5; 0.7; 0.9\}$. All combinations return positive $\{\varepsilon^0, \mu^0\}$ and are used as initial guesses. Since the benchmark PIN model requires less estimates than our extension, fewer initial guesses are necessary to reach the global maximum. Concerning the extension of Duarte and Young (2009), we find $\mu^0 = (\bar{B} - \bar{S}) / [\alpha^0 \times (1 - 2 \times \delta^0)]$ and $\Delta^0 = [B \times (\delta^0 + \gamma^0 - 2 \times \gamma^0 \times \delta^0) - S \times (1 - \delta^0)] / [\theta^0 \times (2 \times \delta^0 - 1)]$, given $\varepsilon^0 = \gamma^0 \times \bar{B}$.

2.10.4 Appendix IV: Simulations

2.10.4.1 Motivations

Popular tick-by-tick data provider like ISSM (1983-1992) or TAQ (1993-2014) do not allow the researcher to identify the party whose decision causes the trade to occur. Regarding this lack of information, several trade classification algorithms (TCAs) have been proposed. The Lee-Ready (LR hereafter) by Lee and Ready (1991) is the most popular. Ellis et al. (2000) and Chakravarty et al. (2007) have proposed their own revision of LR, in order to improve the overall accuracy. Since TCAs are imperfect proxies for the true initiation, some transactions are actually misclassified. Lee and Radhakrisna (2000) have analyzed a very specific dataset that provides the "true" initiation for NYSE stocks, and find a misclassification rate of 7% when using the LR algorithm. Using the same dataset, this figure soars to 15% in Odders-White (2000) and Funicane (2000). Ellis et al. (2000) find an overall disagreement rate of 18.95% on a sample of NASDAQ stocks.[21]

Boehmer et al. (2007) analyze the impact of trade misclassification on the probability of informed trading. They find that the PIN based on TCA underestimates the "true" PIN by 18%, putting in evidence that the misclassification rate induces bias in structural parameters. Since our econometric model rely on trade classification, it is necessary to control for the effect of misclassification on estimates, even if the PIN metric itself is not used to tackle our research question. To convince that our results are robust to misclassification, simulations are performed.

2.10.4.2 Approach

Since $\alpha_S \times \mu_S$ and $\alpha_I \times \mu_I$ are non-linear combination of two parameters, it is important to analyze to what extent these measures is impacted by the misclassification rate. To do so, structural parameters are generated, BITs and SITs time series are simulated and finally, simulated values are compared to estimated values. In a the first set of simulations, we ignore the possiblitity of misclassification while a *net* misclassification rate of 5% is voluntary introduced in the second set of simulations.

Our simulation exercise involves four virtual stocks. For each stock $i = \{1, 2, 3, 4\}$, we randomly assign a value to ε_i from a specific interval. The intervals are: $I_i = [k_i + 1; k_i + 100]$ where $k_i = \{0, 100, 200, 300\}$. Hence, the four stocks experience different trading intensities, from the less to the most liquid. $\{\mu_S^i, \mu_I^i\}$ values are generated by drawing numbers from these intervals and multiplying these values by 0.25 because informed trades usually account for a small portion of all trades in a given day. The probabilities are generated using the uniform distribution. We obtain a vector set

$$\left\{\alpha_S^j, \delta_S^j, \alpha_I^{j,1}, \delta_I^{j,1}, \varepsilon_I^{j,1}, \mu_S^{j,1}, \mu_I^{j,1}, ..., \alpha_I^{j,4}, \delta_I^{j,4}, \varepsilon_I^{j,4}, \mu_S^{j,4}, \mu_I^{j,4}\right\}$$

where $j = \{1, ..., 100\}$ indexes the simulation number. The total number of parameters to be estimated is 22. A binary variable is then generated from each probability parameter with the binomial distribution. This forms a chain. For instance, $\left\{\alpha_S^i, \delta_S^i, \alpha_I^{j,i}, \delta_I^{j,i}\right\}$ returns 0-1-0-1-0. It gives the path chosen by the nature among the 9 possibilities given by the trading process plotted **Figure III**. The number of BITs and SITs are generated by a Poisson distribution, where the intensity is defined at the end of the branch. For each vector j, the procedure is repeated 63 times (representing one quarter of trading days).

100 time series of $\{BIT; SIT\}$ are generated under this procedure, with 63 observations per path. Then we use the time series of $\{BIT; SIT\}$ as inputs and estimate the structural parameters by maximum likelihood. This gives a first set of simulated - estimated parameters. We also generate a second set where 5% of BITs and SITs are voluntarily missclassified. It works as follows: For each trading day, 10% of the daily amount of BITs are picked up and transfered it to the SITs amount. This happens with a probability of 50%. Otherwise, the alteration goes in the opposite way. This app echoes empirical findings, and thus give an idea of the bias magnitude with real data.

[21] Misclassification rate differs across stock exchanges. See Aitken and Frino (1996) for the Australien Stock Exchange and Theissen (2001) for the Frankfurt Stock Exchange.

2.10.4.3 Results

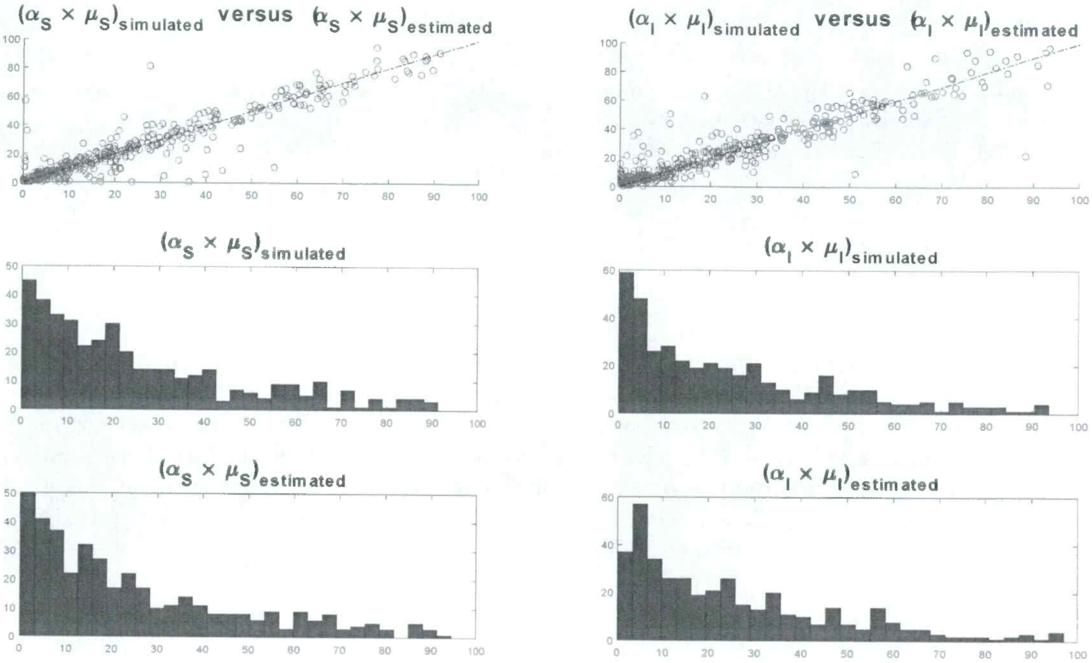
Table A.I reports several statistics on $\alpha_S^j \times \mu_S^{j,i}$ (simulated) and $\hat{\alpha}_S^j \times \hat{\mu}_S^{j,i}$ (estimated) as well as $\alpha_I^{j,i} \times \mu_I^{j,i}$ and $\hat{\alpha}_I^{j,i} \times \hat{\mu}_I^{j,i}$. Additional statistics on the cross-correlation matrix for BITs, SITs and order-flow imbalance (OFIs) are provided. **Figure A.I** panel A (B) shows $\alpha_S^j \times \mu_S^{j,i}$ and $\alpha_I^{j,i} \times \mu_I^{j,i}$ on the x-axis versus $\hat{\alpha}_S^j \times \hat{\mu}_S^{j,i}$ and $\hat{\alpha}_I^{j,i} \times \hat{\mu}_I^{j,i}$ on the y-axis, respectively, without (with) misclassification. Cross-sectional distributions of the variables are also exhibited.

Mean, median, and standard deviation of simulated and estimated values are fairly close except for the unliquid stock. One can easily observe that the RMSEs, in percentage of the mean, are the largest for stock 1. Moreover, Wilcoxon ranksum tests confirm that the medians derived from simulation are significantly different from the medians derived from estimations. For $\alpha_I \times \mu_I$, *z-stat* = 2.134 (significant at 5%) under the first set of simulation and *z-stat* = 2.603 (significant at 1%) in the second set of simulations. This result echoes Boehmer et al. (2007) who document that the bias induced by misclassification rate is more pronounced for stocks with little trading activity. In order to take this finding into account, a minimum of 100 BITs and 100 SITs is required in the empirical part. Doing so, unreliable estimates are avoided.

A positive, significant cross-correlation emerges from the simulated order-flow. Without misclassification, correlation coefficients lie between 20% and 41%. When some trades are misclassified, the correlation level is between 18% and 37%. We find that for all cross-correlation measures between stock i and stock j, at least 25 coefficients out of 100 are significant at 5%, with or without trade misclassification. In some cases, more than 50 coefficients, out of 100, are significant. To the best of our knowledge, no model was able to reproduce this pattern in the order-flow.

2.10.5 Appendix V: Additional exhibits

Figure A.I Panel A: Theoretical versus estimated parameters - Without misclassification -



The graph presents the results of the simulation exercise performed on four virtual stocks. Intensity parameters $\left\{\varepsilon^{i,j}, \mu_S^{i,j}, \mu_I^{i,j}\right\}$ where $i = 1, ..., 4$ (number of stocks) and $j = 1, ..., 100$ (number of simulations) are uniformly at random in $[100 \times (i-1); 100 \times i]$ for stock i. $\left\{\alpha_S^j, \delta_S^j, \alpha_I^{i,j}, \delta_I^{i,j}\right\}$ are randomly drawn from a vector that contains values from 0.01 to 0.99. From a set of values, a 63-day time series of buyer-initiated trades (BITs) and seller-initiated trades (SITs) is generated using the trading process depicted Figure III. For each day, BITs and SITs are derived as follows: Among the nine branches of the trading process, one is selected following the sequence of probabilities returned by binomial draws. Then a Poisson distribution generates the daily amount of BITs and SITs. Accordingly, the associated intensity is observed at the branch end. Binomial and Poisson random generation process is repeated 63 times to obtain a time series. Finally, the 100 time series of BITs and SITs serve as inputs in the objective function, equation (3), and structural parameters are estimated by maximum likelihood (ML). See Appendix II for ML details. Panel A shows data not contaminated by the misclassification rate while in panel B, 5% of SITs (BITs) are erroneously classified as BITs (SITs) with a probability of 50% (50%), for each stock-day observation. Introducing these features aims at reflecting empirical facts of stock market microstructure. On the scatter plots, simulated (estimated) values are on the x-axis (y-axis).

Figure A.I Panel B: Theoretical versus estimated parameters - With misclassification -

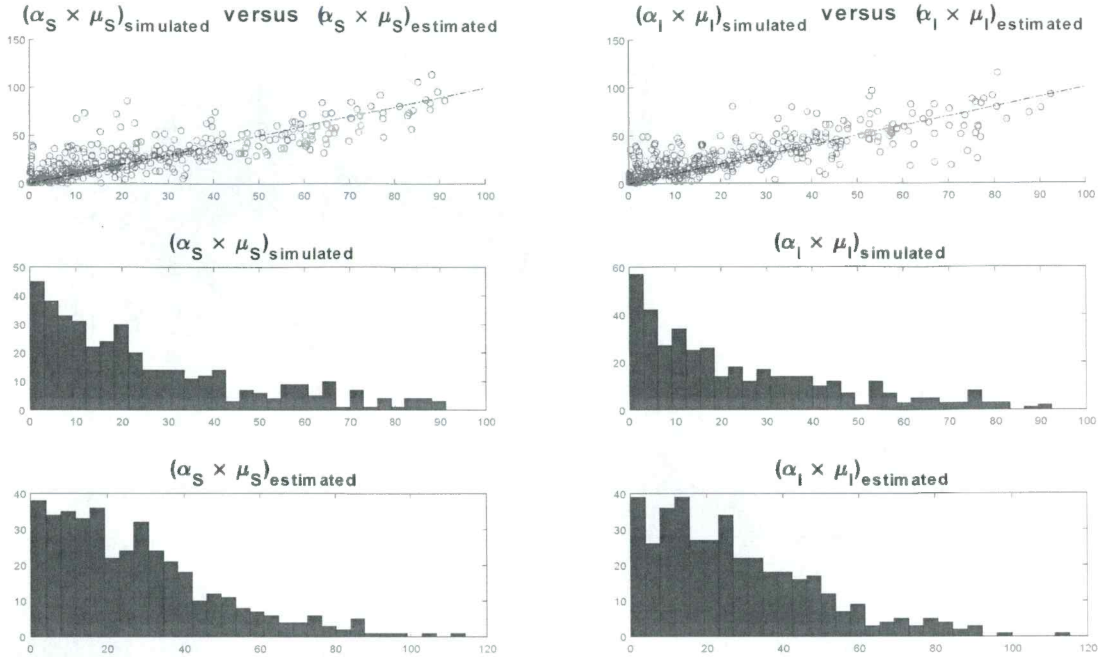
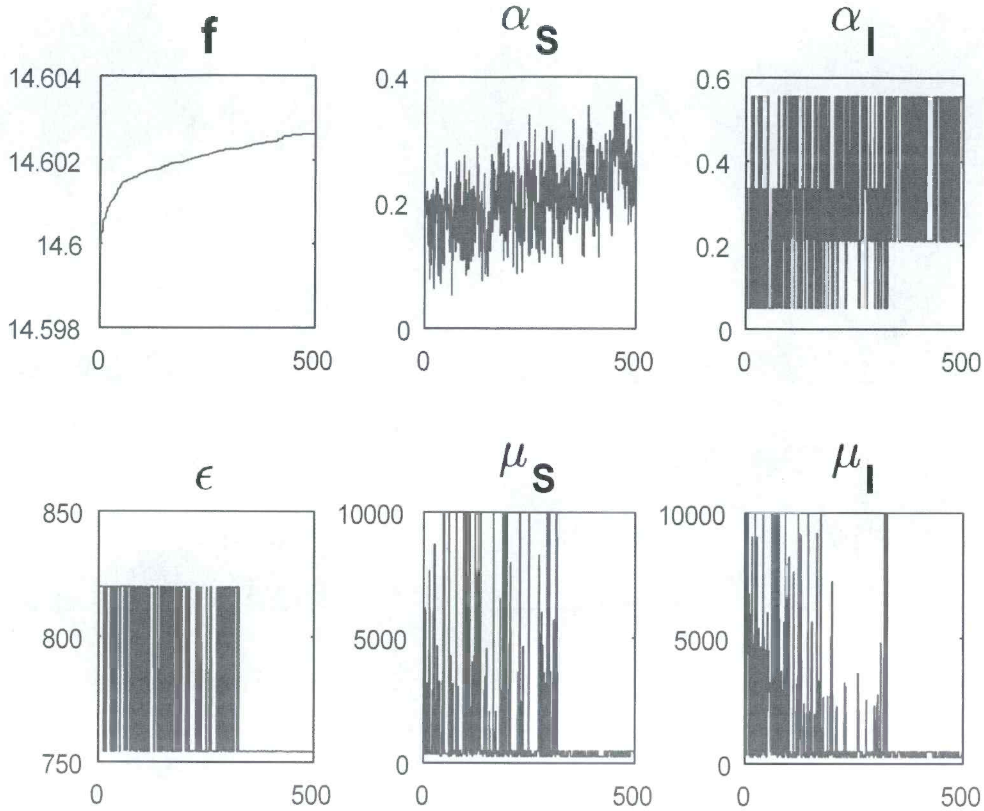


Figure A.II: Initial guesses and convergence



This figure shows how parameters converge to their final values as we move from the 500th "worst" initial value (IV) set (returning the lowest objective function) to the 1th "best" IV set (returning the highest objective function). It provide evidence on the sensitivity of maximum likelihood to initial values. For each stock-quarter observation, 500 initial values are plugged into the objective function before MATLAB "fminsearch" starts running. Once estimates are done, the objective function (f) and the parameter sets $\{\alpha_S, \alpha_I, \varepsilon, \mu_S, \mu_I\}$ are saved into a matrix, one parameter per column, one IV set per line. Then, rows are sorted according to the first dimension, i.e. the objective function. Here is an example of parameter convergence for the company "Du Pont de Nemours", for the period 01/16/1999 - 04/19/1999. Similar plots for the other stocks are available upon request.

Table A.I: Root mean square errors (RMSEs)

		Without misclassification				With misclassification			
		stock 1	stock 2	stock 3	stock 4	stock 1	stock 2	stock 3	stock 4
				a. Simulated					
$\alpha_S \times \mu_S$	Mean	7.029	18.682	31.375	44.547	7.029	18.682	31.375	44.547
	Median	5.113	17.389	29.430	41.796	5.113	17.389	29.430	41.796
	Std. dev.	6.011	11.783	18.852	26.423	6.011	11.783	18.852	26.423
$\alpha_I \times \mu_I$	Mean	5.941	18.752	29.100	43.772	5.941	18.465	29.795	42.538
	Median	4.446	18.930	28.524	45.918	4.446	17.737	29.992	41.396
	Std. dev.	5.199	11.328	18.423	26.505	5.199	12.007	18.192	25.555
				b. Estimated					
$\alpha_S \times \mu_S$	Mean	6.525	18.434	30.777	45.519	6.943	20.833	33.149	49.863
	Median	4.417	17.424	30.465	46.859	5.251	19.361	32.092	45.648
	Std. dev.	6.207	11.688	19.326	26.807	5.213	10.059	13.997	23.443
	Median std. err.	2.029	6.154	9.543	12.782	1.776	5.338	7.657	10.008
	RMSE	3.208	4.715	10.202	10.717	4.310	9.424	14.301	19.177
$\alpha_I \times \mu_I$	Mean	7.039	19.942	30.481	44.578	7.663	20.536	36.420	47.668
	Median	5.765	20.178	31.294	47.644	7.116	18.134	34.334	44.191
	Std. dev.	4.858	10.914	18.274	26.801	5.241	10.713	16.114	22.416
	Median std. err.	3.712	8.055	10.537	16.350	3.672	5.746	8.176	9.386
	RMSE	3.384	4.989	9.759	11.682	5.235	10.152	15.644	20.744

Above are reported some statistics on the simulations. $\{\alpha_S, \delta_S\}$ and $\{\alpha_I^i, \delta_I^i\}$ for $i = 1, 2, 3, 4$ are randomly drawn from a uniform distribution. ε_i and $\{\mu_S^i, \mu_I^i\}$ are also drawn from a uniform distribution, over the interval $[k_i + 1; k_i + 100]$ where $k_i = \{0, 100, 200, 300\}$. This reflects difference in liquidity level across stocks. Binary variables are generated given $\{\alpha_S^j, \delta_S^j, \alpha_I^{i,j}, \delta_I^{i,j}\}$ where $j = 1, ..., 100$ stands for the number of simulations. The chain formed by the binary variable is used to identify the path chosen by the nature among the nine possibilities. $\{BITs, SITs\}$ are randomly generated from a Poisson distribution whose expected intensity is the combination $\{\varepsilon^i, \mu_S^i, \mu_I^i\}$ observed for the state of nature. The is repeated 63 times per simulation. Then structural parameters are estimated by maximum likelihood, initial values being $\{\frac{1}{2}, \frac{1}{2}, \frac{1}{2}, \frac{1}{2}, 0.8 \times \bar{B}, 0.1 \times \bar{B}, 0.1 \times \bar{B}\}$, where $\bar{B}$ is the BIT mean. The left side set of results are obtained under the assumption of no misclassification while the right side set is obtained under the assumption that 5% of $BITs$ and $SITs$ are misclassified. This second scenario aims at reflecting empirical evidence in data. "Std. dev." stands for standard deviation while "Median std. err." gives the median of parameter standard errors derived with the delta method. The differences between simulated and estimated variable distributions are tested with the Wilcoxon ranksum test. * (**) indicates a significant difference at 5% (1%). "RMSE" stands for Root Mean Square Errors and is defined as the difference of squared errors as $\varepsilon_i = (\hat{y}_{1,i} - y_i)^2 - (\hat{y}_{2,i} - y_i)^2$ and t-stat $= \sqrt{(2/n)} \times (m_d/\sigma_d)$ where m_d and σ_d are the mean and the standard deviation of the ε series, respectively and $n = 100$. * means that results are significant at 5% level. The last part of the table indicates median cross-correlation matrix for BITs and SITs. Results are summarized with the following notation. ^{a}: At least 25 coefficients, out of 100, are statistically significant at 5%. ^{b}: At least 50% are significant. ^{c}: at least 75% are significant.

Table A.I: Continued

	Without misclassification				With misclassification			
	stock 1	stock 2	stock 3	stock 4	stock 1	stock 2	stock 3	stock 4
				c. Wilcoxon ranksum tests				
$\alpha_S \times \mu_S$	-1.005	-0.155	-0.334	-0.226	-0.417	-1.589	-1.005	-1.497
$\alpha_I \times \mu_I$	-2.134*	-0.590	-0.527	-0.263	-2.603**	-1.372	-2.525*	-1.367
				d. Median cross-correlation				
BITs	0.235^a				0.182^a			
	0.204^a	0.313^b			0.219^a	0.283^b		
	0.232^a	0.342^b	0.386^b		0.204^a	0.272^b	0316^b	
SITs	0.252^b				0.238^a			
	0.305^b	0.387^b			0.226^a	0.310^b		
	0.325^b	0.378^b	0.408^c		0.265^b	0.314^b	0.366^b	

Table A.II: Stock-level microstructure

	Share price ($)	BIT	SIT	Outside quotes (%)	At quotes (%)	Inside quotes (%)	At midpoint (%)	PRE IPIN (s.e.)	PRE SPIN (s.e.)	PRE I/S-Ratio (s.e.)	POST IPIN (s.e.)	POST SPIN (s.e.)	POST I/S-Ratio (s.e.)
							GICS 10: Energy						
BHI	20.7	389	360	0.03	0.70	0.07	0.22	0.094	0.084	1.114	0.087	0.085	1.019
								(0.015)	(0.005)	(0.222)	(0.013)	(0.005)	(0.175)
CHV	83.2	448	450	0.05	0.58	0.15	0.23	0.054	0.050	1.080	0.055	0.033	1.689
								(0.017)	(0.003)	(0.356)	(0.012)	(0.003)	(0.461)
DO	26.1	372	313	0.04	0.76	0.07	0.14	0.105	0.119	0.885	0.128	0.084	1.524
								(0.009)	(0.007)	(0.096)	(0.008)	(0.005)	(0.146)
ESV	11.7	322	320	0.03	0.84	0.02	0.13	0.122	0.111	1.101	0.093	0.152	0.610
								(0.007)	(0.005)	(0.085)	(0.013)	(0.008)	(0.097)
HAL	32.7	711	585	0.05	0.69	0.08	0.19	0.112	0.096	1.160	0.079	0.081	0.983
								(0.006)	(0.009)	(0.139)	(0.010)	(0.005)	(0.150)
NBR	15.1	236	223	0.03	0.83	0.02	0.13	0.140	0.124	1.128	0.096	0.098	0.981
								(0.012)	(0.008)	(0.142)	(0.009)	(0.005)	(0.105)
OXY	18.9	220	213	0.02	0.79	0.04	0.16	0.041	0.066	0.616	0.089	0.068	1.309
								(0.014)	(0.013)	(0.197)	(0.007)	(0.004)	(0.129)
RDC	11.4	302	261	0.03	0.83	0.02	0.15	0.100	0.121	0.830	0.122	0.096	1.270
								(0.007)	(0.007)	(0.069)	(0.011)	(0.005)	(0.146)
SLB	51.8	841	697	0.04	0.62	0.10	0.25	0.112	0.102	1.106	0.089	0.052	1.716
								(0.004)	(0.007)	(0.081)	(0.008)	(0.003)	(0.197)
WMB	31.9	343	305	0.05	0.70	0.09	0.17	0.091	0.142	0.641	0.090	0.081	1.117
								(0.013)	(0.008)	(0.114)	(0.008)	(0.005)	(0.127)

Here are report some stock-level descriptive statistics (column 2 to 8) and parameter estimates (column 9 to 14). Stock tickers are reported column 1. Share price is the end-of-day trading price. BIT and SIT stand for buyer-initiated and seller-initiated trades, respectively. Trades are classified with the Lee and Ready (1991) algorithm. The next four columns indicate the proportion of trades outside quotes, at quotes, inside quotes and at midpoint, respectively. These figures are averages over the period 08/19/1998 - 11/16/1998. Hence, the sum of columns 5 to 8 might slightly differs from one. Column 9 to 11 and 12 to 14 show parameter estimates for the pre-event (08/19/1998 - 11/16/1998) and the post-event period (01/19/1999 - 04/19/1999), respectively. IPIN (SPIN) stands for the probability that the market incorporates the information of type firm-specific (sector-specific) times the trading intensity of traders specializing in trading the firm-specific (sector-specific) risk, divided by the total trading intensity. I/S-Ratio is the ratio IPIN to SPIN and reflects a relative trading intensity. The minimum and maximum IS-Ratio, that is the largest imbalance between S-trades and I-traders activity, stands for the company Abbot Laboratories (0.33) and Caterpillar (1.67), respectively. "s.e." stands for standard errors.

Table A.II: Stock-level microstructure (continued)

	Share price ($)	BIT	SIT	Outside quotes (%)	At quotes (%)	Inside quotes (%)	At midpoint (%)	PRE IPIN (s.e.)	PRE SPIN (s.e.)	PRE I/S-Ratio (s.e.)	POST IPIN (s.e.)	POST SPIN (s.e.)	POST I/S-Ratio (s.e.)
GICS 15: Materials													
AA	67.7	312	277	0.04	0.64	0.16	0.17	0.095	0.074	1.292	0.074	0.072	1.024
								(0.007)	(0.005)	(0.145)	(0.019)	(0.005)	(0.262)
BS	8.6	208	200	0.01	0.87	0.01	0.12	0.115	0.116	0.988	0.086	0.104	0.830
								(0.009)	(0.006)	(0.096)	(0.029)	(0.009)	(0.329)
DD	57.8	889	781	0.06	0.68	0.10	0.17	0.073	0.065	1.133	0.086	0.042	2.072
								(0.005)	(0.004)	(0.105)	(0.006)	(0.003)	(0.219)
DOW	93.3	265	267	0.04	0.62	0.19	0.16	0.104	0.066	1.582	0.051	0.101	0.508
								(0.007)	(0.004)	(0.119)	(0.009)	(0.008)	(0.118)
HM	10.4	203	203	0.02	0.87	0.01	0.12	0.129	0.134	0.963	0.065	0.075	0.865
								(0.010)	(0.007)	(0.105)	(0.007)	(0.005)	(0.121)
IP	44.3	445	440	0.04	0.68	0.11	0.18	0.105	0.068	1.550	0.048	0.079	0.612
								(0.005)	(0.004)	(0.127)	(0.019)	(0.005)	(0.234)
NEM	19.6	362	340	0.03	0.76	0.04	0.18	0.122	0.107	1.143	0.098	0.051	1.908
								(0.009)	(0.006)	(0.129)	(0.014)	(0.004)	(0.257)
SHW	26.5	179	176	0.01	0.68	0.14	0.17	0.107	0.130	0.825	0.103	0.039	2.612
								(0.009)	(0.007)	(0.086)	(0.006)	(0.003)	(0.305)
UK	43.5	293	287	0.04	0.70	0.11	0.16	0.097	0.144	0.675	0.107	0.048	2.213
								(0.009)	(0.007)	(0.078)	(0.010)	(0.004)	(0.305)
X	24.6	218	184	0.02	0.68	0.11	0.20	0.121	0.091	1.334	0.106	0.082	1.296
								(0.006)	(0.005)	(0.118)	(0.008)	(0.007)	(0.173)

Table A.II: Stock-level microstructure (continued)

	Share price ($)	BIT	SIT	Outside quotes (%)	At quotes (%)	Inside quotes (%)	At midpoint (%)	PRE IPIN (s.e.)	PRE SPIN (s.e.)	PRE I/S-Ratio (s.e.)	POST IPIN (s.e.)	POST SPIN (s.e.)	POST I/S-Ratio (s.e.)
GICS 20: Industrials													
GE	94.8	1472	1406	0.09	0.66	0.08	0.19	0.084	0.081	1.040	0.040	0.028	1.448
								(0.005)	(0.004)	(0.084)	(0.006)	(0.003)	(0.200)
BA	35.9	1026	1093	0.04	0.79	0.02	0.16	0.094	0.085	1.108	0.056	0.031	1.797
								(0.006)	(0.004)	(0.077)	(0.019)	(0.004)	(0.809)
CAT	47.8	604	487	0.05	0.73	0.09	0.16	0.138	0.082	1.672	0.087	0.090	0.960
								(0.006)	(0.005)	(0.135)	(0.008)	(0.010)	(0.166)
DE	35.3	383	352	0.03	0.68	0.08	0.22	0.105	0.100	1.045	0.074	0.086	0.857
								(0.005)	(0.005)	(0.081)	(0.023)	(0.006)	(0.274)
EMR	60.3	302	265	0.04	0.61	0.20	0.16	0.090	0.072	1.255	0.079	0.037	2.149
								(0.006)	(0.005)	(0.127)	(0.029)	(0.003)	(0.836)
LUV	25.5	391	351	0.03	0.79	0.04	0.16	0.110	0.121	0.915	0.062	0.042	1.484
								(0.009)	(0.006)	(0.086)	(0.007)	(0.003)	(0.244)
MMM	76.2	437	439	0.05	0.59	0.18	0.19	0.050	0.066	0.755	0.048	0.058	0.834
								(0.006)	(0.004)	(0.113)	(0.007)	(0.006)	(0.144)
TYC	66.9	476	351	0.03	0.58	0.18	0.21	0.104	0.068	1.521	0.138	0.094	1.464
								(0.006)	(0.004)	(0.126)	(0.033)	(0.009)	(0.447)
UNP	47.2	236	225	0.02	0.62	0.14	0.22	0.084	0.090	0.927	0.090	0.056	1.616
								(0.007)	(0.005)	(0.104)	(0.006)	(0.005)	(0.176)
UTX	106.3	299	255	0.05	0.59	0.23	0.14	0.080	0.063	1.263	0.072	0.070	1.040
								(0.004)	(0.004)	(0.116)	(0.006)	(0.006)	(0.124)

Table A.II: Stock-level microstructure (continued)

	Share price ($)	BIT	SIT	Outside quotes (%)	At quotes (%)	Inside quotes (%)	At midpoint (%)	PRE IPIN (s.e.)	PRE SPIN (s.e.)	PRE I/S-Ratio (s.e.)	POST IPIN (s.e.)	POST SPIN (s.e.)	POST I/S-Ratio (s.e.)
GICS 25: Consumer Discretionary													
CBS	32.4	522	490	0.03	0.73	0.07	0.18	0.077	0.175	0.440	0.084	0.092	0.909
								(0.008)	(0.012)	(0.069)	(0.007)	(0.004)	(0.095)
DIS	31.2	1487	1238	0.05	0.81	0.01	0.14	0.110	0.078	1.413	0.067	0.039	1.718
								(0.012)	(0.006)	(0.246)	(0.003)	(0.002)	(0.121)
F	54.9	583	526	0.05	0.67	0.10	0.20	0.096	0.157	0.607	0.069	0.063	1.100
								(0.006)	(0.011)	(0.071)	(0.004)	(0.003)	(0.088)
GM	74.1	550	598	0.04	0.70	0.07	0.20	0.055	0.071	0.785	0.101	0.077	1.308
								(0.011)	(0.006)	(0.186)	(0.005)	(0.003)	(0.101)
HD	51.9	1158	937	0.06	0.77	0.04	0.15	0.090	0.085	1.055	0.073	0.053	1.376
								(0.013)	(0.007)	(0.205)	(0.004)	(0.002)	(0.104)
MAT	29.7	330	286	0.03	0.69	0.09	0.20	0.056	0.089	0.623	0.054	0.164	0.332
								(0.011)	(0.006)	(0.118)	(0.010)	(0.007)	(0.065)
MCD	64.8	569	555	0.05	0.69	0.09	0.19	0.076	0.073	1.034	0.112	0.081	1.377
								(0.006)	(0.005)	(0.106)	(0.005)	(0.004)	(0.100)
NKE	45.1	314	410	0.04	0.69	0.12	0.16	0.076	0.104	0.724	0.097	0.072	1.345
								(0.021)	(0.007)	(0.212)	(0.018)	(0.004)	(0.283)
SPLS	33.1	851	690	0.08	0.76	0.05	0.10	0.093	0.104	0.894	0.094	0.079	1.188
								(0.012)	(0.007)	(0.104)	(0.005)	(0.004)	(0.095)
TWX	79.3	525	417	0.05	0.60	0.18	0.19	0.063	0.074	0.856	0.096	0.082	1.167
								(0.010)	(0.006)	(0.186)	(0.005)	(0.004)	(0.083)

Table A.II: Stock-level microstructure (continued)

	Share price ($)	BIT	SIT	Outside quotes (%)	At quotes (%)	Inside quotes (%)	At midpoint (%)	PRE IPIN (s.e.)	PRE SPIN (s.e.)	PRE I/S-Ratio (s.e.)	POST IPIN (s.e.)	POST SPIN (s.e.)	POST I/S-Ratio (s.e.)
GICS 30: Consumer Staples													
CAG	29.1	303	261	0.03	0.71	0.09	0.18	0.110	0.090	1.223	0.070	0.098	0.708
								(0.084)	(0.012)	(1.094)	(0.006)	(0.007)	(0.077)
COST	68.3	673	629	0.11	0.68	0.11	0.11	0.128	0.117	1.099	0.112	0.068	1.651
								(0.071)	(0.024)	(0.825)	(0.007)	(0.005)	(0.189)
KMB	47.9	318	332	0.04	0.68	0.10	0.19	0.049	0.065	0.766	0.019	0.041	0.467
								(0.014)	(0.003)	(0.212)	(0.014)	(0.003)	(0.356)
KO	66.9	1055	964	0.07	0.77	0.01	0.17	0.120	0.095	1.271	0.068	0.062	1.100
								(0.045)	(0.007)	(0.399)	(0.005)	(0.005)	(0.137)
MO	45.8	974	947	0.05	0.77	0.05	0.15	0.058	0.108	0.538	0.076	0.075	1.010
								(0.005)	(0.011)	(0.092)	(0.006)	(0.005)	(0.114)
PEP	36.6	837	828	0.04	0.74	0.01	0.23	0.065	0.069	0.944	0.057	0.036	1.557
								(0.024)	(0.012)	(0.506)	(0.003)	(0.003)	(0.180)
PG	86.7	788	698	0.07	0.64	0.15	0.15	0.052	0.084	0.617	0.059	0.040	1.481
								(0.017)	(0.013)	(0.155)	(0.004)	(0.003)	(0.155)
SLE	41.3	344	335	0.03	0.67	0.12	0.18	0.052	0.071	0.727	0.071	0.053	1.349
								(0.024)	(0.004)	(0.364)	(0.005)	(0.004)	(0.153)
SWY	50.6	432	360	0.06	0.65	0.13	0.17	0.088	0.094	0.930	0.081	0.061	1.325
								(0.014)	(0.015)	(0.267)	(0.006)	(0.005)	(0.151)
WMT	74.7	1093	925	0.07	0.72	0.04	0.19	0.066	0.104	0.637	0.095	0.093	1.022
								(0.019)	(0.012)	(0.120)	(0.009)	(0.006)	(0.088)

Table A.II: Stock-level microstructure (continued)

	Share price ($)	BIT	SIT	Outside quotes (%)	At quotes (%)	Inside quotes (%)	At midpoint (%)	PRE IPIN (s.e.)	PRE SPIN (s.e.)	PRE I/S-Ratio (s.e.)	POST IPIN (s.e.)	POST SPIN (s.e.)	POST I/S-Ratio (s.e.)
GICS 35: Health Care													
ABT	46.2	642	575	0.04	0.74	0.07	0.16	0.020	0.061	0.334	0.064	0.037	1.719
								(0.015)	(0.004)	(0.250)	(0.003)	(0.002)	(0.150)
AMGN	83.9	1001	987	0.12	0.69	0.09	0.09	0.093	0.127	0.733	0.088	0.085	1.026
								(0.004)	(0.008)	(0.067)	(0.005)	(0.005)	(0.114)
BMY	103.1	702	611	0.06	0.56	0.21	0.19	0.038	0.075	0.508	0.077	0.061	1.268
								(0.023)	(0.007)	(0.351)	(0.004)	(0.003)	(0.111)
CNTO	39.7	485	479	0.09	0.73	0.08	0.10	0.115	0.155	0.742	0.090	0.096	0.938
								(0.016)	(0.011)	(0.151)	(0.008)	(0.004)	(0.088)
JNJ	83.3	709	653	0.05	0.72	0.07	0.17	0.082	0.091	0.900	0.053	0.038	1.406
								(0.006)	(0.006)	(0.106)	(0.003)	(0.002)	(0.100)
LLY	82.4	735	696	0.06	0.57	0.17	0.21	0.099	0.121	0.820	0.084	0.075	1.123
								(0.005)	(0.008)	(0.079)	(0.003)	(0.005)	(0.082)
MDT	67.1	636	460	0.04	0.59	0.18	0.19	0.072	0.091	0.790	0.149	0.104	1.442
								(0.012)	(0.006)	(0.161)	(0.006)	(0.006)	(0.077)
MRK	123.1	1085	936	0.08	0.55	0.19	0.20	0.071	0.065	1.095	0.081	0.062	1.303
								(0.006)	(0.004)	(0.116)	(0.003)	(0.003)	(0.079)
SGP	75.1	847	672	0.07	0.68	0.14	0.13	0.062	0.072	0.862	0.093	0.063	1.464
								(0.016)	(0.004)	(0.207)	(0.002)	(0.003)	(0.084)
UNH	44.3	237	221	0.03	0.66	0.13	0.19	0.092	0.101	0.915	0.098	0.092	1.065
								(0.017)	(0.005)	(0.148)	(0.005)	(0.005)	(0.090)

Table A.II: Stock-level microstructure (continued)

	Share price ($)	BIT	SIT	Outside quotes (%)	At quotes (%)	Inside quotes (%)	At midpoint (%)	PRE IPIN (s.e.)	PRE SPIN (s.e.)	PRE I/S-Ratio (s.e.)	POST IPIN (s.e.)	POST SPIN (s.e.)	POST I/S-Ratio (s.e.)
GICS 40: Financials													
AIG	98.5	651	487	0.06	0.54	0.22	0.19	0.093	0.118	0.790	0.044	0.081	0.544
								(0.059)	(0.016)	(0.587)	(0.065)	(0.017)	(0.893)
ALL	39.7	506	468	0.05	0.72	0.09	0.15	0.037	0.094	0.396	0.069	0.071	0.970
								(0.018)	(0.011)	(0.204)	(0.023)	(0.010)	(0.351)
AXP	101.5	639	551	0.08	0.64	0.16	0.14	0.123	0.096	1.277	0.071	0.067	1.070
								(0.018)	(0.016)	(0.334)	(0.019)	(0.007)	(0.324)
BK	35.0	433	365	0.03	0.74	0.08	0.17	0.076	0.095	0.796	0.076	0.068	1.117
								(0.030)	(0.014)	(0.422)	(0.032)	(0.006)	(0.478)
CNC	32.4	471	439	0.04	0.66	0.11	0.21	0.075	0.103	0.732	0.071	0.171	0.414
								(0.026)	(0.012)	(0.238)	(0.015)	(0.016)	(0.105)
FNM	67.8	634	508	0.04	0.70	0.08	0.19	0.069	0.076	0.911	0.063	0.082	0.768
								(0.011)	(0.006)	(0.160)	(0.031)	(0.009)	(0.407)
MEL	64.5	351	337	0.04	0.61	0.14	0.23	0.087	0.111	0.782	0.067	0.071	0.943
								(0.040)	(0.012)	(0.432)	(0.032)	(0.008)	(0.488)
JPM	108.1	556	445	0.08	0.61	0.21	0.11	0.094	0.118	0.799	0.100	0.104	0.967
								(0.143)	(0.034)	(1.443)	(0.018)	(0.010)	(0.199)
PNC	51.2	247	228	0.04	0.71	0.12	0.15	0.098	0.099	0.996	0.078	0.103	0.759
								(0.073)	(0.022)	(0.955)	(0.015)	(0.014)	(0.227)
STI	68.0	226	191	0.04	0.65	0.14	0.18	0.099	0.128	0.772	0.054	0.079	0.676
								(0.046)	(0.011)	(0.416)	(0.025)	(0.009)	(0.326)

Table A.II: Stock-level microstructure (continued)

	Share price ($)	BIT	SIT	Outside quotes (%)	At quotes (%)	Inside quotes (%)	At midpoint (%)	PRE IPIN (s.e.)	PRE SPIN (s.e.)	PRE I/S-Ratio (s.e.)	POST IPIN (s.e.)	POST SPIN (s.e.)	POST I/S-Ratio (s.e.)
							GICS 45: Information Technology						
AMAT	44.9	1589	1637	0.13	0.71	0.04	0.11	0.079	0.062	1.272	0.068	0.051	1.327
								(0.007)	(0.004)	(0.183)	(0.008)	(0.002)	(0.176)
COMS	32.9	1417	1453	0.11	0.77	0.02	0.10	0.091	0.065	1.405	0.073	0.076	0.965
								(0.027)	(0.001)	(0.422)	(0.004)	(0.003)	(0.076)
CPQ	34.7	1654	1648	0.07	0.80	0.01	0.13	0.053	0.053	0.986	0.042	0.033	1.263
								(0.010)	(0.005)	(0.128)	(0.002)	(0.001)	(0.088)
CSCO	89.5	2861	2680	0.23	0.59	0.06	0.12	0.057	0.085	0.678	0.081	0.073	1.105
								(0.074)	(0.011)	(0.967)	(0.003)	(0.002)	(0.053)
DELL	70.7	2770	2690	0.27	0.54	0.07	0.12	0.058	0.151	0.384	0.119	0.134	0.891
								(0.031)	(0.012)	(0.232)	(0.008)	(0.004)	(0.078)
INTC	103.3	2640	2627	0.23	0.60	0.06	0.11	0.053	0.077	0.687	0.076	0.061	1.246
								(0.043)	(0.006)	(0.615)	(0.002)	(0.002)	(0.045)
MSFT	123.8	2818	2700	0.24	0.59	0.06	0.11	0.071	0.078	0.904	0.076	0.057	1.335
								(0.016)	(0.004)	(0.191)	(0.003)	(0.002)	(0.071)
MU	45.9	866	863	0.08	0.71	0.07	0.16	0.104	0.130	0.804	0.074	0.070	1.058
								(0.021)	(0.004)	(0.160)	(0.003)	(0.003)	(0.063)
ORCL	33.9	1411	1507	0.10	0.79	0.02	0.09	0.144	0.119	1.209	0.085	0.055	1.556
								(0.024)	(0.007)	(0.271)	(0.003)	(0.002)	(0.084)
SUNW	75.2	1987	1876	0.16	0.67	0.05	0.11	0.114	0.106	1.073	0.085	0.111	0.763
								(0.030)	(0.005)	(0.327)	(0.003)	(0.004)	(0.043)

Table A.II: Stock-level microstructure (continued)

	Share price ($)	BIT	SIT	Outside quotes (%)	At quotes (%)	Inside quotes (%)	At midpoint (%)	PRE IPIN (s.e.)	PRE SPIN (s.e.)	PRE I/S-Ratio (s.e.)	POST IPIN (s.e.)	POST SPIN (s.e.)	POST I/S-Ratio (s.e.)
GICS 55: Utilities													
AES	39.3	211	185	0.03	0.67	0.13	0.18	0.118	0.147	0.804	0.077	0.122	0.633
								(0.008)	(0.008)	(0.076)	(0.015)	(0.009)	(0.136)
D	43.3	168	153	0.02	0.72	0.09	0.19	0.088	0.157	0.560	0.084	0.187	0.448
								(0.006)	(0.007)	(0.049)	(0.007)	(0.017)	(0.062)
DUK	61.0	284	236	0.03	0.68	0.13	0.17	0.074	0.080	0.924	0.085	0.058	1.462
								(0.011)	(0.006)	(0.167)	(0.011)	(0.006)	(0.312)
ED	48.9	126	137	0.02	0.60	0.19	0.20	0.079	0.109	0.724	0.098	0.094	1.044
								(0.015)	(0.007)	(0.150)	(0.021)	(0.007)	(0.278)
ETR	29.6	129	143	0.01	0.67	0.05	0.28	0.133	0.155	0.860	0.105	0.050	2.110
								(0.008)	(0.008)	(0.076)	(0.009)	(0.008)	(0.440)
PCG	31.8	145	189	0.02	0.76	0.06	0.16	0.105	0.097	1.087	0.227	0.068	3.323
								(0.015)	(0.006)	(0.191)	(0.015)	(0.005)	(0.362)
PEG	38.4	136	163	0.02	0.68	0.10	0.20	0.103	0.117	0.875	0.119	0.073	1.635
								(0.012)	(0.006)	(0.125)	(0.021)	(0.013)	(0.551)
UCM	36.9	131	140	0.02	0.72	0.11	0.16	0.091	0.091	1.005	0.078	0.082	0.952
								(0.015)	(0.006)	(0.207)	(0.009)	(0.006)	(0.131)
SO	27.4	264	262	0.02	0.78	0.03	0.18	0.059	0.075	0.784	0.066	0.105	0.636
								(0.013)	(0.005)	(0.219)	(0.017)	(0.015)	(0.249)
TXU	43.7	254	190	0.02	0.75	0.05	0.18	0.081	0.084	0.973	0.047	0.097	0.489
								(0.011)	(0.005)	(0.150)	(0.110)	(0.023)	(1.246)

3

Informed Trading across Strikes

We solve a Bayesian learning model applied to a financial market with a margin system. In our setting, uninformed investors, informed traders and market-makers negotiate a single asset through an equity or an option market. After deriving the Nash equilibrium, our parameters are calibrated regarding Regulation T and CBOE margin rates. We study the relative allocation of informed trading across markets and moneyness. We find that the asymmetry in margins between long and short option position conveys into difference in option informed trading (OIT) probability. In our benchmark case, OIT reaches 14% when signals are low and 23% when signal are high. In addition, OIT exceeds 50% for some information set / moneyness combinations.[1]

Keywords: Option market, informed trading, margin requirement
JEL Classification: G14, C70

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3.1 Introduction

Insiders must balance expected returns with the cost of being detected by financial market authorities. This trade-off is likely to vary across the set of financial instruments available. For instance, the option looks to be a very attractive financial product for a wealth-constrained investor. He can take advantage of the leverage provided by the option while the probability of being detected is not larger than the one on the equity market. A brief examination of SEC litigations files shows that a significant share of prohibited insider trades actually takes place on the option market. 63 litigation cases occur between 1996 and 2012 for illegal trading of options.[2] The activity of insiders and to a larger extent, of sophisticated traders, makes that some piece of information are incorporated in the options markets before flowing into the stock market. As a result, option markets contribute to the price discovery process (Chakravarty et al., 2004; Anan and Chakravarty, 2007) and option volume has a predictive ability for future stock returns (Easley et al., 1998; Pan and Poteshman, 2006; Roll et al., 2010).

Yet, little is known on where informed investors are the most likely to trade across strikes. As Easley et al. (1998) mentioned: "*... within option series the question of pooling versus separating equilibria will arise because informed traders may prefer to trade specific types of contracts.*" The question of which option contract is the most likely to be selected by an informed investor deserves a deep investigation and this paper is a theoretical contribution on this research question. We examine how sophisticated investors reallocate trades following a modification of the strike price. We develop a market microstructure model in the spirit of Glosten and Milgrom (1985), extended to multimarket trading, like in Easley et al. (1998), John et al. (2003) and Huh et al. (2015).

There is one single asset but all investors are offered the possibility to trade a put on the stock or the stock itself. There is an exogenous amount of non-informed investors, also called liquidity traders, and an amount of informed traders whose trading activity

[2] The trials usually involve several defendants, which are sentenced to pecuniary penalties. Internet link: https://www.sec.gov/news/pressreleases

across markets is endogenous. Investors have access to a margin system. Hence, wealth-constrained investors, informed or not, can participate. Under this framework, which takes root in John et al. (2003), informed traders seek to maximize expected returns. Traders arrive in a sequential way and trade against marker-makers, who use the order-flow to update bid and ask prices. A Nash equilibrium is characterized by a probability of option informed trading (OIT). We assess how this measure varies with moneyness, relative liquidity and total informed trading.

In the benchmark case, OIT reaches 14% of total informed trading when signals are low and 23% negotiate the option when signals are high. OIT emerges because the option provides a strong leverage effect, and the large bid/ask spread that characterizes the stock market makes the option market profitable for a fraction of informed investors. In addition, we find that when the option/stock liquidity ratio is high and total informed trading is low, OIT exceeds 50%. Then, we connect OIT to moneyness. Four stock values ("very low", "low", "high" and "very high") are the possible outcomes in our model. This specific market structure allows to generate three areas for the strike, leading to three specific moneyness types for the option contract: Out-the-money (OTM), near-the-money (NTM) or in-the-money option (ITM). By adding strike preference to market preference, we provide a broad picture on the pattern of informed trading in the option market. When the private information reveals bad news for the stock, OTM put returns the highest OIT, because the leverage is the highest for these options. When signals are high, OIT is the largest for ITM put.[3]

Our findings give some echoes to empirical findings provided by the literature. Within our model, OIT moves between 5% and 30% according to parameter values. It means that private information incorporates mainly through the stock market, and to a lesser

[3] In our model, there is no range of option contracts available to investors. The multimarket property is reflected through one stock and one a put. John et al. (2003) also use a put while Capelle-Blancard (2005) and Huh et al. (2015) use a call option. In our framework, replacing the put by the call does not modify the key finding, because the initial margin requirements are equivalent to buy position on call or put and are equivalent for sell position on call or put. The only one difference comes from the payoff function: $\max\{K - S; 0\}$ for the put and $\max\{S - K; 0\}$ for the call. Hence, informed traders would initiate a short (long) position on the call rather than a long (short) position on the put when their private information indicates bad (good) news. Our conclusions on put trading when signals are low (high) lead to similar conclusions on call trading when signals are high (low).

extent, through the option market. This ranking in informed trading shares should also be reflected in the participation rate to the price discovery process. Actually, Chakravarty et al. (2004) and Rourke (2013) find a minor contribution of the option market to the price discovery process: 17% on average in Chakravarty et al. (2004) and 14% on average in Rourke (2013).

Lakonishok et al. (2006) show that written option positions account for a larger part of the trading volume than purchased positions. We obtain a somewhat similar result within our model: The equilibrium OIT when informed traders take a short position on the put is always greater than the one derived with a long position. We are able to provide an explanation to this phenomenon: Asymmetry between long put and short put margin requirements is responsible for this difference in OIT magnitude. Traders can achieve larger returns by writing a put when signals are high than purchasing a put when signals are low.

Moreover, our analysis sheds light on the O/S volume, a metric developed by Roll et al. (2010) and subsequently analyzed in Johnson and So (2012) and Ge et al. (2016). According to Roll et al. (2010), O/S increases prior to earning announcements because informed traders are more active. However, we show that OIT is negatively related to total informed trading. Hence, a change in this variable alone would not be able to induce a higher O/S ratio. Only an improvement in the relative option/stock liquidity favors OIT and offsets the first effect.

Section 2 gives a literature review on the incorporation of private information in a multimarket setting. Section 3 introduces the market structure and bid and ask values. Section 4 presents the Nash equilibria that emerge without and with the presence of a margin system. Section 5 discusses the equilibrium. Section 6 concludes.

3.2 Option markets and the incorporation of private information

Is private information incorporated in the option market prior to the stock market? This question has been addressed in different ways. Empirical studies can be classified in two different streams of literature. The first stream assesses whether or not options contain useful information for stock return predictability. Easley et al. (1998) and Pan and Poteshman (2006) provides evidence in favor of a positive answer: Option trading volume seems to predict stock returns. More recently, Hu (2014) introduces a new methodology that decomposes the order flow in the stock market into a component induced by option transaction and a component unrelated to option trading. The imbalance induced by option trading significantly predicts stock returns.

The second stream of literature focuses directly on price discovery measures and the conclusions cast doubt on the idea that the option market plays a key role for the incorporation of information. Stephan and Whaley (1990) find that the stock market incorporates information first, with a 15-minutes lead over the option market. Chakravarty et al. (2004) develop an extension of Hasbrouck's (1995) bounds in order to assess the contribution of the option market to the price discovery process. They find an average of 17%, providing strong support for stock market leadership. Choy and Wei (2012) claim that there is no incorporation of private information in option markets, the trading volume being purely driven by disagreement. Muravyev et al. (2013) study put-call parity violation and analyze where the adjustment takes place. They find that this is the option market quote that adjusts to eliminate the disagreement and conclude that no significant discovery process occurs in the stock market. Overall, these studies support this idea that the option market has no importance for the price discovery process. One notable exception to this trend is the paper of Hen et al. (2011). Using reactions to CNBC's Mad Money recommendations as laboratory, they claim that the stock market is less efficient than the option market.

Despite inconclusive answers on the informativeness of the option market on every day basis, several studies support the idea that option markets contain alarming signs of informed activity prior to specific corporate events. Cao et al. (2005) examine call volume prior to takeovers and find that the targets experiencing the largest call imbalance during the pre-announcement period also experience the highest announcement-day returns. Goyenko et al. (2014) find that option bid/ask spread increases prior to earning announcements, after controlling for various factors. Augustin et al. (2015) also document on higher option bid/ask spread and abnormal positive trading volume prior to M&A announcements. Ge et al. (2014) and Augustin et al. (2015) provide similar analysis in the context of bankruptcy filling announcements and spin-offs announcements, respectively and find abnormal trading volume prior to the corporate events. Outside of the corporate event framework, Poteshman (2006) shows that an unusual option market activity has been detected ahead of the terrorist attack of September 11, 2001.

Only two papers analyze, theoretically, how the option market provides an interesting trading venues for investors holding private information. Easley et al. (1998) are the first to extend the sequential model of Glosten and Milgrom (1985) by allowing multimarket trading.[4] A separating equilibrium (no informed trading on the option market) or a pooling equilibrium (informed trading occurs in both markets) can emerge at equilibrium, depending on where non-informed trades concentrate. If it occurs in real financial markets then option volumes should contain useful information to predict stock returns. With a sample of intraday data on 50 companies, the authors bring evidence consistent with this idea. More recently, Huh et al. (2015) use a sequential trading model with the multimarket option - stock feature and impose hedging activity to the market markers, in addition to their classic trading activity. They show that the hedging activity has a wider impact on option spread than stock spread.

John et al. (2003) introduce the idea that expected returns should be used instead of expected profits to determine, at equilibrium, the proportion of informed traders that choose the option rather than the underlying security. They show how a margin system

[4] Another notable extention of the Glosten and Milgrom (1985) paper is Easley and O'Hara (1987), who study the influence of the trade size for the pattern of informed trading. For other extension, see Avery and Zemsky (1998) and Colliard (2014)

drives up this proportion. In addition, they quantify the efficiency gain that is generated from allowing option trading along the stock.[5] Our paper is close to John et al. (2003) regarding the approach: Informed traders benefit from the presence of a margin system and seek to maximize expected returns. However, our analysis differs in two aspects. First, our research question is on how the strike set in the option contract influences the pattern of informed trading in the option market. To address this question, four underlying states of nature are possible instead of two, as set in their paper. Second, there is a major difference in our paper regarding the margin formula for selling a put. We apply the complete formula provided in the CBOE margin calculator and do not impose the put to be in the money, unlike them.

3.3 Our model

3.3.1 The market structure

There is one risk-free asset and one risky asset in our model. Each investor can buy or sell a single share of stock or a single option on this stock. As usual in sequential trading model, the continuum of stock prices is reduced to a small set of possible outcomes. Hence, the true stock price, which is revealed at the end of the trading session, takes four values $\tilde{v} = \{v_{VL}, v_L, v_H, v_{VH}\}$, depending on the underlying state of nature $\theta = \{\theta_{VL}, \theta_L, \theta_H, \theta_{VH}\}$. "$VL$", "$L$", "$H$", "$VH$" stand for "very low", "low", "high" and "very high". These possible outcomes for the stock price are common knowledge among market participants. We assume that the states are equally likely to occur, that is $P\{\theta = \theta_i\} = 1/4$ for any i.[6] The put contract has a strike price $K \in]v_{VL}, v_{VH}]$. Following Easley et al. (1998) and John et al. (2003), the expiration date of the option coincides with the discovery of the state of nature. When the option expires, the stock price is v_i and the put is worth $\max\{K - v_i; 0\}$, denoted $(K - v_i)^+$ hereafter.

[5] For theoretical works on options and efficiency with rational expectation equilibrium models, see Back (1993), Biais and Hillion (1994), Brennan and Cao (1996) and Cao (1999). For an empirical analysis of efficiency for optioned stock versus non-optioned stocks, see Hyland et al. (2003).

[6] Outcomes with equal probabilities are also in Huh et al. (2015). Setting the probabilities as variables has no interesting implication for the Nash equilibria derived later, and fixed values greatly simplify algebra.

There are two types of investors. The first type are the informed traders, also called sophisticated investors throughout this paper. They possess private information or have skills to extract signals from public releases that are not reflected into the stock price yet. They trade to make money. There are also investors of type uninformed (also named liquidity traders). They negotiate securities for hedging purpose, portfolio rebalancing and other motivations independent of asset payoffs. Liquidity traders represent the portion $1-\alpha$ of the investor pool. Their trading activity is exogenously determined and distributed between the stock (η_U) and option markets ($1-\eta_U$). The presence of these liquidity traders is necessary because informed traders need them to be able to hide their trade. Without their presence, a no-trade equilibrium emerges, as depicted in Milgrom and Stokey (1982).

Informed traders acquire signals about the underlying states of nature. The private information (i.e. the signal) indices bad news ($PI = B$) or good news ($PI = G$). However, they may be wrong regarding the true state of nature. Formally, the private signals they acquire is correct with a certain probability. We define the following notations:

- $P\{PI = G \mid \theta = \theta_H\} = P\{PI = B \mid \theta = \theta_L\} = \mu_1$
- $P\{PI = G \mid \theta = \theta_{VH}\} = P\{PI = B \mid \theta = \theta_{VL}\} = \mu_2$

The probability of observing the right signal is never guaranteed ($\mu_1 < 1$ and $\mu_2 < 1$).[7] However, the probabilities are high when the true state of nature is one of the most extremes values $\{\theta_{VL}; \theta_{VH}\}$, and lower for the moderate ones $\{\theta_L; \theta_H\}$.[8] The proportion of informed traders is given (α) but the portion that choose to trade the stock (η_I) instead of the option is determined in the next section.

There are numerous option and stock market-makers (MM) present on the floor. They are either put option dealers, buying at B_P or selling at A_P, or stock dealers, displaying B_S or A_S to buy or sell. By providing a service of constant presence on the floor to trade, MMs cannot spend time and effort to gather information on corporations, unlike a sophisticated

[7] Within a two states of nature context, a similar assumption is set up in John et al. (2003) and Huh et al. (2015).

[8] Our approach is bounded by two interesting cases. First, assuming perfect knowledge would lead to $\mu_1 = \mu_2 = 1$. Informed become insiders. Assuming $\mu_1 = \mu_2 = \frac{1}{2}$ means that trading on a signal is not better than trading based on the outome of a coin tossing. This happens for traders who believe to have superior information while they are not truly informed

trader. Unless they leave out the financial market, they have no choice but experiencing losses by trading against more informed traders. By selling at prices higher than buying ones, the MM recoups losses.[9] MMs also use the information on the incoming order (a buy or a sell order) to update their own estimate of the future value of the asset. Their learning process is of Bayesian type.[10] This learning process guarantees that, throughout the trading rounds, prices are gradually adjusted, reflecting the incorporation of private information.

An important feature of our market structure is on information set sharing. Investors, whether informed or uninformed do not share their motivations for transactions. However, equity (option) MMs watch the order-flow on the option (equity) markets, so that they all share the same information set. This assumption rules out any arbitrage strategy by investors, as all MMs have the same expected asset value. Finally, option (stock) MMs do not hedge their open interest with stock (option) positions.

Now we turn to the event sequence. A trading round is made with three stages, as given below:

- $t = 0$

  The share α of the investor population acquires some private information, represented by a single signal with two possible content $PI = \{B, G\}$.[11]

- $t = 1$

  A trader is randomly selected by the representative MM. Consistent with trader group assignment at time $t = 0$, this is a liquidity trader with a probability $1 - \alpha$ or an informed trader with a probability α. Then, the selected liquidity investor (informed trader) chooses the stock market with a probability η_U (η_I) and submit a buy or sell order to a market-maker and a trade, of a one single share, occurs. The informed

[9] Copeland and Galai (1983) are the first to formalize the idea that the bid-ask spread exists so that penny losses by trading with informed traders are offset by pennies earned with investors trading for reasons exogenous to terminal value of assets. Information alone is sufficient to induce spread.

[10] Only MM beliefs are updated, not the investors' one. This guarantees that the probabilities of buy or sell orders are constant over time.

[11] There is no specific assumption on the cost structure related to signal acquisitions. This is beyond the scope of this paper.

trader initiates a position consistent with its signal.

- $t = 2, ..., T$

  The rational, representative MM updates her quotations to reflect information revealed by the trade. All dealers observe the transaction and update their quotes, too. Then, a new trade, on the equity or option market takes place, and so on up to a distant date T.

- $t = T + 1$

  The state of the nature is realized and observed by all market participants. Stock and option values, $\tilde{v}$ and $\max\{K - \tilde{v}; 0\}$, are known. The game, starting at $t = 0$, may repeat.

The acquisition of private information occurs before the stock exchange opens. Then, the representative MM displays a bid and an ask and only one trade occurs. The stock exchange closes immediately after. Our model requires several assumptions.[12] These are:

(A1) Liquidity traders are equally likely to buy or sell in the stock market and equally likely to buy or sell in the option market

(A2) η_U, α, μ_1, μ_2 are common knowledge among MMs.

(A3) MMs are risk-neutral

(A4) MMs do not experience order-processing cost

(A5) A Bertrand competition occurs between MMs

(A6) The risk-free rate is set to zero

(A7) Incorporation of private information occurs every periods

(A8) Only one unit of the stock or the put are traded at a time

(A9) Cross-trading is not allowed

[12] See de Jong and Rindi (2009) for an exhaustive presentation of sequential trading models.

The purpose of this paper is not to focus on liquidity trader behaviors. So assumption A1 is enforced to avoid unnecessary complexity in the model.[13] A2 is necessary so that the representative MM set posterior probabilities from prior ones, and updates bid and ask values. The assumption A3 means that MMs do not require a compensation for bearing an inventory. Hence, this assumption rules out the possibility of inventory risk.[14] A Bertrand-type competition (assumption A5) is necessary so that there is no rent extraction by MMs.[15] No MM has any market power, even small, over the investors. Combining A2, A3 and A4 results in bid/ask spread generated by informational asymmetry and nothing else. This is a key property of the sequential trading model in the spirit of Copeland and Galai (1983) and Glosten and Milgrom (1985).

Regarding the sequence of events (trading round starts the morning of a day while the state of nature is revealed at the end of that day), assuming a null risk-free rate (assumption A6) is fair. A8 means that no multiple trades is allowed. This is a key assumption on the trading protocol because it implies that an informed trader cannot negotiate as much as possible to extract the largest payoff possible, she has to go back to the trader pool after the transaction.[16] A9 means that two or more trades executed simultaneously is not possible. To buy a protective put, the trader would have to purchase the stock first, wait in the option trader queue before being able to buy the put. To set up bull/bear put spread and other type of advanced strategies, the trader must also be patient.

By providing four possible values for the underlying stock, we are able to classify option contracts by moneyness. Because there is no prior for the stock value, the moneyness in our model is based on the probability associated to each state of nature. Consider a market participant that has no private information, like the market maker, but knows the

[13] Endogenizing non-informed trading activity looks perilious, as it would be complicated to obtain a stable Nash equilibrium. Indeed, an equilibrium where MM, informed trader and non-informed ones do not deviate from their strategy is quite hard to demonstrate.

[14] This assumption involves that MMs can accumulate stock, options or cash to infinity if all investors trade in one direction.

[15] Under a Bertrand competition, prices are pushed down until equaling the marginal cost. First, a small increase of the price by one MM would trigger investors move toward competitors. Second, a price decrease could lead to a negative profitability. At equilibrium, prices equal marginal costs. Note that this outcome emerges if (i) collusion is not allowed between market markers and (ii) each investor has a costless access to all MMs (i.e. no search cost).

[16] For an analysis of trade size within option trading, see Anand and Chakravarty (2007).

probability set $\{\frac{1}{4}, \frac{1}{4}, \frac{1}{4}, \frac{1}{4}\}$. From her perspective, every put contract whose strike lies in the interval $]v_{VL}; v_L]$ has 25% of chance to end up in the money ($K > v_{VL}$ at expiration) and 75% to expire out-the-money ($K \leq v_L$). It is reasonable to assume that these puts are viewed to be out-the-money when the trading round is about to start. Likewise, every put contract whose strike lies in the interval $]v_H; v_{VH}]$ has 25% of chance to end out-the-money ($K \leq v_{VH}$ at expiration) and 75% to expire in-the-money ($K > v_L$). It is reasonable to assume that these puts are viewed to be in-the-money before markets open. For strikes in $]v_L; v_H[$ the probability for the put to be in-the-money or out-the-money is 50%. These option contracts can be viewed to be near-the-money before a trading round starts. Based on this reasoning, we propose the following definitions:

- Option contracts characterized by $v_{VL} < K \leq v_L$ are defined to be out-the-money (OTM) options because the probability to expire in-the-money is 25%.
- Option contract characterized by $v_L < K \leq v_H$ are near-the-money (NTM) options because the probability to expire in-the-money or out-the-money is equal.
- Option contract characterized by $v_H < K \leq v_{VH}$ are in-the-money (ITM) options because the probability to expire out-the-money is 25%.

3.3.2 Informed trader strategies

When the private information indicates positive news, the trader can simply buy the stock. This leads to a payoff defines as the expected value of the stock, given the information type, minus the price paid to acquire the stock, this is $E\{\tilde{v} \mid PI = G\} - A_S$. The other possibility consists in writing a put, and the payoff is the bid price minus the expected put payoff, given that the signal is high. This is $B_P - E\{(K - \tilde{v})^+ \mid PI = G\}$. When signals are low, the informed trader can either short-sell the stock, which generates the payoff $B_S - E\{\tilde{v} \mid PI = B\}$, or buying the put, which gives $E\{(K - \tilde{v})^+ \mid PI = B\} - A_P$.

3.3.3 Bid and ask on the stock market

The Bertrand-type competition between MMs pushes expected profits to zero. By denoting Π_B (Π_A) the expected profits following and incoming sell (buy) order, the condition is

$$E\{\Pi_B \mid sell_S\} = 0 \tag{1}$$

$$E\{\Pi_A \mid buy_S\} = 0 \tag{2}$$

With the arrival of a sell order, the profit pocket by MMs will be the stock observed at time $t = T + 1$ minus the bid price B_S. At $t = 1$, the stock value is a random variable $\tilde{v}$, so that $\Pi_B = \tilde{v} - B_S$. Given the arrival of a buy order, we have $\Pi_A = A_S - \tilde{v}$. Substituing these expressions into (1) and (2), we obtain

$$B_S = E\{\tilde{v} \mid sell_S\} \tag{3}$$

$$A_S = E\{\tilde{v} \mid buy_S\} \tag{4}$$

These expectations can be re-written as the sum of stock values weighted by the probability of state occurrence, that is

$$B_S = \sum_{j=\{VL;L;H;VH\}} v_j \times P\{\theta = \theta_j \mid sell_S\} \tag{5}$$

$$A_S = \sum_{j=\{VL;L;H;VH\}} v_j \times P\{\theta = \theta_j \mid buy_S\} \tag{6}$$

MMs are acting as Bayesian learners, so that the conditional probabilities in (5) and (6) can be derived using Bayes' law. After some algebra, we obtain

$$B_S = \bar{v} - \frac{\eta_I \times \Omega_1}{\xi_1 + \alpha \times \eta_I} \tag{7}$$

$$A_S = \bar{v} + \frac{\eta_I \times \Omega_1}{\xi_1 + \alpha \times \eta_I} \tag{8}$$

with

$\bar{v} = \frac{1}{4}(v_{VL} + v_L + v_H + v_{VH})$,

$\xi_1 = (1-\alpha) \times \eta_U$ and $\Omega_1 = \frac{1}{2} \times \alpha \times \left[(\mu_2 - \frac{1}{2}) \times (v_{VH} - v_{VL}) + (\mu_1 - \frac{1}{2}) \times (v_H - v_L)\right]$.

$\bar{v}$ is the unconditional stock value while ξ_1 is the fraction of liquidity traders negotiating the stock. MMs extract the revenues $A_S - \bar{v}$ and $\bar{v} - B_S$. The bid/ask spread

$$\triangle_S = \frac{2 \times \eta_I \times \Omega_1}{\xi_1 + \alpha \times \eta_I} \tag{9}$$

is growing in the stock price variability $(v_{VH} - v_{VL})$, which is consistent with facts: MMs usually widen their spread when the stock volatility increases. $\triangle_S$ is also positively related to signal precision (μ_1 and μ_2), which looks quite intuitive: When the fractions of informed traders pocketing gains go up, dollar losses experienced by MMs go up, too. Hence, $\triangle_S$ is set wider when MMs revise upwardly μ_1 and μ_2.

An examination of the first derivatives show that $\triangle_S$ is increasing in the proportion of sophisticated traders α as well as the share of informed trading the stock η_I. Calculus details and derivative computations are provided in **Appendix A.1**.

3.3.4 Bid and ask on the option market

MM profits on this market are also pushed to zero. The trade direction is also for updating purpose. Hence, the way bid and ask on the option market are derived is pretty similar to the methodology to derive stock ones, after replacing the stock payoff $\tilde{v}$ by put payoff $(K - \tilde{v})^+$. The bid (ask) is defined as the expected value of the option, given the arrival of a put sale (buy) order

$$B_P = E\{(K - \tilde{v})^+ \mid sell_P\} \tag{10}$$

$$A_P = E\{(K - \tilde{v})^+ \mid buy_P\} \tag{11}$$

that is

$$B_P = \sum_{j=\{VL;L;H;VH\}} \max\{K - v_j; 0\} \times P\{\theta = \theta_j \mid sell_P\} \tag{12}$$

$$A_{(P)} = \sum_{j=\{VL;L;H;VH\}} \max\{K - v_j; 0\} \times P\{\theta = \theta_j \mid buy_P\} \tag{13}$$

After a few steps of calculations, we obtain

$$B_P = \bar{P}^j - \frac{(1-\eta_I) \times \Omega_2^j}{\xi_2 + \alpha \times (1-\eta_I)} \tag{14}$$

$$A_P = \bar{P}^j + \frac{(1-\eta_I) \times \Omega_2^j}{\xi_2 + \alpha \times (1-\eta_I)} \tag{15}$$

Due to the non-linear payoff of the option, the bid and ask depend on the value of the strike set in the option contract. This is the reason why $\bar{P}$ and Ω_2 have superscript j. Regarding the stock price range, there are three solutions

Case 1 $j = 1 : v_{VL} < K \leq v_L$

$$\begin{cases} \Omega_2^1 = \frac{1}{2} \times \alpha \times (K - v_{VL}) \times (\mu_2 - \frac{1}{2}) \\ \bar{P}^1 = \frac{1}{4}(K - v_{VL}) \end{cases}$$

Case 2 $j = 2 : v_L < K \leq v_H$

$$\begin{cases} \Omega_2^2 = \frac{1}{2} \times \alpha \times \left[(K - v_{VL}) \times (\mu_2 - \frac{1}{2}) + (K - v_L) \times (\mu_1 - \frac{1}{2})\right] \\ \bar{P}^2 = \frac{1}{4}(2 \times K - v_L - v_{VL}) \end{cases}$$

Case 3 $j = 3 : v_H < K \leq v_{VH}$

$$\begin{cases} \Omega_2^3 = \frac{1}{2} \times \alpha \times \left[(K - v_{VL}) \times (\mu_2 - \frac{1}{2}) + (v_H - v_L) \times (\mu_1 - \frac{1}{2})\right] \\ \bar{P}^3 = \frac{1}{4}(3 \times K - v_H - v_L - v_{VL}) \end{cases}$$

MMs knows the set of possible outcomes for the underlying security. As the strike goes up, the unconditional value of the put increases ($\bar{P}^3 > \bar{P}^2 > \bar{P}^1$) and the spread is wider ($\Omega_2^1 < \Omega_2^2 < \Omega_2^3$). It can be also showed that as more informed traders concentrate on the stock market, the option bid/ask spread $\triangle_P = A_P - B_P$ is

$$\triangle_P = \frac{2 \times (1-\eta_I) \times \Omega_2^j}{\zeta_2 + \alpha \times (1-\eta_I)} \tag{16}$$

We observe $\frac{\partial \triangle_P}{\alpha} > 0$ and $\frac{\partial \triangle_P}{\eta_I} < 0$. Hence, the option bid and ask spread is an increasing function of the overall proportion of informed traders and decreasing in the proportion of them choosing the stock market for executing a transaction. See **Appendix A.2** for proofs.

3.4 Nash equilibrium

3.4.1 Equilibrium OIT with profit equalization across markets

As a first step, we derive the equilibrium with a simple assumption regarding the informed traders: They choose the market that maximize their expected profits. This approach follows Easley et al. (1998). The pool of informed investors will split across markets, η_I for the stock and $1 - \eta_I$ for the option, only if expected profits are the same. $\eta_I^* < 1$ indicating a *pooling equilibrium*, will be guaranteed for some parameter ranges. However, it is also possible to have $\eta_I^* = 1$ under a different range of values. This situation reflects a *separating equilibrium*, that is, all informed traders concentrate on a single market. Under bad signals, equation reflecting profits equalization is

$$B_S - E\{\tilde{v} \mid PI = B\} = E\{(K - \tilde{v})^+ \mid PI = B\} - A_P \tag{17}$$

When signals are high, the equation becomes

$$E\{\tilde{v} \mid PI = G\} - A_S = B_P - E\{(K - \tilde{v})^+ \mid PI = G\} \tag{18}$$

Then, we derive the equilibrium value $\eta_I^{G\star}$ and $\eta_I^{B\star}$ so that (17) and (18) holds. This leads to the following proposition:

PROPOSITION 1 *In a financial market where investors can negotiate a stock or a put and under the assumption that (i) the representative market-maker acts as a risk-neutral Bayesian-learner agent and (ii) informed traders seek to maximize expected profits, there* *exists a Nash equilibrium where some informed traders prefer to trade the put option rather than the stock. This equilibrium is characterized by:*

The condition

$$\xi_1 < \frac{\Omega_2^j}{\Gamma^j} \tag{19}$$

is satisfied.

The probability that an informed trader submits an order on the stock market is

$$\eta_I^{G\star} = \eta_I^{B\star} = \frac{\xi_1 \times (\Omega_1 + \Gamma^j \times \xi_2)}{\Omega_1 \times \xi_1 + \Omega_2^j \times \xi_2} \tag{20}$$

Equilibrium stock bid and ask are

$$B_S = \bar{v} - (\Omega_1 + \Gamma^j \times \xi_2) \tag{21}$$

$$A_S = \bar{v} + (\Omega_1 + \Gamma^j \times \xi_2) \tag{22}$$

Equilibrium option bid and ask are

$$B_P = \bar{v} - (\Omega_2^j + \Gamma^j \times \xi_1) \tag{23}$$

$$A_P = \bar{v} + (\Omega_2^j + \Gamma^j \times \xi_1) \tag{24}$$

With

$\Gamma^1 = \frac{1}{2} \times (v_{VH} - K) \times (\mu_2 - \frac{1}{2})$ under $v_H < K \leq v_{VH}$

$\Gamma^2 = \frac{1}{2} \times \left[(v_{VH} - K) \times (\mu_2 - \frac{1}{2}) + (v_H - K) \times (\mu_1 - \frac{1}{2})\right]$ under $v_L < K \leq v_H$

$\Gamma^3 = \frac{1}{2} \times \left[(v_{VH} - K) \times (\mu_2 - \frac{1}{2}) + (v_H - v_L) \times (\mu_1 - \frac{1}{2})\right]$ under $v_{VL} < K \leq v_L$

Details on the algebra that leads to the equilibrium are given in **Appendix B.1** and the proof that this is a Nash equilibrium is provided in **Appendix B.2**. The equilibrium bid/ask spreads $\triangle_S$ and $\triangle_P$ are

$$\Delta_S = 2 \times (\Omega_1 + \Gamma^j \times \xi_2) \tag{25}$$

$$\Delta_P = 2 \times (\Omega_2^j + \Gamma^j \times \xi_1) \tag{26}$$

One can easily observe that this difference is always positive:

$$\Delta_S - \Delta_P = 2 \times \Gamma^j \tag{27}$$

First, since all quantities $\{\xi_1, \xi_2, \Omega_1, \Omega_2^j, \Gamma^j\}$ are defined positive, η_I^* is greater than zero. Second, using $\xi_1 + \xi_2 = 1 - \alpha$, the condition $\xi_1 < \frac{\Omega_2^j}{\Gamma^j}$ can be reformulated as $\xi_2 > 1 - \alpha - \frac{\Omega_2^j}{\Gamma^j}$. It shows that the mixed-strategy equilibrium emerges only if liquidity investors on the option market, as a fraction of the total amount of traders, is large enough. Later in the paper, we put in evidence that $1 - \eta_I^*$ is null under numerous calibration schemes.

3.4.2 Equilibrium OIT with return equalization across markets

With a margin system, an investor does not pay the entire bid price. A fraction of the amount is borrowed with a counterparty (stock exchange or broker). To deal with the credit risk of the trader, an initial margin amount is required and daily margin calls occur, according to the price fluctuation. This system is enforced to guarantee that the broker is paid in full even if when the asset value falls below the loan value. If the trader is unable to support the daily margin, the position is automatically liquidated. Hence, the whole margin system is designed to provide some leverage effect for the investor while limiting the lender exposure to the investor's credit risk.

There are two consequences of introducing a margin system: (i) Wealth-constrained investor can participate in the market, (ii) instead of maximizing expected profits, investors seek to maximize an expected return, that is the expected profits divided by the capital engaged on margin. To buy or sell a share of stock, a trader has to invest a fraction m_S of the stock value, $1 - m_S$ representing the loan obtained with the counterparty for a buy position or the extra-margin for a short-sell position.[17] As a consequence, the expected returns from buying (selling) a stock is the expected payoffs in equation 18 (17) divided by $m_S \times A_S$ ($m_S \times B_S$). To buy a put, the margin is A_P so the payoffs is divided by A_P (in 17). To sell the put, the initial margin is 100% of option proceeds, plus the maximum of these two values (i) a fraction m_p of underlying security value minus the out-of-the-money amount, if any, and (ii) a fraction m_K of the strike price. Accordingly, the payoff in (18) is divided by $\max\left\{m_P \times E\{\tilde{v} \mid sale_P\} + (E\{\tilde{v} \mid sale_P\} - K)^+ ; m_K \times K\right\}$. We follow John et al. (2003) by using $E\{\tilde{v} \mid sale_P\}$, that is the expected stock value conditional of the sell order, as the underlying security value.

At first glance, the initial margin requirement for a put sale position looks pretty technical. Actually, it reflects the definition given by the CBOE margin calculator. To assess whether or not this definition is popular across financial markets, we have checked the practice on several famous trading platforms. It turns out that this definition is pretty common and enforced by market participants. Definitions found on trading platform websites and internet link are exhibited in **Table I**. By introducing a margin system to the market structure, two additional assumptions must be added:

(A11) All investors, informed or not, can buy and sell assets on margin

(A12) There is no margin call

A11 prevents the representative MM to identify the investors using margin system as the ones possessing private information. A12 makes sense regarding our market structure: The true stock price is revealed ($t = T + 1$) after the transaction session ($t = 1, ..., T$) and the game restarts ($t = 0$). There is no need to introduce margin call as there is no fluctuation in the stock price before the information is revealed.

If the signal observed by an informed trader is of type "bad", she either sells the stock or buys the put. A mixed strategy equilibrium (i.e. pooling equilibrium) emerges only if the expected returns are equal across markets, that is

[17] The complete margin for a stock short-sell position is $(1 + m_S) \times B_S$. However, 100% of the stock value is covered by the proceed, so that only $m_S \times B_S$ are from the investor's pocket. Hence, there is a symmetric situation in terms in initial margin requirement between a buy and a sell position.

$$\frac{B_S - E\{\tilde{v} \mid PI = B\}}{m_S \times B_S} = \frac{E\{(K - \tilde{v})^+ \mid PI = B\} - A_P}{A_P} \tag{28}$$

When informed traders receive positive news, they can buy the stock or sell the put. In that situation, the condition for the mixed-strategy equilibrium becomes

$$\frac{E\{\tilde{v} \mid PI = G\} - A_S}{m_S \times A_S} = \frac{B_P - E\{(K - \tilde{v})^+ \mid PI = G\}}{Max\{m_P \times E\{\tilde{v} \mid sale_P\}; m_K \times K\}} \tag{29}$$

if $E\{\tilde{v} \mid sale_p\} - K < 0$ or

$$\frac{E\{\tilde{v} \mid PI = G\} - A_S}{m_S \times A_S} = \frac{B_p - E\{(K - \tilde{v})^+ \mid PI = G\}}{Max\{(1 + m_P) \times E\{\tilde{v} \mid sale_P\} - K; m_K \times K\}} \tag{30}$$

if $E\{\tilde{v} \mid sale_p\} - K > 0$. It is a priori unclear what is the impact of margins on how informed traders split their trades. An option on one share is far cheaper than the share itself, so that the option market looks more interesting for a wealth-constrained investor. However, the possibility to buy the stock on margin improves the attractiveness of the stock, which is already, between the two securities, the most sensitive one to the information flow. It is also unclear how the strike will influence the relative allocation of informed trading, because the initial margin requirement for writing a put differs according to the strike set in the option contract.

PROPOSITION 2 *In a financial market where investors can negotiate a stock or a put and under the assumption that (i) the representative market-maker acts as a risk-neutral Bayesian-learner agent, (ii) informed traders seek to maximize expected returns, there exists a Nash equilibrium where some informed traders prefer to trade the put option rather than the stock. This equilibrium is characterized by:*

If a trader holds superior information indicating negative news for the company, the *probability that she chooses to trade the stock is*

$$\eta_I^{B\star} = \frac{\Omega_1 \times \xi_1 \times A}{\xi_1 \times \Omega_1 \times B + \xi_2 \times \Omega_2^j \times C} \tag{31}$$

with

$$\begin{aligned}
A &= \bar{P}^j + \tfrac{1}{\alpha} \times \Omega_2^j + \tfrac{1}{\alpha} \times \xi_2 \times (\bar{P}^j - m_S \times \bar{v} \times \tfrac{\xi_2}{\Omega_1}) \\
B &= \bar{P}^j + \tfrac{1}{\alpha} \times \Omega_2^j \\
C &= m_S \times (\bar{v} + \tfrac{1}{\alpha} \times \Omega_1)
\end{aligned}$$

and the probability to trade the option is $1 - \eta_I^{B\star}$.

If a trader holds superior information indicating positive news for the company, the probability that she chooses to trade the stock is

$$\eta_I^{G\star} = \frac{\Omega_1 \times \xi_1 \times A'}{\xi_1 \times \Omega_1 \times B' + \xi_2 \times \Omega_2^j \times C'} \tag{32}$$

under $v_{VL} < K \leq v_L$ *and* $v_L < K < \frac{1-m_P}{1-m_K} \times \bar{v}$, *and:*

$$\eta_I^{G\star} = \frac{\Omega_1 \times \xi_1 \times A''}{\xi_1 \times \Omega_1 \times B'' + \xi_2 \times \Omega_2^j \times C''} \tag{33}$$

under $\bar{v}+1 < K \leq v_H$ *and* $v_H < K \leq v_{VH}$. *The probability to trade the option is* $1 - \eta_I^{G\star}$. A', B', C', A'', B'' *and* C'' *are:*

$$\begin{aligned}
A' &= (\bar{P}^j + m_K \times K) \times (\tfrac{1}{\alpha} \times \xi_2 + 1) - \tfrac{1}{\alpha} \times \Omega_2^j \times (1 + m_S \times \bar{v} \times \tfrac{\xi_2}{\Omega_1}) \\
B' &= \bar{P}^j + m_K \times K \\
C' &= m_S \times (\bar{v} + \tfrac{1}{\alpha} \times \Omega_1)
\end{aligned}$$

$$\begin{aligned}
A'' &= m_P \times (\bar{v} + \tfrac{1}{\alpha} \times \Omega_1) + (\bar{P}^j - \tfrac{1}{\alpha} \times \Omega_2^j) + \tfrac{1}{\alpha} \times \xi_2 \times (\bar{P}^j + m_P \times \bar{v} - m_S \times \tfrac{\Omega_2^j}{\Omega_1} \times \bar{v}) \\
B'' &= m_p \times (\bar{v} + \tfrac{1}{\alpha} \times \Omega_1) + (\bar{P}^j - \tfrac{1}{\alpha} \times \Omega_2^j) \\
C'' &= m_S \times (\bar{v} + \tfrac{1}{\alpha} \times \Omega_1)
\end{aligned}$$

Necessary conditions for (31), (32) and (33) to hold are: $\eta_U < \left[\frac{\Omega_1}{\Omega_2^j} \times \frac{A-B}{C} + 1\right]^{-1}$, $\eta_U < \left[\frac{\Omega_1}{\Omega_2^j} \times \frac{A'-B'}{C'} + 1\right]^{-1}$ *and* $\eta_U < \left[\frac{\Omega_1}{\Omega_2^j} \times \frac{A''-B''}{C''} + 1\right]^{-1}$, *respectively.*

The proof is given in **Appendix C.1.** The proof of the stability is the same than the one given when informed traders equalize expected profits. Then, one can derive the equilibrium bid/ask spread. For the stock, this is

$$\Delta_S = \frac{2 \times \Omega_1 \times A}{\alpha \times A + \xi_1 \times B + \xi_2 \times \frac{\Omega_2^j}{\Omega_1} \times C} \tag{34}$$

while the option bid/ask spread is

$$\Delta_P = \frac{2 \times \Omega_2^j \times \left[\Omega_1 \times \xi_1 \times (B - A) + \Omega_2^j \times \xi_2 \times C\right]}{\Omega_1 \times \xi_1 \times [B \times (1 - \xi_1) - \alpha \times A] + \Omega_2^j \times \xi_2 \times C \times (1 - \alpha)} \tag{35}$$

When informed traders equalize expected payoffs across markets, it is easy to put in evidence that Δ_S is always greater than Δ_P. When they equalize expected returns instead, nothing prevents Δ_P from being lower than Δ_S in the resulting equilibrium. This happens because $1 - \eta_I^{G\star}$ and $1 - \eta_I^{B\star}$ can become fairly large under certain parameter ranges.

3.4.3 Calibration

Regulation T of the Federal Reserve Bank imposes the initial margin requirement for positions on stocks. To take a long position on stock, a trader can borrow up to 50% of the stock value. By buying at this margin, she puts on the table only 50% of the share price. For a short equity position, a margin of 150% is required. As 100% of the stock value is generated by the sale position, the trader only engages the additional 50% required. Following the Regulation T, $m_S = 0.5$. The CBOE is a well-known benchmark for practitioners. A put can be bought on margin because it is already highly leveraged. To write a put, the initial margin requirement as specified by the CBOE is 100% of option proceeds plus the maximum of the two following values: (i) 20% of the underlying security value minus the out-of-the-money amount, if any, and (ii) 10% of the strike price. Accordingly, we set $m_P = 0.2$ and $m_K = 0.1$.

α is matched to recent available proxies provided by the literature. For α, we would need a measure of total informed trading encompassing stock and option market. Such a measure has not been created yet and we must rely on the available proxy developed just on the stock market. Put differently, there are empirical estimates of $\alpha \times \eta_I$ but not of α in the literature. Hence, the values chosen should be viewed as lower bounds. The Probability of Informed Trading (PIN) metric developed by Easley et al. (1996) looks as a good candidate to calibrate α. At trade level, it captures the probability that the market maker negotiates against someone more informed. Duarte and Young (2009) provide estimates of PIN for a long period of time and a large cross-section (48,512 firm-years between 1983 and 2004). Moreover, they provide an adjusted measure of the PIN, that accommodates the possibility of order-flow shock occurring simultaneously on the buy and sell side of the market. Doing so, they purify a PIN from an embedded liquidity component. α values reflect the 5th, 50th and 95th percentiles reported in the table 5, pp. 131 of their paper. $\alpha = \{8\%, 17\%, 37\%\}$.[18]

To proxy for the relative liquidity trading (η_U), we use the values from Johnson and So (2012). They provide stock and options volumes over a large panel of US stocks provided by the popular option dataset OptionMetrics, over the period 1996-2010. From the first table of their paper, we compute $OPTVOL/(EQVOL + OPTVOL)$ reported for the deciles 1, 3, 5, 7 and 9. $1 - \eta_U$ is calibrated on these values $\{0.5\%; 1.7\%; 3.2\%; 5.8\%, 10.8\%\}$. Finally, $\{v_{VL}, v_L, v_H, v_{VH}\}$ is set at $\{\$30, \$40, \$60, \$70\}$. This gives an unconditional asset value ($\bar{v}$) of \$50 and returns a standard deviation representing 36.5% of $\bar{v}$. To the best of our knowledge, there is no empirical study that could provide a benchmark to set μ_1 and μ_2. We choose $\mu_1 = 0.6$ and $\mu_2 = 0.8$.[19] Calibration choices are summarized in **Table II**.

[18] Collin-Dufresne and Fos (2015) analyze the trading strategy of the Schedule 13D Filers. The 13D Filers have accessed to superior information and fit well the defintion of an informed trader. Hence, the authors are able to provide some direct measure of the informed trading activity and do not rely on an underlying structural model that infer estimates from trade and quote data, like the PIN does. Around filing dates, the median informed volume to total volume ratio is 8% and the probability that a filer trades at least one share of stock on a given day is approximately 25%.

[19] Huh et al. (2015) have a single measure of private information precision. In their calibration, they set $0.85 \leq \mu \leq 0.99$.

3.5 Equilibrium properties

3.5.1 The pattern of informed trading in the option market

3.5.1.1 Expected profits versus expected returns

Table III summarizes our main findings regarding the pattern of informed trading across strikes. OIT ($1 - \eta_I^\star$) is derived under two scenarios (i) informed traders equalize expected profits across markets, (ii) informed traders equalize expected returns, and for various combinations of $\{\alpha, 1 - \eta_U, K\}$. Here is an example on how to interpret one entry: In a our sequential trading, when $\alpha = 17\%$, $1 - \eta_U = 3.2\%$ and the put contract has a strike set between v_{VL} and v_L, the equilibrium proportion of informed traders that negotiate the option is market is 14.4% when signals are low and 5.3% when signals are high, on average.

When informed traders equalize expected profits across markets, they are almost always absent of the option market. If the option is NTM, the proportion is null except in very few cases where α is very high. When the option contract specifies a large strike (ITM), at most 8.1% of informed traders are present on the option market. Overall, this evidence suggests that no OIT should emerge on the option market if traders truly equalize expected profits in the stock and option market.[20] This pattern is consistent with the interpretation of John et al. (2003): The information sensitivity of the stock is always wider than that of the option because the option delta is bounded by one. Unless the option is deep in the money (that is delta almost equals one), there is no reason to trade the option for an informed investor. Because $\eta_I^{B\star} = \eta_I^{G\star}$, this outcome holds whatever the direction of the private information.

When informed traders equals expected returns across markets, a pattern completely different emerges. Over the 165 different configurations that are tested in **Table III**, 57 values of $1 - \eta_I^\star$ are greater than 10%, 28 are greater than 25% and even 10 are greater

[20] Another way to show that a little amount of informed trades occurs in the option market when expected profits is used is to assess the condition under which $1 - \eta_I > 0$ holds. If the strike is at equal distance between v_{VL} and v_{VH} and between v_L and v_H, we obtain $\frac{\Omega_2^j}{\Gamma^j} \approx 1$. So all informed traders trade the stock if $\eta_U = \frac{\alpha}{1-\alpha}$ and some of them trade the option if $\eta_U < \frac{\alpha}{1-\alpha}$. According to the last inequality and given that the median α is 17% for US stocks, η_U would be below 20.5% ($\frac{0.17}{1-0.17}$). This is not compatible with empirical facts: The option volume is always marginal compared to the stock volume.

than 50%. This happens because the specific option margin system cancels the stock superiority. The payoff from buying a put is divided by the put price, which is very low for OTM option ($v_{VL} < K \leq v_L$), dramatically increasing the expected returns (leverage). For a put sale, the additional cash beyond the proceed is not that much: $m_K \times K$ for small K and $m_P \times E\{\tilde{v} \mid sale_P\}$ for large K. This produces the same effect. Hence, $1 - \eta_I^{B\star}$ and $1 - \eta_I^{G\star}$ become fairly large when informed traders equalize expected returns, rather than expected profits, across markets. Under $PI = B$, $\alpha = 17\%$ and $1 - \eta_U = 3.2\%$, we obtain that OIT is 14.4%, 10.4% and 6.9% for OTM ($v_{VL} < K \leq v_L$) or NTM ($v_L < K \leq v_H$) or ITM ($v_H < K \leq v_{VH}$) put contract, respectively. When $PI = G$ and given the same figure for α and $1 - \eta_U$, the fractions are 5.3%, 15.3%, 16.8% and 22.8%, respectively.

3.5.1.2 OIT and moneyness

Our results also suggest a substantial portion of informed traders will prefer to trade the option rather than the underlying stock when (i) option liquidity is large and (ii) the total informed activity is low. These results are consistent with the findings of Easley et al. (1998), who shed light on the fact that liquidity is required for the trader to be able to hide her trade. Our entries suggest that $1 - \eta_I^\star$ looks pretty sensitive to $1 - \eta_U$ and somewhat sensitive to α. $1 - \eta_I^{B\star}$ is maximized for a trading model involving an OTM put and $1 - \eta_I^{G\star}$ is maximized with an NTM or ITM put. For instance, for $PI = B$, $\alpha = 8\%$ and $1 - \eta_U = 5.8\%$, more than half of the informed traders would trade an OTM put, on average. This is 35.8% if the put is NTM and 76.1% if it is ITM. If $1 - \eta_U$ soars to 10.8%, 90.1% of sophisticated traders would negotiate the OTM option while 63.6% would trade an NTM option. All informed traders would trade the option if $v_H < K \leq v_{VH}$ (ITM).

The pattern of informed trading is different according the content of the private information. For $PI = B$, we find that the largest fraction is observed for equilibria where the put option contract has a low K. $1 - \eta_I^{B\star}$ under $v_{VL} < K \leq v_L$ is always higher than $v_L < K \leq v_H$ and $v_H < K \leq v_{VH}$. For $PI = G$, this is different: $1 - \eta_I^{B\star}$ is at its highest level under $v_H < K \leq v_{VH}$. However, we must highlight the fact that the option volume widely differ from moneyness type in practise, from highly liquid contract for NTM options to somewhat liquid for OTM options and completely illiquid for ITM options. It involves that, for a given $1-\eta_U$, comparisons of $1-\eta_I^{B\star}$ or $1-\eta_I^{G\star}$ across strike areas are spurious. For instance, $1-\eta_I^{B\star}(v_L < K \leq v_H; 1-\eta_U = 5.8\%)$ should be compared to $1-\eta_I^{B\star}(v_{VL} < K \leq v_L; 1-\eta_U < 3.2\%)$ and $1-\eta_I^{B\star}(v_H < K \leq v_{VH}; 1-\eta_U < 3.2\%)$, everything else being equal for other parameters. Under this perspective, one can observe that NTM contract returns the largest $1-\eta_I^{B\star}$ and $1-\eta_I^{G\star}$.

3.5.1.3 Equilibrium bid/ask spread

When informed traders equalize expected profits across markets, we show that the option bid/ask spread is always lower than the stock bid/ask spread. However, nothing guarantees the inequality when informed traders equalize expected returns. In **Table IV**, one can observe that $\triangle_P$ switches above $\triangle_S$ in the cases where (i) $K > v_H$ when $PI = B$ and $K > \bar{v} + 7$ when $PI = G$ and (ii) a substantial portion of the whole informed trading activity occur on the option market. Because the stock is always very liquid compared to the option ($\eta_U > 0.8$), $\triangle_S$ represents a small proportion of the unconditional stock value $\bar{v}$, between 2% and 10%. For the option, $\triangle_P$ moves between 19% and 70% with a average of 40%. This is above the proportional bid/ask spread observed on financial markets as documented by Wei and Zheng (2010).

3.5.2 Sensitivity analysis

3.5.2.1 Sensitity to relative liquidity trading

Relative liquidity trading is a central variable in Easley et al. (1998). The magnitude of this variable has a large effect on the likelihood of finding a outcome pooling ($\eta_I^\star < 1$) versus a separating one ($\eta_I^\star = 1$). Here we quantify how much a decline by 1% of η_U generates in terms of OIT. We compute the values $\left[1-\eta_I^{B\star}(\eta_U - \varepsilon, \bullet)\right] - \left[1-\eta_I^{B\star}(\eta_U, \bullet)\right]$ and $\left[1-\eta_I^{G\star}(\eta_U - \varepsilon, \bullet)\right] - \left[1-\eta_I^{G\star}(\eta_U, \bullet)\right]$ with $\varepsilon = 1\%$ and $\bullet$ referring to other parameters held constant. **Figure I** shows the outcome under the 15 $\{\alpha, 1-\eta_U\}$ combinations. We find that an incremental increase in $1-\eta_U$ triggers a large reallocation of informed trading that favors the option market. Under $PI = B$, $\alpha = 8\%$ and $1-\eta_U = 3.2\%$, and $v_{VL} < K \leq v_L$, a 1% increase of this amount leads to a new equilibrium where $1 - \eta_I^{B\star}$ increases by 8.6% on average. For $v_L < K \leq v_H$ and $v_H < K \leq v_{VH}$, the soar is 6.1% and 3.8% on average, respectively. Under $PI = G$, we document a similar increase in OIT, by 2.85%, 8.17%, 9.25% and 12.65% for $v_{VL} < K \leq v_H$, $v_L < K < \frac{1-m_P}{1-m_K} \times \bar{v}$, $\bar{v} + 7 < K \leq v_H$ and $v_H < K \leq v_{VH}$, respectively.

Following a small reallocation of liquidity traders that favors the option market, we should observe a large reallocation of informed trading away of the stock market and toward the option market. This is a strong effect if the put is OTM when the market incorporates bad news, and if the put is ITM when the market incorporates positive information.

3.5.2.2 Sensitivity to total informed trading

Informational asymmetry and adverse-selection costs tend to go up prior to corporate events. Within our model, it might be interested to assess how a 1% increase in the total trading activity disseminates across markets. We compute the values $\left[1 - \eta_I^{B\star}(\alpha + \varepsilon, \bullet)\right] - \left[1 - \eta_I^{B\star}(\alpha, \bullet)\right]$ and $\left[1 - \eta_I^{G\star}(\alpha + \varepsilon, \bullet)\right] - \left[1 - \eta_I^{G\star}(\alpha, \bullet)\right]$ with $\varepsilon = 1\%$ and $\bullet$ referring to other parameters held constant. **Figure II** shows the outcome under the 15 set of $\{\alpha, 1 - \eta_U\}$. We find that an increase in the total informed trading reduces the amount of informed trading on the option market. For $\alpha \geq 17\%$, (i.e. strong competition between the informed) the results are not economically wide and close to zero. However, this is fairly large for $\alpha = 8\%$. Under $PI = B$, $\alpha = 8\%$ and $1 - \eta_U = 3.2\%$, and $v_{VL} < K \leq v_L$, a 1% increase of this amount leads to an new equilibrium where $1 - \eta_I^{B\star}$ ($\eta_I^{B\star}$) has declined (increased) by 3.60% (3.60%) compared to the old one, on average. $1 - \eta_I^{B\star}$ has declined by 2.05% under $v_L < K \leq v_H$ and by 1.17% under $v_H < K \leq v_{VH}$. Under $PI = G$, we document a decline by 0.64%, 2.69%, 3.15% and 4.5% for $v_{VL} < K \leq v_H$, $v_L < K < \frac{1-m_P}{1-m_K} \times \bar{v}$, $\bar{v} + 7 < K \leq v_H$ and $v_H < K \leq v_{VH}$, respectively.

This finding, i.e. the negative impact of total informed trading on OITs suggests a reallocation of informed trading prior to events characterized by a growing informational asymmetry between market participants. In the context of earning announcements, there is usually a leakage of confidential materials when the announcement date is close. This generates more informed trading activity and our model shows that OTM put should experience the greatest lost when $PI = B$ and ITM and NTM put should experience the greatest loss when $PI = G$.

3.5.2.3 Sensitivity to margin rates

If the margin rate required to take a position on the stock moves up, the resulting equilibrium $1 - \eta_I^\star$ should be greater. By lowering the expected returns from trading stock, a increase in m_S makes the option market more attractive. In **Figure III**, we provide some evidence on the impact of a 10% change in m_S on $1 - \eta_I^\star$ for various combinations of $\{\alpha, \eta_U\}$. As we did before, we compute the values $\left[1 - \eta_I^{B\star}(m_S + \varepsilon, \bullet)\right] - \left[1 - \eta_I^{B\star}(m_S, \bullet)\right]$ and $\left[1 - \eta_I^{G\star}(m_S + \varepsilon, \bullet)\right] - \left[1 - \eta_I^{G\star}(m_S, \bullet)\right]$ with $\varepsilon = 1\%$ and $\bullet$ referring to other parameters held constant. Under $PI = B$, $\alpha = 8\%$ and $1 - \eta_U = 3.2\%$, and $v_{VL} < K \leq v_L$, a 10% increase of this amount leads to an new equilibrium where $1 - \eta_I^{B\star}$ has increased by 9.94% with respect to the former equilibrium, on average. $1 - \eta_I^{B\star}$ soars by 8.68% under $v_L < K \leq v_H$ and by 7.55% under $v_H < K \leq v_{VH}$. Under $PI = G$, effects are wider: A 10% increase in m_S triggers a soar by 8.79%, 12.08%, 11.94% and 14.06% on average, for $v_{VL} < K \leq v_H$, $v_L < K < \frac{1-m_P}{1-m_K} \times \bar{v}$, $\bar{v} + 7 < K \leq v_H$ and $v_H < K \leq v_{VH}$, respectively. The effect can be above 20% if the option market is highly liquid and the total trading activity is low. We also find that the effect is a little bit stronger for OTM options when $PI = B$ and ITM options when $PI = G$. Effects across strikes are flat.

The effect of changes in m_K or m_P are asymmetric on the equilibrium $1 - \eta_I^\star$. Indeed, these values do not count to compute the margin for a long position on the put and only matter for a short position. It turns out that a change in these values do not modify $1 - \eta_I^\star$ when informed traders negotiate on bad news but it does if they trade on good news.[21] **Figure III** shows how $1-\eta_I^{G\star}$ is affected following a simultaneous 10% change in m_K and m_P. Interestingly, the effects are wider compared to what is observed following a 10% change in m_S. With $\alpha = 8\%$ and $1-\eta_U = 3.2\%$, the magnitude $\left[1-\eta_I^{G\star}(m_P+\varepsilon, m_K+\varepsilon, \bullet)\right] - \left[1-\eta_I^{G\star}(m_P, m_K, \bullet)\right]$ is -20.78%, -12.22% and -14.46% on average, for $v_L < K < \frac{1-m_P}{1-m_K} \times \bar{v}$, $\bar{v}+7 < K \leq v_H$ and $v_H < K \leq v_{VH}$, respectively. We must also highlight that any changes in m_S, m_K or m_P have almost no impact on that $1-\eta_I^\star$ when α is high (too many informed traders) and $1-\eta_U$ is low (shortage of liquidity).

On the US financial markets, the margin rate has shifted several times. Hardouvelis (1990) documents that official initial margin requirements were adjusted 22 times through the period 1934-1994. The lowest (highest) recorded change is 10% (25%). Our findings suggest that new changes in the initial margin requirement could widely affect the relative price discovery between markets for stock with a highly liquid market. Especially, the option market could play a more important role for the incorporation of private information if regulatory requirement for trading stocks become stricter.

3.6 Conclusion

In this paper, we develop a theoretical model of market microstructure adapted to accommodate multimarket trading, in the spirit of John et al. (2003) and Hu et al. (2015). Three market participants negotiate a single asset through the equity or the option market. Market-makers are risk-neutral Bayesian learning agents who provide a buy and sell service to investors. Uninformed traders negotiate for reasons exogenous to asset payoff while informed traders observe a signal on the price direction and seek to maximize expected returns from trading. When expected payoffs are equal in the stock and option market, the pool of informed traders will split. We derive several Nash equilibria under this assumption. By calibrating margin parameters to the CBOE margin requirements and other parameter to recent empirical studies, we find that the split is likely to emerge. Then, we

[21] This asymmetric change of $1-\eta_I^\star$ in $PS=H$ and $PS=L$ is also present in the call market. Hence, in a real derivative market with calls and puts, the global trading activity on the option market is affected by changes in m_K and m_P but we do not expect an asymmetric impact wif the market is incorporating bad news or good news.

study the relative allocation of informed trading across markets and across moneyness. In the benchmark case, 14% of informed traders negotiate the option when signals are low and 23% negotiate the option when signal are low. Option informed trading (OIT) can reach 50% when the relative liquidity favors the option.

Our findings give some support to Chakravarty et al. (2004) and Rourke (2013). Their figures regarding the contribution of the option market to the price discovery process have similar magnitude to our OIT percentage. Moreover, our results give echoes to Lakonishok et al. (2006) who shed light on the fact that nonmarket-maker written option positions account for a wider part of the trading volume than purchased positions. In our model, the equilibrium OIT when informed traders take a short position on the put is always greater the one derived with long position. We are able to provide an explanation to this phenomenon: Asymmetry between long put and short put margins requirements is responsible for this difference in OIT magnitude. Traders can achieve larger returns by writing a put when signals are high than purchasing a put when signals are low. The option to stock volume ratio, the O/S metric developed by Roll et al. (2010), seems to increase prior to earning announcement. This can be solely generated by an increase in informed trading because OIT responds negatively to this amount. Only an improvement in the relative option/stock liquidity favors OIT and offsets the first effect.

3.7 References

[1] Augustin, P., Brenner, M., Hu, J., Subrahmanyam, M., 2015, "Are corporate spin-offs prone to insider trading?", Working Paper

[2] Augustin, P., Brenner, M., Subrahmanyam, M., 2015, "Informed options trading prior to M&A announcements: Insider trading?", Working Paper

[3] Anand, A., Charkravarty, S., 2007, "Stealth trading in options markets", Journal of Financial and Quantitative Analysis, Vol. 42, pp. 167-188

[4] Avery C., Zemsky, P., 1998, "Multidimentional uncertainty and herd behavior", American Economic Review, Vol. 88, No. 4, pp. 724-748

[5] Back, K., 1993, "Asymmetric information and options", Review of Financial Studies, Vo. 6, pp. 435-472

[6] Biais, B., Hillion, P., 1994, "Insider and liquidity trading in stock and options markets", Review of Financial Studies, Vol. 7, pp. 743-780

[7] Brennan, J., Cao, H., 1996, "Information, trade and derivative securities" Review of Financial Studies, Vol. 9, pp. 163-208

[8] Cao, C., Chen, Z., Griffin, J., 2005, "Informational content of option volume prior to takeovers", Journal of Business, Vol. 78, pp. 1073-1109

[9] Cao, H., 1999, "The effect of derivative assets on endogenous information acquisition and price behavior in a rational expectations equilibrium", Review of Financial Studies, Vol. 12, pp. 131-163

[10] Capelle-Blancard, G., 2005, "Volatility trading in options market: How does it affect where informed traders trade", Working paper.

[11] Chakravarty, S., Gulen, H., Mayhew, S., 2004, "Informed trading in stock and option markets", Journal of Finance, Vol. 59, No. 3, pp. 1235-1258

[12] Chen, C., Diltz, D., Huang, Y., Lung, P., 2011, "Stock and option market divergence in the presence of noisy information", Journal of banking and Finance, Vol. 35, pp. 2001-2020

[13] Colliard, J., 2014, "Catching falling knives: Speculation on market overreaction", SSRN Working Paper

[14] Collin-Dufresne, P., Fos, V., 2015, "Do prices reveal the presence of informed trading", Journal of Finance, Vol. 70, pp. 1555-1582

[15] Copeland, T., Galai, D., 1983, "Information effects on the bid-ask spread", Journal of Finance, Vol. 38, No. 5, pp. 1457-1469

[16] De Jong, F., Rindi, B., 2009, "The microstructure of financial markets", Cambridge University Press

[17] Duarte J., Young, L., 2009, "Why is PIN priced?" Journal of Financial Economics, Vol. 91, pp. 119-138

[18] Easley, D., O'Hara, M., 1987, "Price, trade size, and information in securities markets", Journal of Financial Economics, Vol. 19, pp. 69-90

[19] Easley, D., O'Hara, M., 1998, "Option volume and stock prices: Evidence on where informed traders trade", Journal of Finance, Vol. 53, No. 2, pp. 431-465

[20] Ge, L., Lin, T-C., Pearson, N., 2016, "Why does the option to stock volume ratio predict stock returns?", Journal of Financial Economics, Vol. 120, pp. 601-622

[21] Glosten, L., Milgrom, P. 1985. "Bid, ask and transaction prices in a specialist market with heterogeneously informed traders", Journal of Financial Economics, Vol. 14, pp. 71-100

[22] Goyenko, R., Ornthanalai, C., Tang, S., 2015, "Trading cost dynamics of market making in equity options", Working Paper

[23] Hardouvelis, G., 1990, "Margin requirements, volatility, and the transitory component of stock prices", American Economic Review, Vol. 80, pp. 736-762

[24] Hu, J., 2014, "Does option trading convey stock price information?", Journal of Financial Economics, Vol. 111, pp. 625-645

[25] Huh, S., Lin, H., Mello, A., 2015, "Options market makers' hedging and informed trading: Theory and evidence", Journal of Financial Markets, Vol. 23, pp. 26-58

[26] Hyland, D., Sarkar, S., Tripathy, N., 2003, "Insider trading when an underlying option is present", Financial Analysts Journal, Vol. 59, pp. 69-77

[27] John, K., Koticha, A., Narayanan, R., Subrahmanyam, M., 2003, "Margin rules, informed trading in derivatives, and price dynamics", SSRN Working Paper

[28] Johnson, T., So, E., 2012, "The option to stock volume ratio and future returns", Journal of Financial Economics, Vol. 106, pp. 262-286

[29] Milgrom, P., Stokey, N., 1982, "Information, trade and common knowledge", Journal of Economic Theory, Vol. 26, pp. 17-27

[30] Muravyev, D., Pearson, N., Broussard, J., 2013, "Is there price discovery in equity options?", Journal of Financial Economics, Vol. 107, pp. 259-283

[31] Lakonishok, J., Lee, I., Pearson, N., Poteshman, A., 2007, "Option market activity", Review of Financial Studies, Vol. 20, pp. 813-857

[32] Pan, J., Poteshman, A., 2006, "The information in option volume for future stock prices", Review of Financial Studies, Vol. 19, pp. 871-908

[33] Poteshman, A., 2006, "Unusual option market activity and the terrorist attacks of September 11, 2001", Journal of Business, Vol. 79, pp. 1703-1726

[34] Roll, R., Schwartz, E., Subrahmanyam, A., 2010, "O/S: The relative trading activity in options and stock", Journal of Financial Economics, Vol. 96, pp. 1-17

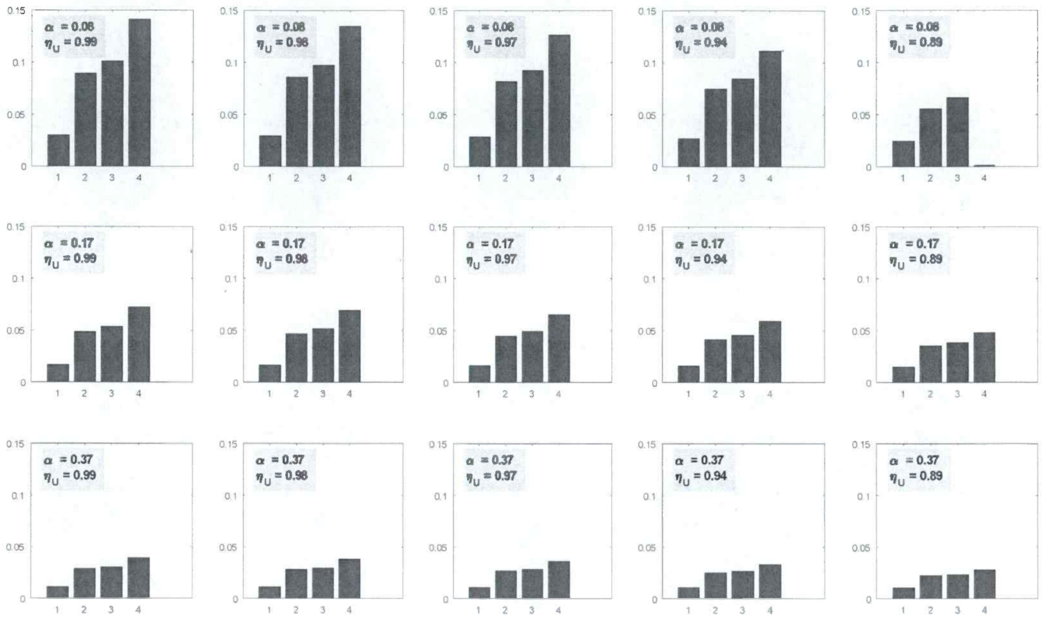
[35] Rourke, T., 2013, "Price discovery in near- and away-from-the-money option markets", Financial Review, Vol. 48, pp. 25-48

[36] Stephan, J., Whaley, R., 1990, "Intraday price change and trading volume relations in the stock and stock option markets", Journal of Finance, Vol. 45, No. 1, pp. 191-220

[37] Wei, J., Zheng, J., 2010, "Trading activity and bid-ask spreads of individual equity options", Journal of Banking and Finance, Vol. 34, pp. 2897-2916

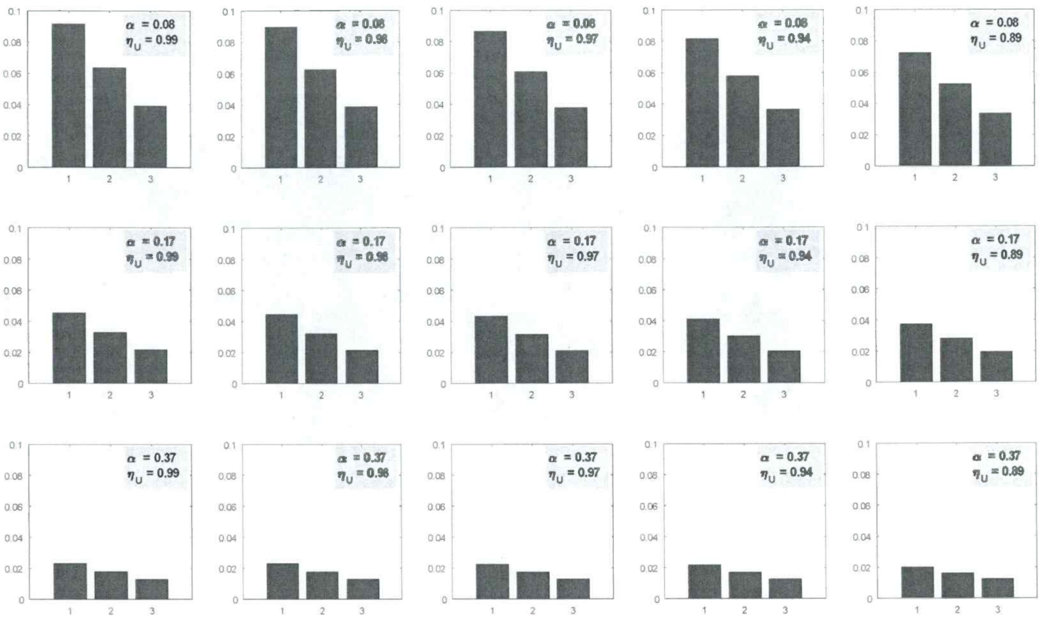
3.8 Figures

Figure I: Sensitivity of OIT to variation in the uninformed trading activity



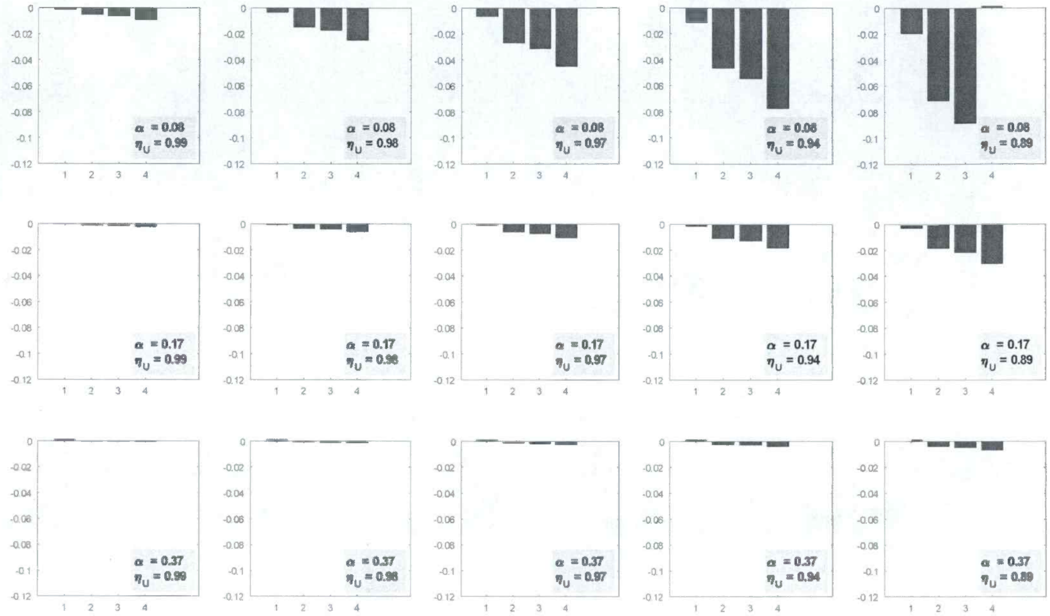
Panel A: Signals are high

We quantify the variation in the equilibrium option informed trading (OIT) following a 1% increase in the option liquidity trading. In Panel A, the private information content indicates positive news, so that informed traders buy a stock or write a put. Under this scenario, the bars reflect the magnitude $\left[1-\eta_I^{G\star}(\eta_U-\varepsilon,\bullet)\right]-\left[1-\eta_I^{G\star}(\eta_U,\bullet)\right]$, with $\varepsilon=1\%$, for various parameter set $(\bullet)$. Within each plot, each bar stands for a different strike area: (i) $v_{VL}<K\leq v_L$ (ii) $v_L<K<\frac{1-m_P}{1-m_K}\times\bar{v}$ (iii) $\bar{v}+7\leq K\leq v_H$ and (iv) $v_H<K\leq v_{VH}$. K moves by 50¢ in the intervals, so changes in $1-\eta_I^{G\star}$ are averages across strikes. In Panel B, the private information content indicates bad news, so that informed traders short-sell the stock or purchase the put. Here, bars reflect $\left[1-\eta_I^{B\star}(\eta_U-\varepsilon,\bullet)\right]-\left[1-\eta_I^{B\star}(\eta_U,\bullet)\right]$ for different strike area: (i) $v_{VL}<K\leq v_L$ (ii) $v_L<K\leq v_H$ and (iii) $v_H<K\leq v_{VH}$. Values for α and η_U are provided in bottom-right side of each plot. Other model parameters are fixed as follows: $\{v_{VL},v_L,v_H,v_{VH}\}=\{\$30,\$40,\$60,\$70\}$ and $\{\mu_1,\mu_2\}=\{0.6,0.8\}$.



Panel B: Signals are low

Figure II: Sensitivity of OIT to variation in total informed trading



Panel A: Signals are high

We quantify the variation in the equilibrium option informed trading (OIT) following a 1% increase in the total informed trading. In Panel A, the private information content indicates positive news, so that informed traders buy a stock or write a put. Under this scenario, the bars reflect the magnitude $\left[1-\eta_I^{G\star}(\alpha+\varepsilon,\bullet)\right]-\left[1-\eta_I^{G\star}(\alpha,\bullet)\right]$, with $\varepsilon = 1\%$, for various parameter set $(\bullet)$. Within each plot, each bar stands for a different strike area: (i) $v_{VL} < K \leq v_L$ (ii) $v_L < K < \frac{1-m_P}{1-m_K} \times \bar{v}$ (iii) $\bar{v}+7 \leq K \leq v_H$ and (iv) $v_H < K \leq v_{VH}$. K moves by 50¢ in the intervals, so changes in $1-\eta_I^{G\star}$ are averages across strikes. In Panel B, the private information content indicates bad news, so that informed traders short-sell the stock or purchase the put. Here, bars reflect $\left[1-\eta_I^{B\star}(\alpha+\varepsilon,\bullet)\right]-\left[1-\eta_I^{B\star}(\alpha,\bullet)\right]$ for different strike area: (i) $v_{VL} < K \leq v_L$ (ii) $v_L < K \leq v_H$ and (iii) $v_H < K \leq v_{VH}$. Values for α and η_U are provided in bottom-right side of each plot. Other model parameters are fixed as follows: $\{v_{VL}, v_L, v_H, v_{VH}\} = \{\$30, \$40, \$60, \$70\}$ and $\{\mu_1, \mu_2\} = \{0.6, 0.8\}$.

Panel B: Signals are low

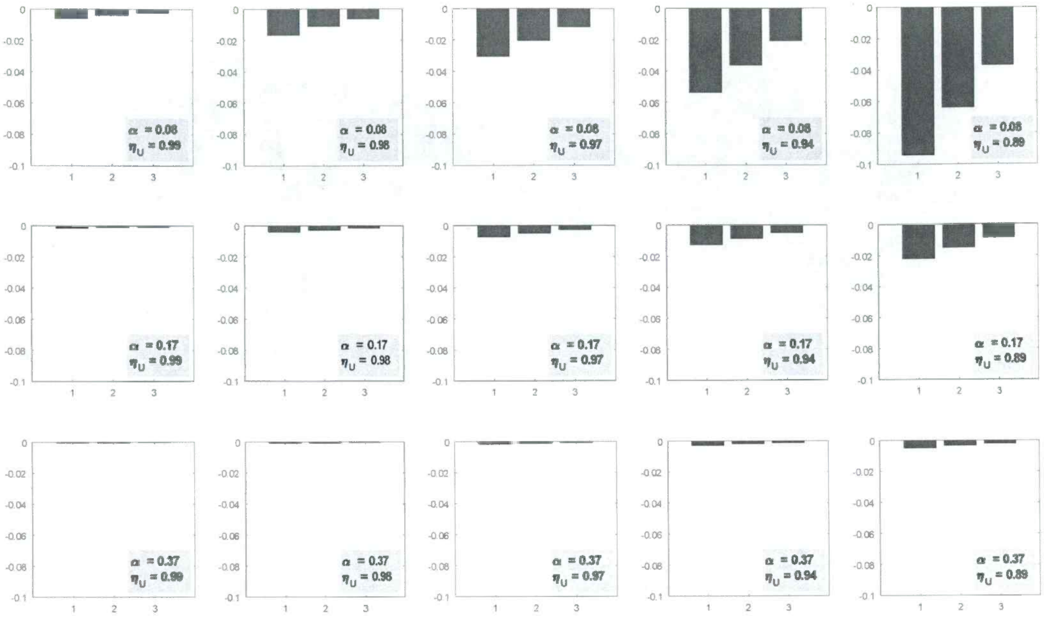
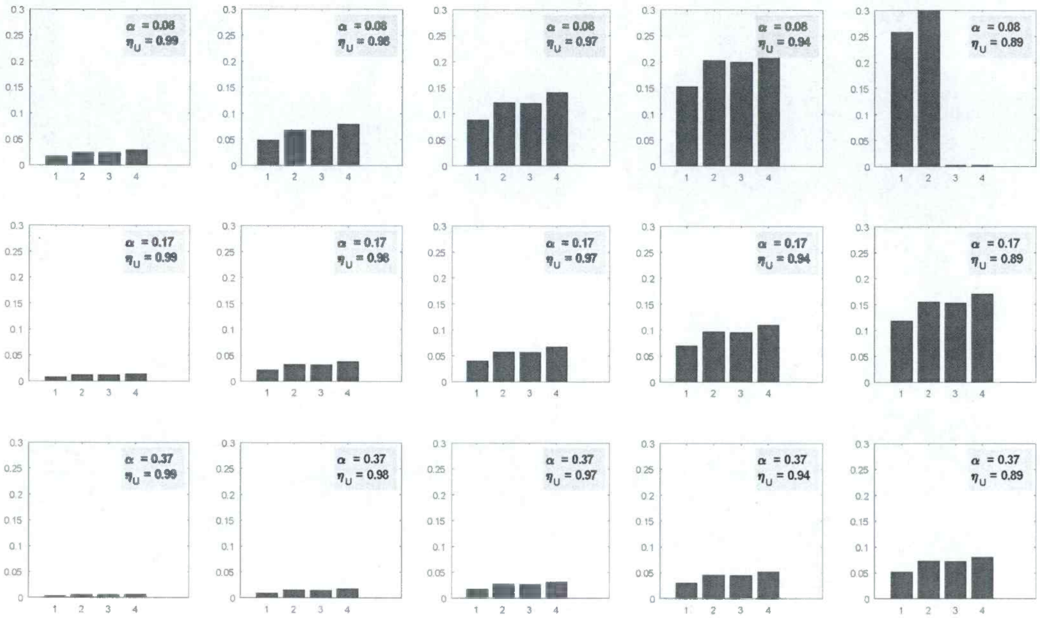
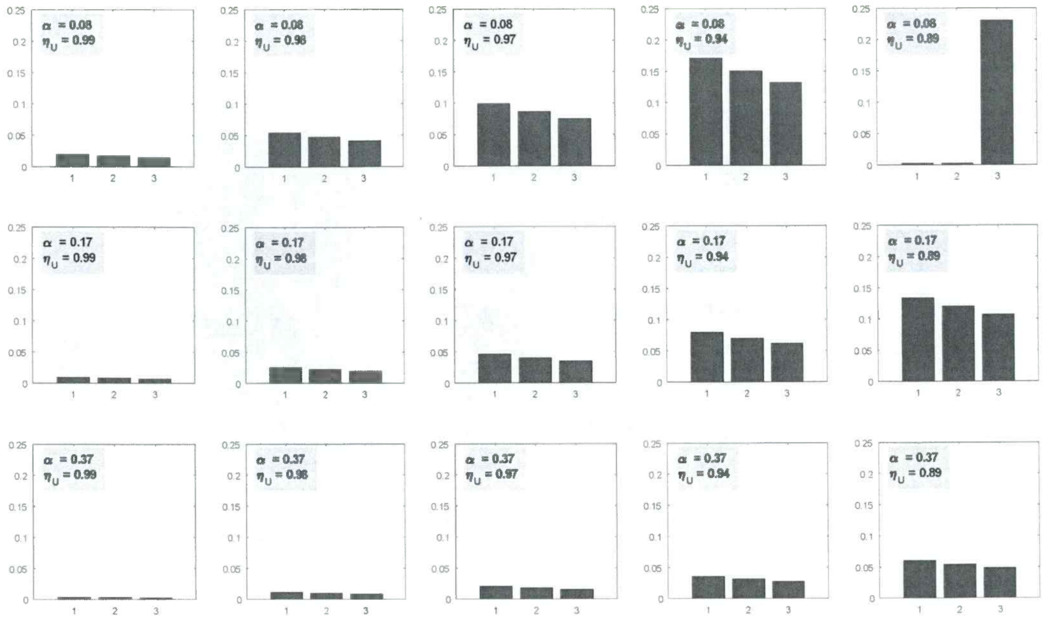


Figure III: Sensitivity of OIT to variation in the stock margin rate m_S



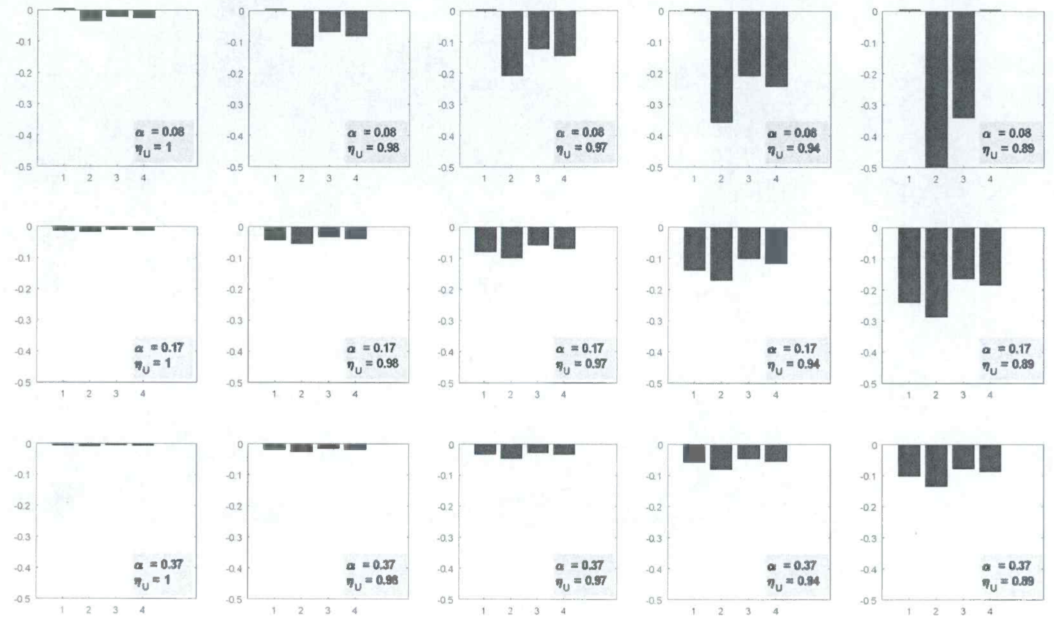
Panel A: Signals are high

We quantify the variation in the equilibrium option informed trading (OIT) following a 1% increase in the stock margin rate m_S. In Panel A, the private information content indicates positive news, so that informed traders buy a stock or write a put. Under this scenario, the bars reflect the magnitude $\left[1-\eta_I^{G\star}(m_S+\varepsilon,\bullet)\right]-\left[1-\eta_I^{G\star}(m_S,\bullet)\right]$, with $\varepsilon=1\%$, for various parameter set $(\bullet)$. Within each plot, each bar stands for a different strike area: (i) $v_{VL}<K\leq v_L$ (ii) $v_L<K<\frac{1-m_P}{1-m_K}\times\bar{v}$ (iii) $\bar{v}+7\leq K\leq v_H$ and (iv) $v_H<K\leq v_{VH}$. K moves by 50¢ in the intervals, so changes in $1-\eta_I^{G\star}$ are averages across strikes. In Panel B, the private information content indicates bad news, so that informed traders short-sell the stock or purchase the put. Here, bars reflect $\left[1-\eta_I^{B\star}(m_S-\varepsilon,\bullet)\right]-\left[1-\eta_I^{B\star}(m_S,\bullet)\right]$ for different strike area: (i) $v_{VL}<K\leq v_L$ (ii) $v_L<K\leq v_H$ and (iii) $v_H<K\leq v_{VH}$. Values for α and η_U are provided in bottom-right side of each plot. Other model parameters are fixed as follows: $\{v_{VL},v_L,v_H,v_{VH}\}=\{\$30,\$40,\$60,\$70\}$ and $\{\mu_1,\mu_2\}=\{0.6,0.8\}$.



Panel B: Signals are low

Figure IV: Sensitivity of OIT to variation in the option margin rates m_P and m_K



We quantify the variation in the equilibrium option informed trading (OIT) following a join increase of the option margin rates m_P and m_K by 1%. In Panel A, the private information content indicates positive news, so that informed traders buy a stock or write a put. Under this scenario, the bars reflect the magnitude $\left[1-\eta_I^{G\star}(m_K+\varepsilon, m_P+\varepsilon, \bullet)\right] - \left[1-\eta_I^{G\star}(m_K, m_P, \bullet)\right]$, with $\varepsilon = 1\%$, for various parameter set $(\bullet)$. Within each plot, each bar stands for a different strike area: (i) $v_{VL} < K \leq v_L$ (ii) $v_L < K < \frac{1-m_P}{1-m_K} \times \bar{v}$ (iii) $\bar{v}+7 \leq K \leq v_H$ and (iv) $v_H < K \leq v_{VH}$. K moves by 50¢ in the intervals, so changes in $1-\eta_I^{G\star}$ are averages across strikes. In Panel B, the private information content indicates bad news, so that informed traders short-sell the stock or purchase the put. Here, bars reflect $\left[1-\eta_I^{B\star}(\eta_U-\varepsilon, \bullet)\right] - \left[1-\eta_I^{B\star}(\eta_U, \bullet)\right]$ for different strike area: (i) $v_{VL} < K \leq v_L$ (ii) $v_L < K \leq v_H$ and (iii) $v_H < K \leq v_{VH}$. Values for α and η_U are provided in bottom-right side of each plot. Other model parameters are fixed as follows: $\{v_{VL}, v_L, v_H, v_{VH}\} = \{\$30, \$40, \$60, \$70\}$ and $\{\mu_1, \mu_2\} = \{0.6, 0.8\}$.

3.9 Tables

Table I: Option margin requirements in CBOE and popular trading platforms

CBOE

Long put	:	"Pay in full, no additional cash needed"
Short put	:	"100% of option proceeds, plus 20% of underlying security value less out-of-the-money amount, if any"; "minimum requirement is option proceeds plus 10% of the put's aggregate exercise price (number of contracts x exercise price x $100)"
Link	:	http://www.cboe.com/tradtool/mcalc/

Interactive Brokers

Long put	:	
Short put	:	"Put Price + Maximum ((20% * Underlying Price - Out of the Money Amount), (10% * Strike Price))"
Link	:	https://www.interactivebrokers.com/en/index.php?f=marginnew&p=opt

Optionshouse (E-Trade)

Long put	:	Premium x number of contracts
Short put	:	"Greater of: 25% of the underlying stock price – the out of the money amount (if there is any) + option premium x number of contracts Or 15% of the strike price + option premium x number of contracts
Link	:	https://www.optionshouse.com/margins-buying-power/margin-requirements/

OptionsXpress (Charles Schwab)

Long put	:	"None"
Short put	:	"20% of the underlying market price + the premium - amount out of the money OR 10% of the underlying market price (or strike price for O-T-M puts) + the premium, whichever is greater."
Link	:	http://oxint.optionsxpress.com/about_us/margin_guidelines.aspx

TradeStation (Monex group)

Long put	:	"100% cost of the option"
Short put	:	"Greater of these 3 values: 1. 100% of the option proceeds + (20% of the Underlying Market Value) - (OTM Value) 2. 100% of the option proceeds + (10% of the Strike Price x Multiplier x Contracts) 3. 100% of the option proceeds + ($100/contract)"
Link	:	http://www.tradestation.com/products/options/margin-requirements

TD Direct Investing

Long put	:	"100% of the option's premium"
Short put	:	"100% of premium less any out-of-the-money amount plus margin requirement of the underlying (minimum 5%)"
Link	:	https://www.td.com/ca/products-services/investing/td-direct-investing/accounts/margin.jsp

Table II: Summary of the parameter set

Parameters and definitions			Calibration
θ_{VL}	:	A possible outcome for the state of nature, revealed at the end of the trading session. VL stands for "very low"	$P\{\theta = \theta_{VL}\} = 25\%$
θ_L	:	A possible outcome for the state of nature, revealed at the end of the trading session. L stands for "low"	$P\{\theta = \theta_L\} = 25\%$
θ_H	:	A possible outcome for the state of nature, revealed at the end of the trading session. H stands for "high"	$P\{\theta = \theta_H\} = 25\%$
θ_{VH}	:	A possible outcome for the state of nature, revealed at the end of the trading session. VL stands for "very high"	$P\{\theta = \theta_{VH}\} = 25\%$
v_{VL}	:	Stock value if $\theta = \theta_{VL}$ at the end of the trading session	\$30
v_L	:	Stock value if $\theta = \theta_L$ at the end of the trading session	\$40
v_H	:	Stock value if $\theta = \theta_H$ at the end of the trading session	\$60
v_{VH}	:	Stock value if $\theta = \theta_{VH}$ at the end of the trading session	\$70
α	:	Fraction of investors that possess private information	$\{8\%, 17\%, 37\%\}$
η_U	:	Fraction of uninformed liquidity investors present on the stock market	$\{0.5\%, 1.7\%, 3.2\%, 5.8\%, 10.8\%\}$
η_I	:	Fraction of α that decide to trade the stock	Endogenous
$\eta_I^{B\star}$	:	Fraction of α that decide to trade the stock at equilibrium Informed traders anticipate that the stock value will be low	Endogenous
$\eta_I^{G\star}$	:	Fraction of α that decide to trade the stock at equilibrium Informed traders anticipate that the stock value will be high	Endogenous
μ_1	:	Probability that the signal is high (low) when the true state of the nature is v_H (v_L)	60%
μ_2	:	Probability that the signal is high (low) when the true state of the nature is v_{VH} (v_{VL})	80%
m_S	:	Fraction of stock value hold on margin to trade the stock (i.e. one minus borrowed cash)	50%
m_P	:	Fraction of the option value hold on margin to trade the put	20%
m_K	:	Fraction of the strike value hold on margin to trade the put	10%
B_S	:	Stock market maker bid price	Endogenous
A_S	:	Stock market maker ask price	Endogenous
B_P	:	Option market maker bid price	Endogenous
A_P	:	Option market maker ask price	Endogenous
$\triangle_S$	:	Bid/ask spread on the stock market	Endogenous
$\triangle_P$	:	Bid/ask spread in the option market	Endogenous
r_f	:	Risk-free rate	0

This table summarizes all parameters used in our sequential trading model. Definitions and calibrations are provided in columns 2 and 3, respectively.

Table III: Informed trading activity in the option market

		Informed traders equalize expected profits across markets			Informed traders equal the expected returns across markets: Signals are low			Signals are high			
α	$1-\eta_U$	Area 1	Area 2a	Area 3	Area 1	Area 2a	Area 3	Area 1	Area 2b	Area 2c	Area 3
0.08	0.005	0.000	0.000	0.003	0.047	0.032	0.020	0.015	0.046	0.052	0.073
	0.017	0.000	0.000	0.009	0.156	0.109	0.067	0.051	0.153	0.174	0.243
	0.032	0.000	0.000	0.017	0.290	0.202	0.125	0.095	0.281	0.318	0.443
	0.058	0.000	0.000	0.032	**0.511**	0.358	0.222	0.168	0.488	**0.553**	**0.761**
	0.108	0.000	0.000	0.056	**0.901**	**0.636**	0.399	0.298	**0.835**	**0.946**	**1.00**
0.17	0.005	0.000	0.000	0.003	0.023	0.017	0.011	0.008	0.025	0.027	0.038
	0.017	0.000	0.000	0.009	0.078	0.056	0.037	0.029	0.083	0.092	0.125
	0.032	0.000	0.000	0.016	0.144	0.104	0.069	0.053	0.153	0.168	0.228
	0.058	0.000	0.000	0.030	0.255	0.185	0.123	0.095	0.267	0.294	0.393
	0.108	0.000	0.000	0.056	0.453	0.332	0.223	0.172	0.461	**0.507**	**0.666**
0.37	0.005	0.000	0.001	0.004	0.012	0.009	0.007	0.006	0.015	0.016	0.020
	0.017	0.000	0.004	0.012	0.040	0.030	0.022	0.019	0.049	0.052	0.068
	0.032	0.000	0.007	0.023	0.074	0.057	0.042	0.036	0.091	0.096	0.124
	0.058	0.000	0.014	0.043	0.132	0.102	0.075	0.065	0.160	0.169	0.216
	0.108	0.000	0.027	0.081	0.238	0.186	0.139	0.120	0.281	0.296	0.371

This table shows the proportion of informed traders that choose to negotiate the option rather than the underlying stock, at equilibrium. The states of nature $\{v_{VL}, v_L, v_H, v_{VH}\}$ have equal probability (25%) to be the true stock price revealed at the end of the game. This assumption involves that each put strike (K) within $]v_{VL}; v_L]$ ($]v_H; v_{VH}]$) has a probability 1/4 (1/4) to be in-the-money (out-the-money), so that the put contract is defined to be out-the-money (in-the-money). Each strike within $]v_L; v_H]$ has equal probability to be in-the-money or out-the-money so that the put is defined as near-the-money. The first column gives the proportion of informed traders (α) and the second column gives the proportion of liquidity traders that trade the option $(1-\eta_U)$. See the **Table II** for all parameter calibrations. Columns (3) - (5) returns $1-\eta_I^*$ under the assumption that informed traders equalize expected profits across markets while columns (6) - (12) provides $1-\eta_I^*$ under the assumption that informed traders equalize expected returns. Areas are defined as follows:

Area 1: $v_{VL} < K \leq v_L$ Area 2a: $v_L < K \leq v_H$ Area 2b: $v_L < K < \frac{1-m_P}{1-m_K} \times \bar{v}$ Area 2c: $\bar{v} + 7 < K \leq v_H$ Area 3: $v_H < K \leq v_{VH}$

K moves by 50¢ so the equilibrium values are averages across the strikes. Here is an example on how to interpret the entries: In our sequential trading, when the proportion of informed traders is set to 17%, the proportion of uninformed trading the stock is 3.2% and the tradable option contract has a strike between v_{VL} and v_L, the equilibrium proportion of informed traders that trade the option is market is 14.4% when private signals are low and 5.3% when signals are high, on average. Fractions above 50% are highlighted in bold.

Table IV: Equilibrium bid/ask spread

α	$1-\eta_U$	Signals are low						Signals are high							
		Area 1		Area 2a		Area 3		Area 1		Area 2b		Area 2c		Area 3	
		Δ_S	Δ_P	Δ_S	Δ_P	Δ_S	Δ_P	Δ_S	Δ_P	Δ_S	Δ_P	Δ_S	Δ_P	Δ_S	Δ_P
0.080	0.005	1.077	0.705	1.092	2.474	1.105	3.174	1.109	0.524	1.077	1.739	1.071	4.943	1.049	7.047
0.080	0.017	0.972	0.700	1.023	2.458	1.068	3.156	1.084	0.520	0.975	1.720	0.954	4.891	0.879	6.970
0,080	0,032	0.840	0.694	0.936	2.438	1.021	3.133	1.053	0.514	0.849	1.696	0.808	4.826	0.667	6.873
0.080	0.058	0.605	0.683	0.783	2.403	0.938	3.093	0.998	0.505	0.631	1.654	0.555	4.713	0.301	6.705
0.080	0.108	0.134	0.662	0.478	2.333	0.774	3.014	0.895	0.487	0.306	1.420	0.117	4.324	NaN	NaN
0.170	0.005	2.344	0.766	2.357	2.797	2.368	3.829	2.373	0.610	2.340	1.975	2.335	5.503	2.315	7.620
0,170	0,017	2.257	0.761	2.301	2.783	2.340	3.815	2.356	0.607	2.245	1.957	2.228	5.456	2.160	7.550
0,170	0,032	2.146	0.756	2.231	2.766	2.305	3.796	2.336	0.604	2.127	1.935	2.095	5.397	1.966	7.463
0.170	0.058	1.951	0.746	2.107	2.735	2.242	3.764	2.300	0.597	1.925	1.897	1.864	5.295	1.632	7.312
0.170	0.108	1.562	0.728	1.861	2.676	2.118	3.701	2.232	0.586	1.540	1.825	1.423	5.100	0.996	7.023
0.370	0.005	5.158	0.915	5.167	3.591	5.175	5.443	5.178	0.858	5.148	2.477	5.145	6.727	5.129	8.867
0.370	0.017	5.104	0.912	5.135	3.582	5.162	5.436	5.172	0.857	5.071	2.464	5.062	6.691	5.008	8.814
0.370	0.032	5.036	0.908	5.095	3.570	5.147	5.426	5.165	0.856	4.975	2.447	4.957	6.646	4.857	8.748
0.370	0.058	4.916	0.901	5.025	3.551	5.119	5.410	5.153	0.854	4.810	2.418	4.777	6.568	4.595	8.633
0.370	0.108	4.679	0.888	4.886	3.512	5.065	5.379	5.129	0.849	4.496	2.362	4.432	6.419	4.097	8.414

This table shows the bid/ask spread returned at the equilibrium, for the stock and option market. The states of nature $\{v_{VL}, v_L, v_H, v_{VH}\}$ have equal probability (25%) to be the true stock price revealed at the end of the game. This assumption involves that each put strike (K) within $]v_{VL}; v_L]$ ($]v_H; v_{VH}]$) has a probability 1/4 (1/4) to be in-the-money (out-the-money), so that the put contract is defined to be out-the-money (in-the-money). Each strike within $]v_L; v_H]$ has equal probability to be in-the-money or out-the-money so that the put is defined as near-the-money. The first column gives the proportion of informed traders (α) while the second column gives the proportion of liquidity traders that trade the stock $(1-\eta_U)$. All parameter calibrations are provided in **Table II**. Columns (3) - (5) returns $1-\eta_I^*$ under the assumption that informed traders equalize expected profits across markets while columns (6) - (12) provides $1-\eta_I^*$ under the assumption that informed traders equalize expected returns. Areas are defined as follows:

Area 1: $v_{VL} < K \leq v_L$ Area 2a: $v_L < K \leq v_H$ Area 2b: $v_L < K < \frac{1-m_P}{1-m_K} \times \bar{v}$ Area 2c: $\bar{v} + 7 < K \leq v_H$ Area 3: $v_H < K \leq v_{VH}$

K moves by 50¢ so the equilibrium values are averages across the strikes. Here is an example on how to interpret the entries: In our sequential trading, when the proportion of informed traders is set to 17%, the proportion of uninformed trading the stock is 3.2% and the tradable option contract has a strike between v_{VL} and v_L, the equilibrium proportion of informed traders that trade the option is market is 14.4% when private signals are low and 5.3% when signals are high, on average. Fraction above 50% are highlighted in bold. The formula for the stock and the option bid/ask spread are given Section IV, equation (35) and (35). K moves by half a dollar within each interval so the entries are averages across strikes.

3.10 Appendix

3.10.1 Appendix A.1: Bid, ask and asset payoff on the stock market

The MM derive the bid and the ask by (i) assuming that her expected profit is null and (ii) taking the information conveyed by the order into account. Given that a sale order occurs at the bid and a buy order occurs at the ask, we have

$$B_S = E\{\tilde{v} \mid sell_S\}$$
$$A_S = E\{\tilde{v} \mid buy_S\}$$

We focus on deriving the value of the bid. Deriving the ask is done with a similar reasoning. Regarding the number of states of nature, the stock bid is

$$\begin{aligned} B_S = {} & v_{VL} \times P\{\theta = \theta_{VL} \mid sell_S\} + v_L \times P\{\theta = \theta_L \mid sell_S\} \\ & + v_H \times P\{\theta = \theta_H \mid sell_S\} + v_{VH} \times P\{\theta = \theta_{VH} \mid sell_S\} \end{aligned} \quad (1)$$

Let's start with $P\{\theta = \theta_{VL} \mid sale_S\}$. The MMs behave as Bayesian learners. They have a prior for the conditional probability, receive an order and update the information regarding the nature of the trade, i.e. a buy or sell order. Under Bayes' law, we have:

$$P\{\theta = \theta_{VL} \mid sell_S\} = \frac{P\{\theta = \theta_{VL}\} \times P\{sell_S \mid \theta = \theta_{VL}\}}{P\{sell_S\}} \quad (2)$$

that is:

$$P\{\theta = \theta_{VL} \mid sell_S\} = \frac{P\{\theta = \theta_{VL}\} \times P\{sell_S \mid \theta = \theta_{VL}\}}{\sum\limits_{\{\theta_{VL}, \theta_L, \theta_H, \theta_{VH}\}} P\{\theta = \theta_i\} \times P\{sell_S \mid \theta = \theta_i\}}$$

Because the states of nature are equally likely to occur, this expression collapses to:

$$P\{\theta = \theta_{VL} \mid sell_S\} = \frac{P\{sell_S \mid \theta = \theta_{VL}\}}{\sum\limits_{\{\theta_{VL}, \theta_L, \theta_H, \theta_{VH}\}} P\{sell_S \mid \theta = \theta_i\}} \quad (3)$$

The numerator is:

$$P\{sell_S \mid \theta = \theta_{VL}\} = \frac{1}{2} \times (1-\alpha) \times \eta_U + \alpha \times \eta_I \times \mu_2 \quad (4)$$

The RHS of (4) is the sum of two parts: The portion of uninformed traders $(1-\alpha)$ on the sell side $(1/2)$ of the stock market (η_U) plus the portion of informed traders (α) that receive the right signal (μ_2) and that choose the stock market (η_I). The other probabilities that appear on the denominator are:

$$P\{sell_S \mid \theta = \theta_L\} = \frac{1}{2} \times (1-\alpha) \times \eta_U + \alpha \times \eta_I \times \mu_1 \quad (5)$$

$$P\{sell_S \mid \theta = \theta_H\} = \frac{1}{2} \times (1-\alpha) \times \eta_U + \alpha \times \eta_I \times (1-\mu_1) \quad (6)$$

$$P\{sell_S \mid \theta = \theta_{VH}\} = \frac{1}{2} \times (1-\alpha) \times \eta_U + \alpha \times \eta_I \times (1-\mu_2) \quad (7)$$

Given (4), (5), (6) and (7), (3) is

$$P\{\theta = \theta_{VL} \mid sell_S\} = \frac{\frac{1}{2} \times (1-\alpha) \times \eta_U + \alpha \times \eta_I \times \mu_2}{2 \times [(1-\alpha) \times \eta_U + \alpha \times \eta_I]} \quad (8)$$

By following the procedure (2) to (8) for the other term of (1), we obtain

$$P\{\theta=\theta_L \mid sell_S\} = \frac{\frac{1}{2}\times(1-\alpha)\times\eta_U+\alpha\times\eta_I\times\mu_1}{2\times[(1-\alpha)\times\eta_U+\alpha\times\eta_I]}$$

$$P\{\theta=\theta_H \mid sell_S\} = \frac{\frac{1}{2}\times(1-\alpha)\times\eta_U+\alpha\times\eta_I\times(1-\mu_1)}{2\times[(1-\alpha)\times\eta_U+\alpha\times\eta_I]}$$

$$P\{\theta=\theta_{VH} \mid sell_S\} = \frac{\frac{1}{2}\times(1-\alpha)\times\eta_U+\alpha\times\eta_I\times(1-\mu_2)}{2\times[(1-\alpha)\times\eta_U+\alpha\times\eta_I]}$$

By plugging the last four equations into (1), we obtain

$$\begin{aligned} B_S &= \frac{(1-\alpha)\times\eta_U\times\bar{v}}{\eta_U+(1-\alpha)+\alpha\times\eta_I} \\ &+\frac{\frac{1}{2}\times\alpha\times\eta_I\times[\mu_2\times v_{VL}+\mu_1\times v_L+(1-\mu_1)\times v_H+(1-\mu_2)\times v_H]}{\eta_U\times(1-\alpha)+a\times\eta_I} \end{aligned} \tag{9}$$

where $\bar{v}$ is the unconditional expectation of the nature $\bar{v}=\sum_{\theta=L,H}P\{\theta\}\times v_\theta\equiv(1/4)\times(v_{VL}+v_L+v_H+v_{VH})$. Using the trick $B_S=B_S+(\bar{v}-\bar{v})$, (1) can be written in a more convenient way

$$B_S=\bar{v}-\frac{\frac{1}{2}\times\alpha\times\eta_I\times\left[(\mu_2-\frac{1}{2})\times(v_{VH}-v_{VL})+(\mu_1-\frac{1}{2})\times(v_H-v_L)\right]}{(1-\alpha)\times\eta_U+\alpha\times\eta_I} \tag{10}$$

We follow exactly the same methodology to derive to stock ask. First, A_S is expanded

$$\begin{aligned} A_S &= v_{VL}\times P\{\theta=\theta_{VL}\mid buy_S\}+v_L\times P\{\theta=\theta_L\mid buy_S\} \\ &+v_H\times P\{\theta=\theta_H\mid buy_S\}+v_{VH}\times P\{\theta=\theta_{VH}\mid buy_S\} \end{aligned} \tag{11}$$

Then probabilities formula derived using Bayes' law one more time

$$P\{\theta=\theta_{VL} \mid buy_S\} = \frac{\frac{1}{2}\times(1-\alpha)\times\eta_U+\alpha\times\eta_I\times(1-\mu_2)}{2\times[(1-\alpha)\times\eta_U+\alpha\times\eta_I]}$$

$$P\{\theta=\theta_L \mid buy_S\} = \frac{\frac{1}{2}\times(1-\alpha)\times\eta_U+\alpha\times\eta_I\times(1-\mu_1)}{2\times[(1-\alpha)\times\eta_U+\alpha\times\eta_I]}$$

$$P\{\theta=\theta_H \mid buy_S\} = \frac{\frac{1}{2}\times(1-\alpha)\times\eta_U+\alpha\times\eta_I\times\mu_1}{2\times[(1-\alpha)\times\eta_U+\alpha\times\eta_I]}$$

$$P\{\theta=\theta_{VH} \mid buy_S\} = \frac{\frac{1}{2}\times(1-\alpha)\times\eta_U+\alpha\times\eta_I\times\mu_2}{2\times[(1-\alpha)\times\eta_U+\alpha\times\eta_I]}$$

These four equations are plugged into (11), yielding

$$A_S=\bar{v}+\frac{\frac{1}{2}\times\alpha\times\eta_I\times\left[(\mu_2-\frac{1}{2})\times(v_{VH}-v_{VL})+(\mu_1-\frac{1}{2})\times(v_H-v_L)\right]}{(1-\alpha)\times\eta_U+\alpha\times\eta_I} \tag{12}$$

(8) follows. The second part of the RHS of (10) and (12) is half of the bid/ask spread. Note that if one assumes that there is no longer informed trading in the sequential model ($\alpha=0$), then $B_S=A_S=\bar{v}$. Hence, under the assumption of a purely non-informed trading activity, the bid-ask spread vanishes. This property of our model respect the fundamental property of the sequential trading model of Copeland and Galai (1983) and Glosten and Milgrom (1985) in which the bid-ask spread is fully generated by informational asymmetry. This property holds in our multimarket environment.

Denoting $\Omega_1=\frac{1}{2}\times\alpha\times\left[(\mu_2-\frac{1}{2})\times(v_{VH}-v_{VL})+(\mu_1-\frac{1}{2})\times(v_H-v_L)\right]$ and $\xi_1=(1-\alpha)\times\eta_U$, the stock bid/ask spread $A_S - B_S$ is written

$$\triangle_S = \frac{2 \times \eta_I \times \Omega_1}{\xi_1 + \alpha \times \eta_I}$$

Let's assume $\frac{\partial \triangle_S}{\partial \alpha} > 0$. This is equivalent to

$$\frac{2 \times \frac{1}{\alpha} \times \eta_I \times \Omega_1}{\xi_1 + \alpha \times \eta_I} > \frac{2 \times \eta_I \times \Omega_1 \times (\eta_I - \eta_U)}{(\xi_1 + \alpha \times \eta_I)^2}$$

Which is valid if $\xi_1 > -\alpha \times \eta_U$. This last condition is respected for any α, η_I and η_U. Likewise, $\frac{\partial \triangle_S}{\partial \eta_I} > 0$ would involve

$$\frac{2 \times \Omega_1}{\xi_1 + \alpha \times \eta_I} > \frac{2 \times \eta_I \times \Omega_1 \times (\xi_1 + \alpha)}{(\xi_1 + \alpha \times \eta_I)^2}$$

Which turns out to be true if $\eta_I < 1$. Q.E.D

From the perspective of the informed trader, the final value of the stock is its expected value conditional on the private information she holds. If signals are low, the final value is expected to be $E\{\tilde{v} \mid PI = B\}$ while this is $E\{\tilde{v} \mid PI = G\}$ if signals are high. By developping the former term, we obtain

$$\begin{aligned} E\{\tilde{v} \mid PI = B\} &= v_{VL} \times P\{\theta = \theta_{VL} \mid PI = B\} + v_L \times P\{\theta = \theta_L \mid PI = B\} \\ &+ v_H \times P\{\theta = \theta_H \mid PI = B\} + v_{VH} \times P\{\theta = \theta_{VH} \mid PI = B\} \end{aligned} \tag{13}$$

Using Bayes' rule again, these four probabilities are easily derived

$$P\{\theta = \theta_{VL} \mid PI = B\} = \frac{1}{2} \times \mu_2$$

$$P\{\theta = \theta_L \mid PI = B\} = \frac{1}{2} \times \mu_1$$

$$P\{\theta = \theta_H \mid PI = B\} = \frac{1}{2} \times (1 - \mu_1)$$

$$P\{\theta = \theta_{VH} \mid PI = B\} = \frac{1}{2} \times (1 - \mu_2)$$

And (13) is

$$E\{\tilde{v} \mid PI = B\} = \frac{1}{2}\left[v_{VH} + v_H - \mu_2 \times (v_{VH} - v_{VL}) - \mu_1 \times (v_H - v_L)\right]$$

which can be rewritten

$$E\{\tilde{v} \mid PI = B\} = \bar{v} - \frac{1}{2}\left[(v_{VH} - v_{VL}) \times (\mu_2 - \frac{1}{2}) + (v_H - v_L) \times (\mu_1 - \frac{1}{2})\right]$$

$$E\{\tilde{v} \mid PI = G\} = \bar{v} + \frac{1}{2}\left[(v_{VH} - v_{VL}) \times (\mu_2 - \frac{1}{2}) + (v_H - v_L) \times (\mu_1 - \frac{1}{2})\right]$$

Then by defining

$$\Omega_1 = \frac{1}{2} \times \alpha \times \left[(v_{VH} - v_{VL}) \times (\mu_2 - \frac{1}{2}) + (v_H - v_L) \times (\mu_1 - \frac{1}{2})\right]$$

$$\xi_1 = (1 - \alpha) \times \eta_U$$

bid, ask and asset payoffs are written in the following convenient way

$$B_S = \bar{v} - \frac{\eta_I \times \Omega_1}{\xi_1 + \alpha \times \eta_I}$$

$$A_S = \bar{v} + \frac{\eta_I \times \Omega_1}{\xi_1 + \alpha \times \eta_I}$$

$$E\{\tilde{v} \mid PI = B\} = \bar{v} - \frac{1}{\alpha} \times \Omega_1$$

$$E\{\tilde{v} \mid PI = G\} = \bar{v} + \frac{1}{\alpha} \times \Omega_1$$

3.10.2 Appendix A.2: Bid and ask on the option market

Case $v_H < K \leq v_{VH}$

The option bid (ask) is the expected option value, conditional on the arrival of a sell (buy) order:

$$B_P = E\left\{(K - \tilde{v})^+ | sell_P\right\} \tag{14}$$

$$A_P = E\left\{(K - \tilde{v})^+ | buy_P\right\} \tag{15}$$

where $(K - \tilde{v})^+ = Max\{K - \tilde{v}; 0\}$. Then (14) is developped as follows

$$\begin{aligned} B_P &= (K - v_{VL}) \times P\{\theta = \theta_{VL} \mid sell_P\} + (K - v_L) \times P\{\theta = \theta_L \mid sell_P\} \\ &+ (K - v_H) \times P\{\theta = \theta_H \mid sell_P\} + 0 \times P\{\theta = \theta_{VH} \mid sell_P\} \end{aligned} \tag{16}$$

Although there are four states of nature $\{v_{VL}, v_L, v_H, v_{VH}\}$, the specific option payoff makes that the last term vanishes. Indeed K is bounded upward by v_{VH}. We need the strict inequality $v_H < K$ so that there is no ambiguity regarding $(K - v_L)^+$. Under the assumption that the marker-maker acts as a Bayesian agent, each term $P\{\bullet\}$ can be viewed as the market maker posterior belief regarding the underlying state of the nature. The market maker has a prior belief and this one is modified according to the incoming order. The proportion of non-informed (informed) traders on the option market is $1 - \eta_U$ $(1 - \eta_I)$. Like in the stock market, we posit that half of the non-informed investors buy the put. Then the three probabilities in (16) become

$$P\{\theta = \theta_{VL} \mid sell_P\} = \frac{\frac{1}{2} \times (1 - \alpha) \times (1 - \eta_U) + \alpha \times (1 - \eta_I) \times (1 - \mu_2)}{2 \times [(1 - \alpha) \times (1 - \eta_U) + \alpha \times (1 - \eta_I)]}$$

$$P\{\theta = \theta_L \mid sell_P\} = \frac{\frac{1}{2} \times (1 - \alpha) \times (1 - \eta_U) + \alpha \times (1 - \eta_I) \times (1 - \mu_1)}{2 \times [(1 - \alpha) \times (1 - \eta_U) + \alpha \times (1 - \eta_I)]}$$

$$P\{\theta = \theta_H \mid sell_P\} = \frac{\frac{1}{2} \times (1 - \alpha) \times (1 - \eta_U) + \alpha \times (1 - \eta_I) \times \mu_1}{2 \times [(1 - \alpha) \times (1 - \eta_U) + \alpha \times (1 - \eta_I)]}$$

$$P\{\theta = \theta_{VH} \mid sell_P\} = \frac{\frac{1}{2} \times (1 - \alpha) \times (1 - \eta_U) + \alpha \times (1 - \eta_I) \times \mu_2}{2 \times [(1 - \alpha) \times (1 - \eta_U) + \alpha \times (1 - \eta_I)]}$$

By plugging the results in (14), we obtain

$$B_P = \bar{P} - \frac{\frac{1}{2} \times \alpha \times (1 - \eta_I) \times \left[(K - v_{VL}) \times (\mu_2 - \frac{1}{2}) + (v_H - v_L) \times (\mu_1 - \frac{1}{2})\right]}{(1 - \alpha) \times (1 - \eta_U) + \alpha \times (1 - \eta_I)}$$

with $\bar{P} = (1/4) \times (3 \times K - v_{VL} - v_L - v_H)$. Following the same approach, the option ask is given by the following formula

$$A_P = \bar{P} + \frac{\frac{1}{2} \times \alpha \times (1 - \eta_I) \times \left[(K - v_{VL}) \times (\mu_2 - \frac{1}{2}) + (v_H - v_L) \times (\mu_1 - \frac{1}{2})\right]}{(1 - \alpha) \times (1 - \eta_U) + \alpha \times (1 - \eta_I)}$$

It is easy to see that $\dfrac{\partial A_P}{\partial K} > 0$. The greater the strike, the more valuable the put so that the MM sell it at a higher price. Like in the stock market, the average between the bid and ask is the unconditional asset value.

From an informed trader perspective, the final value of the option is its expected value conditional on the private information she holds. If signals are low (high), the final value is expected to be $E\{(K-\tilde{v})^+ \mid PI = B\}$. By developing the former term, we obtain

$$E\{(K-\tilde{v})^+ \mid PI = B\} = (K - v_{VL}) \times P\{\theta = \theta_{VL} \mid PI = B\}$$
$$+(K - v_L) \times P\{\theta = \theta_L \mid PI = B\} + (K - v_H) \times P\{\theta = \theta_H \mid PI = B\}$$

Using Bayes' law again, we have

$$E\{(K-\tilde{v})^+ \mid PI = B\} = \frac{1}{2} \times [(K - v_{VL}) \times \mu_2 + (K - v_L) \times \mu_1 + (1 - \mu_1) \times (K - v_H)]$$

which can be rewritten

$$E\{(K-\tilde{v}) \mid PI = B\} = \bar{P} + \frac{1}{2}\left[(K - v_{VL}) \times (\mu_2 - \frac{1}{2}) + (v_H - v_L) \times (\mu_1 - \frac{1}{2})\right]$$

We also obtain

$$E\{(K-\tilde{v}) \mid PI = G\} = \bar{P} - \frac{1}{2}\left[(K - v_{VL}) \times (\mu_2 - \frac{1}{2}) + (v_H - v_L) \times (\mu_1 - \frac{1}{2})\right]$$

in a very similar way. By defining

$$\Omega_2^1 = \frac{1}{2} \times \alpha \times \left[(K - v_{VL}) \times (\mu_2 - \frac{1}{2}) + (v_H - v_L) \times (\mu_1 - \frac{1}{2})\right]$$

we have

$$B_P = \bar{P} - \frac{(1-\eta_I) \times \Omega_2^1}{\zeta_2 + \alpha \times (1 - \eta_I)}$$

$$A_P = \bar{P} + \frac{(1-\eta_I) \times \Omega_2^1}{\zeta_2 + \alpha \times (1 - \eta_I)}$$

$$E\{(K-\tilde{v}) \mid PI = B\} = \bar{P} + \frac{1}{\alpha} \times \Omega_2^1$$

$$E\{(K-\tilde{v}) \mid PI = G\} = \bar{P} - \frac{1}{\alpha} \times \Omega_2^1$$

Case $v_L < K \leq v_H$

Due to the non-linearity in the put payoff, the formula changes. By setting $v_L < K$, we guarantee that $Max\{K - v_L; 0\} = K - v_L$.

$$B_{(P)} = (K - v_{VL}) \times E\{\theta = \theta_{VL} \mid sell_P\} + (K - v_L) \times E\{\theta = \theta_L \mid sell_P\}$$

$$A_P = (K - v_{VL}) \times E\{\theta = \theta_{VL} \mid buy_P\} + (K - v_L) \times E\{\theta = \theta_L \mid buy_P\}$$

$$E\{(K-\tilde{v})^+ \mid PI = B\} = (K - v_{VL}) \times P\{\theta = \theta_{VL} \mid PS = B\} + (K - v_L) \times P\{\theta = \theta_L \mid PS = B\}$$

$$E\{(K-\tilde{v})^+ \mid PI = G\} = (K - v_{VL}) \times P\{\theta = \theta_{VL} \mid PS = G\} + (K - v_L) \times P\{\theta = \theta_L \mid PS = G\}$$

The unconditional asset value also changes, it becomes: $\bar{P} = (1/4) \times (2 \times K - v_{VL} - v_L)$. By following the same steps as in the previous part, we obtain

$$B_P = \bar{P} - \frac{\frac{1}{2} \times \alpha \times (1-\eta_I) \times \left[(K - v_{VL}) \times (\mu_2 - \frac{1}{2}) + (K - v_L) \times (\mu_1 - \frac{1}{2})\right]}{(1-\alpha) \times (1-\eta_U) + \alpha \times (1-\eta_I)}$$

$$A_P = \bar{P} + \frac{\frac{1}{2} \times \alpha \times (1-\eta_I) \times \left[(K - v_{VL}) \times (\mu_2 - \frac{1}{2}) + (K - v_L) \times (\mu_1 - \frac{1}{2})\right]}{(1-\alpha) \times (1-\eta_U) + \alpha \times (1-\eta_I)}$$

$$E\{(K-\tilde{v}) \mid PI=B\} = \bar{P} + \frac{1}{2}\left[(K-v_{VL})\times(\mu_2-\frac{1}{2}) + (K-v_L)\times(\mu_1-\frac{1}{2})\right]$$

$$E\{(K-\tilde{v}) \mid PI=G\} = \bar{P} - \frac{1}{2}\left[(K-v_{VL})\times(\mu_2-\frac{1}{2}) + (K-v_L)\times(\mu_1-\frac{1}{2})\right]$$

By defining

$$\Omega_2^2 = \frac{1}{2}\times\alpha\times\left[(K-v_{VL})\times(\mu_2-\frac{1}{2}) + (K-v_L)\times(\mu_1-\frac{1}{2})\right]$$

we have

$$B_P = \bar{P} - \frac{(1-\eta_I)\times\Omega_2^2}{\zeta_2+\alpha\times(1-\eta_I)}$$

$$A_P = \bar{P} + \frac{(1-\eta_I)\times\Omega_2^2}{\zeta_2+\alpha\times(1-\eta_I)}$$

$$E\{(K-\tilde{v}) \mid PI=B\} = \bar{P} + \frac{1}{\alpha}\times\Omega_2^2$$

$$E\{(K-\tilde{v}) \mid PI=G\} = \bar{P} - \frac{1}{\alpha}\times\Omega_2^2$$

Case $v_{VL} \leq K < v_L$

$$B_P = (K-v_{VL})\times E\{\theta=\theta_{VL} \mid sell_P\}$$

$$A_P = (K-v_{VL})\times E\{\theta=\theta_{VL} \mid buy_P\}$$

$$E\{(K-\tilde{v})^+ \mid PI=B\} = (K-v_{VL})\times P\{\theta=\theta_{VL} \mid PI=B\}$$

$$E\{(K-\tilde{v})^+ \mid PI=G\} = (K-v_{VL})\times P\{\theta=\theta_{VL} \mid PI=G\}$$

returning

$$B_P = \bar{P} - \frac{\frac{1}{2}\times\alpha\times(1-\eta_I)\times\left[(K-v_{VL})\times(\mu_2-\frac{1}{2})\right]}{(1-\alpha)\times(1-\eta_U)+\alpha\times(1-\eta_I)}$$

$$A_P = \bar{P} + \frac{\frac{1}{2}\times\alpha\times(1-\eta_I)\times\left[(K-v_{VL})\times(\mu_2-\frac{1}{2})\right]}{(1-\alpha)\times(1-\eta_U)+\alpha\times(1-\eta_I)}$$

with $\bar{P} = (1/4)\times(K-v_{VL})$. Likewise

$$E\{(K-\tilde{v}) \mid PI=B\} = \bar{P} + \frac{1}{2}\left[(K-v_{VL})\times(\mu_2-\frac{1}{2})\right]$$

$$E\{(K-\tilde{v}) \mid PI=G\} = \bar{P} - \frac{1}{2}\left[(K-v_{VL})\times(\mu_2-\frac{1}{2})\right]$$

By defining

$$\Omega_2^3 = \frac{1}{2}\times\alpha\times\left[(K-v_{VL})\times(\mu_2-\frac{1}{2})\right]$$

we have

$$B_P = \bar{P} - \frac{(1-\eta_I)\times\Omega_2^3}{\zeta_2+\alpha\times(1-\eta_I)}$$

$$A_P = \bar{P} + \frac{(1-\eta_I)\times\Omega_2^3}{\zeta_2+\alpha\times(1-\eta_I)}$$

$$E\{(K-\tilde{v}) \mid PI=B\} = \bar{P} + \frac{1}{\alpha}\times\Omega_2^3$$

$$E\{(K-\tilde{v}) \mid PI=G\} = \bar{P} - \frac{1}{\alpha}\times\Omega_2^3$$

The three cases provided Section 3 Subsection 4 follows. The put bid/ask spread $\triangle_P = A_P - B_P$ is

$$\triangle_P = \frac{2 \times (1-\eta_I) \times \Omega_2^j}{\xi_2 + \alpha \times (1-\eta_I)}$$

$\frac{\partial \triangle_P}{\partial \alpha} > 0$ gives

$$\frac{2 \times \frac{1}{\alpha} \times (1-\eta_I) \times \Omega_2^j}{\xi_2 + \alpha \times (1-\eta_I)} > \frac{2 \times (1-\eta_I) \times \Omega_2^j \times (\eta_U - \eta_I)}{\left[\xi_2 + \alpha \times (1-\eta_I)\right]^2}$$

After rearrangements, this expression collapses to $1 - \eta_U > 0$ which is always verified. $\frac{\partial \triangle_P}{\partial \eta_I} < 0$ gives

$$\frac{2 \times \times \Omega_2^j}{\xi_2 + \alpha \times (1-\eta_I)} > \frac{2 \times \alpha \times (1-\eta_I) \times \Omega_2^j}{\left[\xi_2 + \alpha \times (1-\eta_I)\right]^2}$$

which collapses to $\xi_2 > 0$ after few algebra. Hence, if more informed traders prefer to negotiate on the stock market, it limits the informational asymmetry in the option market, and MMs displays narrower bid/ask spread.

3.10.3 Appendix B.1: Equilibrium when informed traders equalize their profits across markets

This appendix shows how to derive the equilibrium value η_I under the assumption that informed traders seek to maximize expected profits. If the expected profit is higher on one market, all informed investors negotiate on this market. This is the separating equilibrium (Easley et al., 1998). A pooling equilibrium (i.e. informed transactions on both markets) emerges only if expected profits are equals across markets. Expected profit depends on the signals observed. If signals are "good", the condition is:

$$E\{\tilde{v} \mid PI = G\} - A_S = B_P - E\{(K - \tilde{v})^+ \mid PI = G\}$$

By replacing bid, ask and expectations by their respective values, we obtain:

$$\bar{v} + \frac{1}{\alpha} \times \Omega_1 - (\bar{v} + \frac{\eta_I^G \times \Omega_1}{\xi_1 + \alpha \times \eta_I^G}) = \bar{P}^j - \frac{(1-\eta_I^G) \times \Omega_2^j}{\xi_2 + \alpha \times (1-\eta_I^G)} - (\bar{P}^j - \frac{1}{\alpha} \times \Omega_2^j)$$

that is:

$$\frac{\frac{1}{\alpha} \times \Omega_1 \times (\xi_1 + \alpha \times \eta_I^G) - \eta_I^G \times \Omega_1}{\xi_1 + \alpha \times \eta_I^G} = \frac{\frac{1}{\alpha} \times \Omega_2^j \times \left[\xi_2 + \alpha \times (1-\eta_I^G)\right] - (1-\eta_I^G) \times \Omega_2^j}{\xi_2 + \alpha \times (1-\eta_I^G)} +$$

that is:

$$\left[\frac{1}{\alpha} \times \Omega_1 \times (\xi_1 + \alpha \times \eta_I^G) - \eta_I^G \times \Omega_1\right] \times \left[\xi_2 + \alpha \times (1-\eta_I^G)\right] =$$
$$\left(\frac{1}{\alpha} \times \Omega_2^j \times \left[\xi_2 + \alpha \times (1-\eta_I^G)\right] - (1-\eta_I^G) \times \Omega_2^j\right) \times (\xi_1 + \alpha \times \eta_I^G)$$

where j denotes the strike position with respect to underlying values (case 1: $v_H < K \leq v_{VH}$, case 2: $v_L < K \leq v_H$, case 3: $v_{VL} < K \leq v_L$). The equation to be solved is quadratic in η_I. Indeed, it can be written as follows:

$$A \times \left(\eta_I^B\right)^2 + B \times \eta_I^B + C = 0$$

with

$$A = \alpha \times \left(\Omega_2^j - \Omega_1\right) + \alpha^2 \times \Gamma^j$$

$$B = \alpha \times \Gamma \times (-\alpha - \xi_2 + \xi_1) + \Omega_1 \times (\xi_2 + \alpha) + \Omega_2^j \times (\xi_1 - \alpha)$$

$$C = \xi_1 \times \left[-\Gamma^j \times (\xi_2 + \alpha) - \Omega_2^j \right]$$

The system collapses to something very easy to solve, since $\Omega_2^j - \Omega_1 = -\alpha \times \Gamma^j \;\; \forall j$, which returns $A = 0$. We obtain the following solution:

$$\eta_I^{G\star} = \frac{\xi_1 \times (\Omega_1 + \Gamma^j \times \xi_2)}{\Omega_1 \times \xi_1 + \Omega_2^j \times \xi_2}$$

with

$$\begin{cases} \Gamma^1 = \frac{1}{2} \times \left[(v_{VH} - K) \times (\mu_2 - \frac{1}{2}) \right] \\ \Gamma^2 = \frac{1}{2} \times \left[(v_{VH} - K) \times (\mu_2 - \frac{1}{2}) + (v_H - K) \times (\mu_1 - \frac{1}{2}) \right] \\ \Gamma^3 = \frac{1}{2} \times \left[(v_{VH} - K) \times (\mu_2 - \frac{1}{2}) + (v_H - v_L) \times (\mu_1 - \frac{1}{2}) \right] \end{cases}$$

$$\begin{cases} \Omega_2^1 = \frac{1}{2} \times \alpha \times \left[(K - v_{VL}) \times (\mu_2 - \frac{1}{2}) + (v_H - v_L) \times (\mu_1 - \frac{1}{2}) \right] \\ \Omega_2^2 = \frac{1}{2} \times \alpha \times \left[(v_{VH} - K) \times (\mu_2 - \frac{1}{2}) + (v_H - K) \times (\mu_1 - \frac{1}{2}) \right] \\ \Omega_2^3 = \frac{1}{2} \times \alpha \times \left[(v_{VH} - K) \times (\mu_2 - \frac{1}{2}) + (v_H - v_L) \times (\mu_1 - \frac{1}{2}) \right] \end{cases}$$

When signals are "bad", the pooling equilibrium condition becomes

$$B_S - E\{\tilde{v} \mid PI = B\} = E\{(K - \tilde{v})^+ \mid PI = B\} - A_P$$

By replacing bid, ask and expectations by their respective values, we get

$$\bar{v} - \frac{\eta_I^G \times \Omega_1}{\xi_1 + \alpha \times \eta_I^G} - (\bar{v} - \frac{1}{\alpha} \times \Omega_1) = \bar{P}^j + \frac{1}{\alpha} \times \Omega_2^j - (\bar{P}^j + \frac{(1 - \eta_I^G) \times \Omega_2^j}{\xi_2 + \alpha \times (1 - \eta_I^G)})$$

After some rearrangements, we finally obtain

$$\eta_I^{B\star} = \frac{\xi_1 \times (\Omega_1 + \Gamma^j \times \xi_2)}{\Omega_1 \times \xi_1 + \Omega_2^j \times \xi_2}$$

When informed investors maximize expected profits, $\eta_I^{G\star} = \eta_I^{B\star}$. One can easily note that $\eta_I^{G\star}$ and $\eta_I^{G\star}$ are equals whatever the strike value. Since $\left\{\xi_1, \xi_2, \Omega_1, \Omega_2^j, \Gamma^j\right\}$ are all defined positive, we have $\eta_I^{G\star} > 0$ and $\eta_I^{G\star} > 0$. Given this solution, one can derive the equilibrium bid/ask spread as follows:
$BA_S = A_S - B_S = (2 \times \eta_I \times \Omega_1)/(\xi_1 + \alpha \times \eta_I)$. After plugging the value for $\eta_I^{B\star}$, it collapses to

$$\Delta_S = 2 \times (\Omega_1 + \Gamma \times \xi_2)$$

In a very similar way, the bid/ask spread of the option is given by

$$\Delta_P = 2 \times (\Omega_2 - \xi_1 \times \Gamma)$$

Finally

$$\Delta_S - \Delta_P = 2 \times \Gamma$$

3.10.4 Appendix B.2: Equilibrium stability

This is a Nash equilibrium if the equilibrium is stable with respect to a unilateral deviation of one of the game participant. The informed trader has 3 possible strategies: (i) Do not trade, (ii) trade following the signal she observes, (iii) trade against the signal. Not trading generates a profit equal to zero.

When the private signals acquired by the informed traders indicate bad news, trading according to the signal generates the payoff $B_S - E\{\tilde{v} \mid PI = B\} = \frac{\frac{1}{\alpha} \times \Omega_1 \times \xi_1}{\xi_1 + \alpha \times \eta_I^{B\star}}$, which is a positive amount. If she trades against her signal, her payoff is given by $E\{\tilde{v} \mid PI = B\} - A_S = -\frac{\frac{1}{\alpha} \times \Omega_1 \times \xi_1 + 2 \times \eta_I^{B\star} \times \Omega_1}{\xi_1 + \alpha \times \eta_I^{B\star}}$, which is a negative amount. Note that it is not necessary to plug the value of $\eta_I^{B\star}$ into the previous equations. This quantity is positive, as well as $\{\alpha, \xi_1, \Omega_1\}$. On the option market, trading according to the signal generates $E\{(K-\tilde{v})^+ \mid PI = B\} - A_P = \frac{\frac{1}{\alpha}\times\Omega_2\times\xi_2}{\xi_2+\alpha\times(1-\eta_I^{B\star})}$ while trading against the signal generates $B_P - E\{(K-\tilde{v})^+ \mid PI = B\} = -\frac{\frac{1}{\alpha}\times\Omega_2\times\xi_2+2\times(1-\eta_I^{B\star})\times\Omega_2}{\xi_2+\alpha\times(1-\eta_I^{B\star})}$, which is negative.

Now consider the second scenario: Signals are high for the informed traders. In that case, negociating according to the signal generates the payoff $E\{\tilde{v} \mid PI = G\} - A_S = \frac{\frac{1}{\alpha}\times\Omega_1\times\xi_1}{\xi_1+\alpha\times\eta_I^{G\star}}$, which is a positive amount. If she trades against her signal, her payoff is given by $B_S - E\{\tilde{v} \mid PI = G\} = -\frac{\frac{1}{\alpha}\times\Omega_1\times\xi_1+2\times\eta_I^{G\star}\times\Omega_1}{\xi_1+\alpha\times\eta_I^{G\star}}$, which is a negative amount. On the option market, trading according to the signal generates $B_P - E\{(K-\tilde{v})^+ \mid PI = G\} = \frac{\frac{1}{\alpha}\times\Omega_2^j\times\xi_2}{\xi_2+\alpha\times(1-\eta_I^{G\star})}$ while trading against the signal generates $E\{(K-\tilde{v})^+ \mid PI = G\} - A_P = -\frac{\frac{1}{\alpha}\times\Omega_2^j\times\xi_2+2\times\Omega_2^j\times(1-\eta_I^{G\star})}{\xi_2+\alpha\times(1-\eta_I^{G\star})}$, which is negative.

3.10.5 Appendix C.1: Equilibrium when informed traders equalize their returns across markets

An investor is indifferent between trading the stock or the option if the expected returns is the same on both market. To assess how the pool of informed traders splits across trading venues, expected returns are equalized. When signals are low, the payoffs from short-selling the stock is equal to the profit from buying the put. Returns are obtained by divided each payoff by the capital engaged by the trader. For a stock purchase, this is below the full asset value ($m_S \times B_S$) while this is the full proceed (A_P) in case of put buy. Formally, returns equalization gives

$$\frac{B_S - E\{\tilde{v} \mid PI = B\}}{m_S \times B_S} = \frac{E\left\{(K-\tilde{v})^+ \mid PI = B\right\} - A_P}{A_P}$$

That is

$$\frac{\left(\bar{v} - \frac{\eta_I\times\Omega_1}{\xi_1+\alpha\times\eta_I}\right) - \left(\bar{v} - \frac{1}{\alpha}\times\Omega_1\right)}{m_{(S)} \times \left(\bar{v} - \frac{\eta_I\times\Omega_1}{\xi_1+\alpha\times\eta_I}\right)} = \frac{\left(\bar{P}^j + \frac{1}{\alpha}\times\Omega_2^j\right) - \left(\bar{P}^j + \dfrac{(1-\eta_I)\times\Omega_2^j}{\xi_2+\alpha\times(1-\eta_I)}\right)}{\bar{P}^j + \dfrac{(1-\eta_I)\times\Omega_2^j}{\xi_2+\alpha\times(1-\eta_I)}}$$

Which yields, after some algebra

$$\eta_I^{B\star} = \frac{\Omega_1\times\xi_1\times A}{\xi_1\times\Omega_1\times B+\xi_2\times\Omega_2^j\times C}$$

with

$$\begin{aligned}
A &= \bar{P}^j + \tfrac{1}{\alpha}\times\Omega_2^j + \tfrac{1}{\alpha}\times\xi_2\times\left(\bar{P}^j - m_S\times\bar{v}\times\tfrac{\Omega_2^j}{\Omega_1}\right)\\
B &= \bar{P}^j + \tfrac{1}{\alpha}\times\Omega_2^j\\
C &= m_S\times\left(\bar{v} - \tfrac{1}{\alpha}\times\Omega_1\right)
\end{aligned}$$

The condition that guarantees a mixed equilibrium to emerge is $\eta_I^{B\star} \in]0;1[$, that is if $\bar{P}^j + \frac{1}{\alpha}\times\Omega_2^j > \frac{1}{\alpha}\times\xi_2\times(m_S\times\bar{v}\times\frac{\Omega_2^j}{\Omega_1} - \bar{P}^j)$ and $\Omega_1\times\xi_1\times(A-B) < \xi_2\times\Omega_2^j\times C$.

When signals are high, the payoffs from buying the stock is equal to the profit from selling the (naked) put. For a stock purchase, the capital engaged by the investor is $m_S \times A_S$ while selling the put requires the maximum between the two values $m_{(P)} \times E\{\tilde{v} \mid sale_P\} - (E\{\tilde{v} \mid sale_P\} - K)^+$ and $m_K \times K$ according to the CBOE margin calculator. Formally, returns equalization gives

$$\frac{E\{\tilde{v} \mid PI = G\} - A_S}{m_S \times A_S} = \frac{B_P - E\{(K-\tilde{v})^+ \mid PI = G\}}{\max\{m_P \times E\{\tilde{v} \mid sale_P\} - (E\{\tilde{v} \mid sale_P\} - K)^+; m_K \times K\}} \tag{17}$$

Using Bayes' law, we obtain $E\{\tilde{v} \mid sale_P\} = \bar{v} + \frac{(1-\eta_I)\times\Omega_1}{\xi_2+\alpha\times(1-\eta_I)}$, rewritten $\bar{v}+\phi$ for convenience. We know that $\phi > 0$ since $\{\alpha, \eta_I, \Omega_1, \xi_2\}$ are all defined positive. Moreover, we find that $\phi < 1$ is valid for various combinations of $\{\alpha, \eta_I, \Omega_1, \xi_2\}$.

In a first step, let's assume that $K < \bar{v}$, so that $\bar{v}+\phi > K$. The margin requirement for selling a put becomes $\max\{K - (1-m_P)\times(\bar{v}+\phi); m_K \times K\}$. $m_K \times K$ is the initial margin requirement if

$$K - (1-m_P)\times(\bar{v}+\phi) < m_K \times K$$

that is

$$\bar{v}+\phi > \frac{1-m_K}{1-m_P} \times K \tag{18}$$

A sufficient condition for (18) to be valid is $\bar{v} > \frac{1-m_K}{1-m_P}\times K$. Hence, the right margin requirement is $m_K \times K$ under the area $v_{VL} < K < v_L$ and $v_L < K < \frac{1-m_P}{1-m_K}\times\bar{v}$. Note that under CBOE margin rule, the last expression is $v_L < K < \frac{8}{9}\times\bar{v}$. When the strike is contained in these two areas, (17) becomes

$$\frac{E\{\tilde{v} \mid PI=G\} - A_{(S)}}{m_S \times A_{(S)}} = \frac{B_{(p)} - E\{(K-\tilde{v}) \mid PI = G\}}{m_K \times K}$$

That is

$$\frac{\left(\bar{v}+\frac{1}{\alpha}\times\Omega_1\right) - \left(\bar{v}+\frac{\eta_I^G\times\Omega_1}{\xi_1+\alpha\times\eta_I^G}\right)}{m_S\times\left(\bar{v}+\frac{\eta_I^G\times\Omega_1}{\xi_1+\alpha\times\eta_I^G}\right)} = \frac{\left[\bar{P} - \frac{(1-\eta_I^G)\times\Omega_2}{\xi_2+\alpha\times(1-\eta_I^G)}\right] - \left(\bar{P}-\frac{1}{\alpha}\times\Omega_2\right)}{m_K\times K}$$

After several steps of calculus, we finally obtain:

$$\eta_I^G = \frac{\Omega_1\times\xi_1\times A'}{\xi_1\times\Omega_1\times B' + \xi_2\times\Omega_2^j\times C'}$$

with

$$\begin{aligned}
A' &= m_K\times K + \tfrac{1}{\alpha}\times\xi_2\times\left(m_K\times K - m_S\times\bar{v}\times\tfrac{\Omega_2^j}{\Omega_1}\right)\\
B' &= m_K\times K\\
C' &= m_S\times\left(\bar{v}+\tfrac{1}{\alpha}\times\Omega_1\right)
\end{aligned}$$

Now let's assume that $K > \bar{v}+\phi$. The initial margin requirement becomes $\max\left\{m_{(P)}\times(\bar{v}+\phi); m_K\times K\right\}$. $m_{(P)}\times(\bar{v}+\phi)$ is the right margin requirement if

$$\frac{m_P}{m_K}\times(\bar{v}+\phi) > K \tag{19}$$

Hence, $m_{(P)}\times(\bar{v}+\phi)$ is the right margin requirement if K if bounded by $\bar{v}+\phi$ and $\frac{m_P}{m_K}\times(\bar{v}+\phi)$. Considering the CBOE margin calculator as the reference and given that $\phi < 7$, we can reasonably set the area to be $\bar{v}+7 < K < 2\times\bar{v}+2$ for convenience. Then, we define $\{v_{VL}, v_L, v_H, v_{VH}\}$ so that $v+7 \le v_H$ and $v_{VH} < 2\times\bar{v}+2$ always hold. Hence $m_{(P)}\times(\bar{v}+\phi)$ is the right margin requirement under $v+1 \le K \le v_H$ and $v_H < K \le v_{VH}$. Then (17) becomes

$$\frac{E\{\tilde{v} \mid PI=G\} - A_S}{m_S\times A_S} = \frac{B_P - E\{(K-\tilde{v})^+ \mid PI=G\}}{m_P\times(\bar{v}+E\{\tilde{v}\mid sale_P\})}$$

That is

$$\frac{\left(\bar{v}+\frac{1}{\alpha}\times\Omega_1\right) - \left(\bar{v}+\frac{\eta_I^G\times\Omega_1}{\xi_1+\alpha\times\eta_I^G}\right)}{m_S\times\left(\bar{v}+\frac{\eta_I^G\times\Omega_1}{\xi_1+\alpha\times\eta_I^G}\right)} = \frac{\left[\bar{P} - \frac{(1-\eta_I^G)\times\Omega_2}{\xi_2+\alpha\times(1-\eta_I^G)}\right] - \left(\bar{P}-\frac{1}{\alpha}\times\Omega_2\right)}{m_P\times\left[\bar{v}+\frac{(1-\eta_I)\times\Omega_1}{\xi_2+\alpha\times(1-\eta_I)}\right]}$$

After some algebra, we finally obtain

$$\eta_I^G = \frac{\Omega_1 \times \xi_1 \times A''}{\xi_1 \times \Omega_1 \times B'' + \xi_2 \times \Omega_2^j \times C''}$$

with

$$A'' = m_P \times (\bar{v} + \frac{1}{\alpha} \times \Omega_1) + \frac{1}{\alpha} \times \bar{v} \times \xi_2 \times (m_P - m_S \times \frac{\Omega_2^j}{\Omega_1})$$
$$B'' = m_p \times (\bar{v} + \frac{1}{\alpha} \times \Omega_1)$$
$$C'' = m_S \times (\bar{v} + \frac{1}{\alpha} \times \Omega_1)$$

4

Footnote Information Accuracy: Evidence from the Reported Dividend Yield

Co-authored with

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We analyze the accuracy of the footnote dividend yield (FDY) reported in the financial statements and used to price stock options. We propose a new methodology to identify deviations from fair measurements, that takes into account the flexibility offered by FASB authoritative guidance. Focusing on companies that reported inaccurate FDYs, we find strong evidence of information revelation motives and moderate evidence of managerial opportunism. In addition, audit fees are positively correlated with the likelihood of an accurate reporting, suggesting that the audit of footnote disclosure depends on the remuneration level of the audit firm. Our study contributes to the growing literature on the importance of footnote information.[3]

JEL classification: M41, M42, M12, G35
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4.1 Introduction

"Ironically, information on the 'true cost' of options is already available in the footnotes on employee options that all public companies are required to report. Many users overlook these footnotes or do not regard them as a useful source of information."

From Ohl (2000), director of PriceWaterhouseCoopers[4]

Since 2006, the Financial Accounting Standards Board requires US companies to expense employee and executive stock-options[5] (ESOs) at the time of grant. Given that the value of a stock-option depends, among others, on the firm's future dividend payments, any firm that grants stock-options must provide an estimate of its future dividend payments in the 10-K financial statements. It is unclear what is in a firm's best interests in that regard and the wide dispersion in effective dividends versus disclosed dividends across firms suggests that different firms follow different principles. First, an overstatement of the dividend yield may be done on purpose by the managerial team in order to convey information to investors. Alternatively, the overstatement can come from a will to reduce the perceived cost of stock-options. Third, providing an unbiased estimate could establish or maintain a reputation for being truthful. Hence, there are (at least) three alternative motives for reporting on dividend yield: Information revelation, managerial opportunism or accuracy. The purpose of this paper is to provide evidence on the degree of report accuracy of the dividend yield and the objectives underlying an inaccurate reporting.

We propose a new methodology to measure report accuracy. Our method is based on 10-K and 10-Q files that are publicly available, and can be replicated by analysts and auditors. Several studies (Hodder et al., 2006; Johnston, 2006; Aboody et al., 2006; Bartov

[4] This statement is from Hirshleifer and Teoh (2003).

[5] An employee stock option is a call option that gives the holder, employee or executive, the right, but not the obligation, to buy shares of their companies for a fixed price (the strike) during a specified period of time. ESOs have features that make them very different of publicly traded American options. ESOs are not transferable and impose time to wait before the possibility to exercise the option (the vesting period). This period is set up to align effort with compensation and prevent from early strategic exercise if the stock price is temporary high for various reasons related to market activity. Once the vesting period is ended, the holder can exercise the option at any time until maturity. This leads to the physical delivery of the stocks by diluting the capital. Stock buybacks following for future delivery is another way to proceed.

et al., 2007; Blacconiere et al., 2011; Choudhary, 2011; Bratten et al., 2016) analyzed the accuracy of the reported dividend yield. However, these papers compare this yield to a single measure while the flexibility allowed by FASB guidance indicates that there is no clear specified method of measurement but rather a range of possible benchmarks.[6] For every observation in our sample, we compute 13 dividend yields. These yields all respect FASB guidance and are acceptable measurements for an auditor or a financial analyst. The minimum (maximum) of these measures is selected as a low (high) bound to detect under- (over-) report. By doing so, our methodology is robust to the heterogeneity of methodologies across firms.

Using a sample of firms unique firms that have granted ESOs between 2006 and 2014, our methodology returns a proportion of fair report at 90.7%, of underreport at 4.3% and of overreport at 5.0%, representing 1,283, 160 and 184 unique firms, respectively. We provide evidence that private information held by managers and variables measuring managerial opportunism bring information to explain the likelihood of biasing the footnote dividend yield over reporting an accurate figure. In addition, a measure of corporate governance quality is negatively correlated to the likelihood of underreporting and the amount of audit fees paid by the company to the audit firm is positively correlated with the likelihood of providing a fair report, suggesting that a higher degree of audit effort leads to more accurate footnotes.

Fields et al. (2001) argue that the choice of specific accounting method may play a central role in the way managers disseminate private information to investors. The idea that the ESO pricing parameter reporting can be a way to convey superior information has been suggested by Hodder et al. (2006). Insiders have more information than investors about their future prospects and a dividend projection may convey information to the market.[7] To test this information revelation hypothesis, we quantify the predictive power

[6] For instance, a company can compute a historical average of the dividend yield. Under this approach, the company has discretion for the selection of the time window. There is also no clear indication of which stock price should be selected as benchmark to derive the yield. The market price at time grant (i.e. the option strike price) is acceptable, the end-of-quarter or end-of-year stock price too. See the document SFAS 123(r) issued by the FASB in 2004 for more details on this flexibility.

[7] Firms can of course formally announce changes in future dividend payments. However, formal dividend announcements commit the firm in a way that a dividend input for stock-options valuation does not. Therefore, firms which are

of the disclosed dividend yield on the one-year-ahead effective yield, in level and growth. Then, we assess whether differences in reported dividend yield accuracy across firms are explained by differences in future performance and growth opportunity measures.

The alternative view to information revelation is managerial opportunism. Granting ESOs dilutes earnings per share (EPS), as opposed to basic EPS. This attributes negatively viewed by analysts and investors. Moreover, excessive stock option granting have been under heavy criticism a decade ago. A recent study by Kuhnen and Nielsen (2012) shows that stock options have a bad reputation among regulators and the press both and option-based plan award is the component of executive compensation that is the most associated with negative press coverage. We posit that overreporting the dividend yield may be optimal if compensation practices are scrutinized by shareholders, the media, politicians or the firm's employees, as hypothesized by Jensen and Murphy (1990), and if managers want to dissimulate the real cost of their compensation, as hypothesized by Bebchuk and Fried (2004). If such managerial objectives exist, the manipulation of dividend yield should be positively associated with analyst coverage and excessive compensation.[8] The likelihood of inaccurate dividend yield report should be statistically correlated with these two variables.

Reporting a fair dividend yield, that is a yield viewed as acceptable by the FASB guidance, might also be an objective. The corporate governance, as well as the audit firm might act toward accurate report, so that a manipulation of the reported dividend yield by the managerial team is not possible. This disciplinary effect is tested two-ways. Following Core et al. (1999) and given the recent findings of Nguyen and Nielsen (2010) and Armstrong et al. (2015), we proxy for corporate governance quality by the proportion of independent board members. Information on audit fees amount is collected and connected to the accuracy of the dividend yield reported. To the best of our knowledge, assessing

uncertain of their future ability to pay higher dividends but which nevertheless expect to be able to do so could use the dividend input to signal this information to investors.

[8] Aboody et al. (2006) find evidence that the manipulation of ESO pricing parameters is related to excessive compensation. We rely on their approach to derive a measure of excessive compensation. Measures of excessive compensation are also derived in Yermack (1998) and in Core et al. (1999) with CEO characteristics as additional regressors.

whether or not the quality of the audit process spans footnote information has not been investigated yet. We predict a positive relationship between these two variables and the precision of the dividend yield reported.

Multinomial logit regressions are performed to identify which objectives are followed by the firms. Thus, report accuracy is regressed against forward-looking information on the firm fundamentals, variables related to managerial opportunism, scaled audit fee amounts and the proportion of independent board members. To guarantee the reliability of our findings, a large set of control variables is included in the regression, as well as year and industry dummies.

Among the three effects tested in this paper, we find strong evidence in support of the information revelation motive. Low Tobin's Q and low total Tobin's Q are strongly associated to the risk of underreport while large decreases in the operating risk favor overreport risk. These results differ from Choudhary (2011) that rejects the information revelation hypothesis. Managerial opportunism receives moderate evidence: Analyst's coverage is strongly associated with underreporting, suggesting that the companies the most exposed to analyst scrutiny are more likely to bias the dividend yield downwardly. However, we find no link between excessive compensation and overreporting risk. Third, a higher proportion of independent directors on the board is associated with less underreporting while higher audit fees are associated to less overreport. All together, our findings suggest that information revelation objective, managerial opportunism and disciplinary effects are all present in our data and influences the relative likelihood of underreporting over a fair report the footnote dividend yield.

Section 2 introduces the three channels driving the dividend yield report accuracy (information revelation, managerial opportunism or disciplinary effects). Section 3 presents methodology and data. Results are reported Section 4. Section 5 concludes.

4.2 Confronting different approaches

4.2.1 Can the footnote dividend yield be informative?

"*Historical experience is generally the starting point for developing expectations about the future. Expectations based on historical experience should be modified to reflect ways in which currently available information indicates that the future is reasonably expected to differ from the past. The appropriate weight to place on historical experience is a matter of judgment, based on relevant facts and circumstances.*" (FASB 2004, pp. 43).

The Black and Scholes (1973) option pricing formula for European call options requires a volatility rate, a risk-free rate and a dividend yield that are supposed to hold for the maturity of the option, that is they are expectations regarding future realizations. In practice, it is proxied by backward-looking estimates. For the dividend yield, the usual approach consists of selecting an average value or simply the most recent realization. In selecting a dividend yield to price ESOs, managers have an opportunity to disclose a forward-looking dividend yield rather than an historical-based one, conveying new information to shareholders. The idea that manager's discretion provides important information to the market takes root in Rees et al. (1996). They consider the possibility that manager do permanent asset impairment to provide signals to investors. They conclude that managers are responding to changes in economic circumstances rather that acting opportunistically. Fields et al. (2001) argue that the choice of specific accounting method may play a central role in the way through which managers (better informed) disseminate private information to investors (less well-informed). The private information is about magnitude and risk of future cash-flow.

Hodder et al. (2006) are the first to apply this perspective to footnote information, and find evidence that subsequent changes in operating risk are related to accuracy for firms that overreport ESO fair values. Shareholders could interpret the footnote dividend yield as an implicit commitment for the future dividend payout policy. Hence, a managerial team must be aware of possible interpretation when setting the dividend yield.[9]

We hypothesize that a managerial team can convey superior information on purpose, by setting a yield that differ significantly from historical patterns. In the short quote placed above, that FASB indicates that deviation from historical benchmarks is justified if executive have information that suggest a break with respect the past payout policy. Regarding the fact that insiders have private information about future cash flows, the footnote dividend yield (FDY hereafter) may reflect, to some extent, this private information. If an upward (downward) change in sale level is anticipated, the FDY should reflect the upcoming changes, being higher (lower) than what historical effective dividend yields. As indicated by FASB, this is fully justified. This leads to our first hypothesis:

Hypothesis 1: The reported dividend yield in the 10-K footnotes conveys new information regarding future dividend payments and cash-flow streams.

4.2.2 Managerial objectives

A natural alternative framework to the information revelation channel is managerial opportunism. This idea that managers use discretion to increase their own compensation was pioneered by Healy (1985). He argues that managers choose current discretionary accruals to maximize both the current period bonus and the expected value of next period's bonus.[10] Because executive pay is a cost for the company, it might be interesting for the manager to hide, rather than increasing, the value of their compensation. One way to do so is to undervalue the options. Yermack (1998) and Aboody et al. (2006) find a positive

[9] For instance, IBM disclose the following statements in the footnotes, for the fiscal year 2010: "*Estimates of fair value are not intended to predict actual future events or the value ultimately realized by employees who receive equity awards, and subsequent events are not indicative of the reasonableness of the original estimates of fair value made by the company.*" it seems that IBM managers are worried about the potential interpretation of the reported dividend yield by investors.

[10] See, amongst others, Gaver et al. (1995), Holthausen et al. (1995) and Guidry et al. (1999) for subsequent empirical researches.

significant statistical association between ESO undervaluation and the excessiveness of executive compensation. Everything else being equal, the greater the excess compensation, the greater the managerial incentive to manipulate the FDY. This leads to our second hypothesis:

Hypothesis 2a: Companies providing an excessive compensation to their CEO have a stronger propensity to manipulate the FDY to hide the true value of CEO compensation.

Managers might be also willing to dissimulate the real cost of their ESOs if the company is under the scrutiny of media and analysts.[11] Dechow et al. (1996) show that lobbyism against the expensing of ESOs, especially coming from the IT industry, arose due to the public scrutiny toward executive compensation. If the amount of ESO granted impact the negativity of the informational content of analyst and press reports, managers might be willing to manipulate upward the FDY to dampen the weight of ESOs in total compensation. We expect a positive relationship between media exposure and overreporting the FDY. Formally,

Hypothesis 2b: Companies under wide analyst coverage have a stronger propensity to manipulate upward the FDY in order to hide the true value of top executive compensation.

Bebchuk and Fried (2004) claim that wider analyst coverage can bring more attention to the excess pay and more criticism to the managers. Consistent with this idea, we should also find a positive correlation between compensation excessiveness time analyst coverage and the extent of FDY manipulation. Formally,

[11] ESOs have bad reputation among shareholders and in press. First, granting stock options induces a future dilution of the capital, which is not in the interest of the current shareholders. Second, the bad reputation of ESOs in the press has been confirmed. Core et al. (2008) analyze the tone of thousands of articles related CEO compensation and show that negative press coverage is associated to large option exercises. By modelling the dynamic endogeneity between compensation composition and press coverage, Khunen and Nielsen (2012) put in evidence that stock options is the most criticized component of executive compensation. Consistent with Weisbach's (2007) prediction, companies tend to reshape the compensation package, putting more weight on components not criticized very much in the press and less weight on the most criticized forms.

Hypothesis 2c: The interaction term between executive compensation excessiveness and analyst coverage is positively correlated with FDY upward manipulation

Interestingly, hypotheses 2b and 2c might not hold for two reasons. First, the analyst coverage might have a disciplining role on the management team, providing incentives to report more accurately. Second, analyst coverage could also provide incentives for being prudent, in which case there are incentives to manipulate downward the dividend yield.

4.2.3 Disciplinary forces

Companies put in place mechanisms to foster truthful reports instead of opportunistic disclosures. It implies that the dividend yield should be more in line with historical patterns when internal or external controls are enforced, limiting overstatement or understatement risk at firm-level. The corporate governance and the audit firm could represent the internal and external control, respectively, and governance and audit quality could influence report accuracy. Aboody et al. (2006) use the corporate governance quality as a control variable and find that it is negatively significantly correlated with the estimated value of options and conclude that weaker corporate governance result in more biased option value estimates. Their result suggests a positive association between corporate governance and report accuracy:

Hypothesis 3: The governance quality is expected to be associated positively with the likelihood of reporting an accurate FDY.

The connection between audit quality and the accuracy of ESO pricing parameters has received little attention. Blacconiere et al. (2011) find that nearly 30% of financial statement audited by Ernest & Young include of statement questioning the reliability of fair value information.[12] Hence, an complete auditing process is supposed to include ESO fair values and the associated pricing inputs. More accurate reporting involves more auditing effort, and more auditing effort will lead to higher audit fees. This suggests a positive association between audit fees and footnote information accuracy. Thus:

Hypothesis 4: The audit fees amount is expected to be positively associated with the likelihood of reporting an accurate FDY.

4.3 The manipulation of ESO pricing parameters

4.3.1 Prior studies

Despite the existence of authoritative guidance[13], there is space for managers to select the dividend rate, the volatility rate used to price ESOs. These parameters are supposed to reflect some expectations regarding future realizations. However, the most recent realizations of these rates are used as proxies for forward-looking measures, in practice. For instance, the volatility may experience different regimes over the period the last 250 days while it looks stable over the last 60 days. The selection of one window over the other leads to different estimate of the historical volatility, which in turns results in different ESO valuations. Different estimates can also be driven by the preference for implied volatility over historical volatility. There are also different ways to estimate the dividend yield: Managers can opt for the closest past dividend yield or a n-year average. Dividend payments are usually persistent over time but if the last cash dividend payment is abnormally high, following exceptional earnings for instance, selecting the most recent dividend payment or an

[12] Bratten et al. (2016) studies the impact of engaging a non-Big Four auditor on the differences between the reported values of ESOs and the benchmark values. They obtain a significantly positive association. However, they do not analyse the influence on each ESO pricing parameter separately.

[13] The SFAS 123 report issued by the FASB is introduced in 1995 and the reform SFAS 123(r) takes place in 2005. Under SFAS 123(r), all companies are required to expense the fair value of ESOs. Before it, the expense is done on a voluntary basis. To avoid any selection-bias in our sample, our sample starts in 2006, the first year under which a unique rule apply for all corporations. For a presentation of the legal framework related to ESO pricing, see Johnston (2006) or Hodder et al. (2006). For a study on the voluntary recognition of stock-based compensations as expenses, see Aboody et al. (2003).

average as benchmark results in different option values. Finally, the maturity has a non-negligible effect on the option value. Managers may be willing to exercise discretion over inputs in order to (i) modify ESO values on purpose, this is the managerial opportunism hypothesis, or (ii) convey superior information to market participant.[14]

Prior research of ESO inputs manipulation does not provide clear evidence whether managerial opportunism or information motivation is dominant.[15] The earliest evidence of managerial opportunism can be founded in Yermack (1998) who shed light on the fact that ESO expected lives are voluntary shorten to reduce the apparent value of managerial compensation. Aboody et al. (2006) also showed that managers use the discretion in input choices afforded by SFAS 123 to opportunistically underreport the fair value of ESOs. The degree of manipulation is connected to the magnitude of the expense and, to a lesser extent, to the excessiveness of CEO compensation [16] However, two studies support the information revelation hypothesis over managerial opportunism. Hodder et al. (2006) find that the joint manipulation over the four inputs enables companies to underreport their ESOs by an amount of \$0.16 a share in average.[17] However, they also find that a significant number of managers use discretion to incorporate relevant information to make more accurate estimates. Blacconiere et al. (2011) analyze the voluntary disclosure of companies that disavow the reliability of mandated fair value. They find evidence consistent with the disavowals being informative and only limited evidence of opportunism.

A specific stream of literature analyzes the behavior of firms that voluntarily recognize stock option as an expense ("recognizing firms") against firms that do not ("disclosing firms"), prior to the accounting regime change in 2006. Johnston (2006) find that

14 The risk-free rate could be manipulated too but FASB 2004 is pretty clear: The right way to proceed is to extract the risk-free rate from the U.S. Treasury yield curve, which leaves narrow space for manipulation. Jonhston (2006) finds that there is very few manipulation over the risk-free rate while Aboody et al. (2006) find that there is no manipulation on this parameter.

15 As Fields et al. (2001) point out: " ... *researchers have not been successful, on average, at distinguishing between managerial opportunism, shareholder wealth maximization, and information motivation.*"

16 This evidence provides a good support to test if the camouflage willing by top managers span ESO pricing parameters. The idea that discretionary accounting choices are related to CEO compensation and political costs has received support in Balsam (1998) and Baker (1999).

17 The manipulation of ESO pricing inputs on other countries is studied in two papers. ESO trades on the Helsinki Stock Exchange are examinated by Ikäheimo et al. (2006), who find a substantial undervaluation, with an average price differential of -14.8%. Bechmann and Hjortshoj (2009) do not find clear evidence of underpricing and no evidence of manipulation in Denmark.

recognizing firms manipulate more than firms that disclosing firms, for the fiscal year 2002. Choudhary (2011), using a sample covering both the pre- and post- SFAS 123(r) periods, also obtains that ESO valuations by recognizing firms are more likely to be underestimated. Using a logistic regression to estimate the likelihood of recognizing ESO as expenses, Aboody et al. (2004) find that key predictive variables are proxies for private incentives of managers and directors and measures of political costs. These papers show strong evidence of managerial opportunism but no evidence of information revelation motivation.

Our results contrast with these findings. Using a large post- SFAS 123(r) period and with a new methodology, we document that information revelation objectives do exist when companies report the dividend yield in the 10-K footnotes. Managerial objectives are present but evidence are limited. In addition, we show that disciplinary objectives exist too. To the best of our knowledge, we are the first to document on this mechanism.

4.3.2 Why do we focus on the dividend yield?

The incentive to manipulate a parameter should increase with the sensitivity of ESO values to that parameter. Given the scrutiny of audit committee and analysts, a managerial team will presumably not take the risk of manipulating a parameter whose influence on option valuation is limited. For ESOs, which are options characterized by a maturity of several years, the option price is highly sensitive to the yield used. Prior studies find evidence that manipulation is exercised mainly over stock price volatility.[18] However, we focus on the dividend yield for two reasons. First, the volatility rate is established by investors depending on market conditions, as opposed to dividends which are chosen by the firm insiders depending on the firm's ability to generate cash. Hence, from the insider viewpoint, conveying private information by the channel dividend yield is feasible while this is not the case with the volatility rate since it is impacted by various factors out of the insider's control. Second, a connection between the disclosed dividend yield and proxies for

[18] See Aboody et al. (2006), Jonhston (2006) and Bartov et al. (2007).

private information on future performance is easily measurable, while linking the disclosed volatility rate to proxies for private information on future performance variability is more perilous and challengeable. Hence, from the econometrician perspective, the disclosed dividend yield is the best instrument among ESO pricing inputs to assess the information revelation hypothesis, and confront it to the managerial opportunism hypothesis.

To show that the dividend yield is a key parameter for the firm's insiders, we provide a sample of 10-K footnotes in **Table I**. These are complementary statements disclosed by the 20 largest dividend payers for the fiscal year 2010. First, one can observe that there is an obvious lack of precision in the statements accompanying the disclosed yield: One could not retrieve the yield based on the statement. Second, there is evidence of heterogeneity. Some companies rely on historical patterns (like Brystol-Meyers and Merck) while other mention an expectation (like Walmart). The comment from Eli Lilly is pretty ambiguous: "*The dividend yield is based on historical experience and our estimate of future dividend yields*". The comment from IBM looks as a warning to investors "*Estimates of fair value are not intended to predict actual future events or the value ultimately realized by employees who receive equity awards, and subsequent events are not indicative of the reasonableness of the original estimates of fair value made by the company*". This shows that IBM managers seem to worry about the potential interpretation of the reported dividend yield by investors. They indicate that estimates do not reflect future actions and warn shareholders tempted to see a signaling component behind the disclosed value. Ford and Verizon use the Black and Scholes formula for non-dividend paying stock so that the FDY is missing. This is is quite intriguing since Ford and Verizon are dividend payers.

4.4 Methodology and data

4.4.1 Identifying ESO granters

To identify companies that grant ESOs and report a dividend yield in the 10-K footnotes accordingly, Compustat files are merged with Execucomp files. On the Execucomp executive compensation file, we sum the options awarded to officers (item OPTION_AWARD_FV) to obtain a total value of options granted (TOT_OPT_AW) at firm level. Then every firm-year observation is matched with the corresponding dividend yield reported (item OPTDR) from the Compustat fundamental annual file. If TOT_OPT_AW is positive while OPTDR is positive or null, the firm-year observation is categorized as an ESO granter. If TOT_OPT_AW and OPTDR and both null or missing, the firm-year observation is not an ESO granter. If TOT_OPT_AW is null and OPTDR missing, the observation is not an ESO granter. For a very small number of observations, Compustat information is not consistent with Execucomp information. These observations are deleted.

We identify 440 firm-year observations with TOT_OPT_AW > 0 and OPTDR missing and 233 observations with TOT_OPT_AW missing and OPTDR >= 0. These observations are removed. The total number of firm-year observations that are identifying as ESO granters is 7,400. Then, the dataset of ESO granters is matched with data from Compustat (firm characteristics), CRSP (common stocks vs. non-common stocks), BoardeX (board structure), I/B/E/S (analyst coverage) and Audit Analytics (audit fees). Non common stocks (ADRs, REITs) and companies operating in the financial industry are removed from the sample.

4.4.2 Predicting dividend yields and growths

To asses whether or not the FDY is useful to predict next year's dividend payment, we perform a simple regression analysis. The one-year-ahead dividend yield is regressed against FDY. We control for current dividend payment and firm characteristics:

$$\frac{DVT_{i,t+1}}{MVE_{i,t}} = \beta_0 + \beta_1 \times q^D_{i,t} + \beta_2 \times \frac{DVT_{i,t}}{MVE_{i,t}} + \sum_k \gamma_k \times X_{i,t,k} \tag{1}$$

where DVT and MVE stands for the dividend amount paid to shareholders and the market value of equity, defined as the end-of-year closing price times common shares outstanding.

q^D is the reported dividend yield in the footnote (item OPTDR divided by 100). Since q^D is a yield, we also scale dividend amounts, contemporaneous and one-year-ahead, by market value of equity. Moreover, the dividend amount paid to shareholders by two different firms might widely differ in magnitude but be close in percentage of the stock price. Hence, adjusted by the market value of equity limits the natural heteroscedasticity in data. $X_{i,t,k}$ is a set of control variables. To control for unobserved heterogeneity across years and industries, we compute two-way clustered standard errors following Gow et al. (2010).[19]

Even though dividends are remarkably persistent over time (DeAngelo et al., 2004), current dividends are not the best available predictor of next year's dividends. The Lintner (1956) model is a well-known approach for predicting future changes in dividend payments. The econometric model generates a prediction of $\Delta DVT_{i,t+1}/MVE_{i,t}$, and we assess if the FDY, adjusted for the realized dividend yield, is able to predict dividend growth, controlling with the predictions and firms characteristics. Formelly:

$$\frac{\Delta DVT_{i,t+1}}{MVE_{i,t}} = \beta_0 + \beta_1 \times \left[q^D_{i,t} - \frac{DVT_{i,t}}{MVE_{i,t}}\right] + \beta_2 \times \left(\frac{\Delta DVT_{i,t+1}}{MVE_{i,t}}\right)^{forecast} + \sum_k \gamma_k \times X_{i,t,k} \quad (2)$$

where

$$\left(\frac{\Delta DVT_{i,\tau+1}}{MVE_{i,\tau}}\right)^{forecast} = \frac{\Delta DVT_{i,\tau+1}}{MVE_{i,\tau}} - \hat{\gamma}_0 - \hat{\gamma}_1 \times \frac{NI_{i,\tau+1}}{MVE_{i,\tau}} - \hat{\gamma}_2 \times \frac{DVT_{i,\tau}}{MVE_{i,\tau'}} \quad (3)$$

(3) corresponds to the specification of Lintner (1956), used in Grullon and Michaely (2002) and Andres et al. (2015). In a first step, γ_i's are estimated by time series, for each company, between 1975 and 2005. This allows us to derive dividend growth forecasts. In a second step, the forecasts are plugged in (2) and this equation is estimated for the period 2006-2014. To rule out the possibility that the results are sensitive to the specification adopted in the first step (3), we estimate a model without intercept, as advocated by

[19] Several papers defend the superiority of this approach over panel regression with fixed effects. See Pedersen (2009), Gow et al. (2010), Cameron et al. (2011) or Thompon (2011) for mathematical details.

Babiak and Fama (1968):

$$\left(\frac{\Delta DVT_{i,\tau+1}}{MVE_{i,\tau}}\right)^{forecast} = \frac{\Delta DVT_{i,\tau+1}}{MVE_{i,\tau}} - \hat{\gamma}_1 \times \frac{NI_{i,\tau+1}}{MVE_{i,\tau}} - \hat{\gamma}_2 \times \frac{DVT_{i,\tau}}{MVE_{i,\tau'}} \qquad (4)$$

4.4.3 Report Accuracy

A new methodology is proposed to assess whether or not the FDY report is accurate or not. For each company-year observation, thirteen measures of dividend yields are computed. These measures share a common root: they all fit with the SFAS 123(r) guidelines and auditors' expectations about what should be a correct estimation. To have an idea of the different methodologies used to derive the disclosed dividend yield, we have read the relevant paragraphs in the SFAS 123 (r) report and we have analyzed the footnotes of a sample of consolidated financial statements. First, SFAS 123(r) does not provide any specific formula to use.[20] Second, the statements reported by the companies never bring sufficient information to be able to replicate the dividend yield reported. it seems that the methodology widely varies across firms. For some of them, it is based on the market price at the time of the grant.[21] For others, this is an historical average, with undefined time length. A sample of these footnote statements are reported in **Table I**.

Since an exact replication of the methodology at firm-level is impossible, we compute several yields that could be acceptable "candidates" for the regulator (FASB) and auditors. First, the Compustat fundamental quarterly file is matched with the Execucomp compensation file. A first yield is computed using the market price at the grant date, the cash dividend paid during the quarter and the last record of common share outstanding. A second yield is computed using the stock price recorded at the end of the quarter that precedes ESO grants, instead of the market price at the grant date. Because the historical pattern of dividend payment is an acceptable estimate, we also compute five additional yields: 4-, 8-, 12-, 16-, 20- quarter averages, where the last quarter of the time series is the one preceding the option grand date quarter. Second, the Execucomp compensation

[20] As mentioned by Choudhary (2011, pp. 86) "*There is no precise method of measurement specified in the authoritative guidance. The absence of a well-specified benchmark makes it difficult to detect evidence of opportunism*".

[21] For 95% of firm-year observations, this is the strike price.

file is matched with the Compustat annual fundamental and five new dividend yields are computed using end-of-fiscal year stock prices: 1-, 2-, 3-, 4-, 5- annual averages. The last computed yield is simply a lag one by one year. This procedure produces a total of thirteen measures of dividend yields, seven with quarterly data, six with annual data. We believe that these measures are viewed as acceptable regarding SFAS 123(r) guidance, auditors and analysts' scrutiny.

For some firm-year observations, options are granted at different quarters in a year. In this situation, firms produce a weighted average, or select a quarter as benchmark, ignoring the others. For instance, if ESOs are granted quarter 1 (price P_1 at the time of the grant) and quarter 2 (price P_2), the firm can derive the dividend yield to price ESOs using P_1 as a benchmark, or P_2 as a benchmark, or $w_1 \times P_1 + w_2 \times P_2$. How w_1 and w_2 are selected by firms is not observable so that we adopt a simple rule: When options are granted at different quarters in a year, we derive the first seven dividend yields presented above for each quarter, with the Compustat quarterly file. For a given firm-year observation granting ESOs, there is underreporting (overreporting) of the FDY when this value is under (above) the minimum (maximum) computed yields.

- $REPORT\_ACC = 1$ if
  $DIS\_DIV\_YLD <$
  $\min\{\min(EST\_YLD_1), ..., \min(EST\_YLD_7), EST\_YLD_8, ..., EST\_YLD_{13}\}$

- $REPORT\_ACC = 2$ if
  $\min\{\min(EST\_YLD_1), ..., \min(EST\_YLD_7), EST\_YLD_8, ..., EST\_YLD_{13}\}$
  $\leq DIS\_DIV\_YLD \leq$
  $\max\{\max(EST\_YLD_1), \max(EST\_YLD_7), EST\_YLD_8, ..., EST\_YLD_{13}\}$

- $REPORT\_ACC = 3$ if
  $DIS\_DIV\_YLD >$
  $\max\{\max(EST\_YLD_1), \max(EST\_YLD_7), EST\_YLD_8, ..., EST\_YLD_{13}\}$

For companies that grant options once time per year for all executive simultaneously, we have no yield variations across quarters so that $\min(EST\_YLD_i) = \max(EST\_YLD_i) = EST\_YLD_i$ for $i = 1, ..., 7$. $REPORT\_ACC = 1$ (3) refers to underreport (overreport) of the dividend yield while $REPORT\_ACC = 2$ defines a fair report. Our methodology requires both Compustat quarterly files and annual files to be available. These documents take sources in the 10-K and 10-Q files that are publicly available. This makes our approach replicable for auditors and analysts. The 13 dividend yield formula are provided in **Appendix A**.

To connect report accuracy to managerial opportunism, information revelation and disciplinary effect, a multinomial logit model is employed. Regarding our measure of accuracy ($REPORT\_ACC$), taking three values ($i = 1, 2, 3$), the relative probability of each outcome (1 versus 2) and (2 versus 3) is a nonlinear function of the independent variables. The two following equations are solved simultaneously:

$$\frac{P\{REPORT\_ACC = 1\}}{P\{REPORT\_ACC = 2\}} = \exp(\sum_{j=1}^{J} \beta_{12,j} \times X) \tag{5}$$

$$\frac{P\{REPORT\_ACC = 3\}}{P\{REPORT\_ACC = 2\}} = \exp(\sum_{j=1}^{J} \beta_{32,j} \times X) \tag{6}$$

where X stands for the set of explanatory variables. This is useless to estimate the last binary logit (1 versus 3) as there is a necessary relationship among the three logit.[22] Let denotes $P\{REPORT\_ACC = i \mid X, \beta_1, ..., \beta_J\}$ the probability of observing $REPORT\_ACC = i$ given X with parameters β_1 to β_J. With p_i being the probability of observing the value taken by $REPORT\_ACC$ for the nth observation. Under the assumption that the observations are independent, the likelihood equation is:

$$L(\beta_1, ..., \beta_J \mid REPORT\_ACC, X) = \prod_{n=1}^{N} p_n \tag{7}$$

The likelihood equation is

$$L(\beta_1, ..., \beta_J \mid REPORT\_ACC, X) = \prod_{i=1}^{3} \left(\prod_{REPORT\_ACC=i} \frac{\exp(\beta_i \times X)}{\sum_{j=1}^{J} \exp(\beta_j \times X)} \right) \tag{8}$$

By taking the log of L, we obtain a log likelihood equation which can be maximized to estimate the β's. Estimates are consistent, asymptotically normal and efficient. Amemiya (1985) demonstrates that, under conditions that are likely to apply, the parameter set obtained by maximum likelihood (ML) is unique.

[22] See J. Scott Long (1997).

4.4.4 Proxies

4.4.4.1 Informational incentives

We use a proxy for the forward-looking private information on (i) dividend payout decision and (ii) cash-flow stability. The first measure is the one-year-ahead growth in earning per share while the second one is the operating cash flow standard deviation over the next eight quarters minus the same measure over the last eight quarters, scaled by total assets. The last variable is used in Core et al. (1999) and Hodder et al. (2006) as a proxy for operating risk.[23] Our report accuracy metric is also connected to proxies for growth opportunities to complement the two measures of future performance presented above. The first measure is the Tobin's Q, that estimates the replacement cost of capital and is a common way to measure growth opportunities. The second measure, developed by Peters and Taylor (2016), improves the first one by including intangible capital.

4.4.4.2 Camouflage strategy

In face of shareholders and analysts scrutiny, managers have incentive to downward (upward) ESO values (footnote dividend yield) in order to hide the perceived compensation. The firm exposure is proxied by the total number of analysts producing EPS forecasts for a given company in a given year. Data are from I/B/E/S Detail History File. To measure the excessive compensation, we follow Aboody et al. (2006) by regressing the CEO total compensation over a set of relevant variables. A somewhat similar regression is presented in Yermack (1998), Core et al. (1999) and Blacconiere et al. (2011).[24]

[23] In a survey addressed to thousands of managerial team, Brav et al. (2005) find that the statement "*Payout decisions convey information about our company to investors*" is ranked 3 amongst the most important factors for dividend and repurchase policy, and "*Stability of future earnings*" is ranked 4. Brav et al.'s (2005) findings give some echoes to our proxies.

[24] Core et al. (1999) introduce variables related to CEO characteristics such as age, experience, etc. Regarding the low predictive power of CEO characteristics, our regressions are not likely to be misspecified.

4.4.4.3 Disciplinary forces

Audit fee amounts are taken by Audit Analytics dataset and adjusted by firm size.[25] The proportion of independent members on the board size is used as a proxy for corporate governance quality. An independent member is neither a member of the managerial team nor someone that has a business relationship with the company other than being on the board. The proportion of independent member is an important characteristic of board structure, negatively associated with the CEO influence and compensation (Core et al., 1999), positively related to firm transparency (Armstrong et al., 2015), working in the shareholders interest (Nguyen and Nielsen, 2010). Because 4,128 firm-year observations have a board full of independent members, we use a dummy variable that takes the value 1 if there is only independent members on the board and 0 otherwise.

4.4.4.4 Additional control variables

Option's expected life It is difficult to predict the average dividend yield over a long horizon. The longer the maturity of the option, the wider the range of possible dividend yield values. Hence, any departure from a fair report could be connected to the expected life of the option rather than managerial opportunism or a will to convey superior information. To control for this possibility, the reported option's life is added as an explanatory variable.

Number of options awarded Auditors might be more willing to check pricing methodology and parameter selection when the number of options granted is high and they may not pay attention if this number is low. We posit that the number of options granted might have an influence over the report accuracy.

[25] To be audited by a Big Four rather than another auditing firm could result in more accurate footnote information. Over the 7,404 firm-year observations in our sample, 6,873 are audited by a Big Four against 531 non audited by a Big Four. This large imbalance makes irrelevant a separation of the sample firm based on the auditing firm identity (Big Four versus non-Big Four). Big Four audit services are usually more expensive than other audit firms and if there is any influence on the report accuracy, it should be captured by audit fees.

Discretionary accruals We believe that firms that are prone to earning management would be those that can manipulate the disclosed dividend yield (and perhaps other ESO pricing inputs) by managerial opportunism. To derive discretionary accruals, we follow the approach of Khotari et al. (2005). Subrahmanyam (1996) shows that discretionary accruals predict dividend changes. Accordingly, this variable also serves as a control variable in the panel regression presented subsection 4.2. Regarding accrual data availability ($N = 2,114$), regressions are performed with and without PMDA.

Firm characteristics Size (defined as the log of total assets), book leverage (long term plus current liability over total assets) and return-on-assets (net income over total assets) are also introduced in the regression to control for the main characteristics of the firm. To avoid multicollinearity trouble, size is excluded from the regressions when the number of analysts is included.

Dummies The multinomial logit model does not allow the use of fixed effects. We introduce dummies variables for every year and every sector of activity, where the industry is defined according the first two digit codes.

See **Appendix B** for all variable definitions. A summary of information on the Lintner's (1956) regressions is given in **Appendix C.I** while information on the excessive compensation regression is provided in **Appendix C.II.**

4.4.5 Sample and summary statistics

Our sample consists of 7,404 firm-year observations that have granted ESOs in the period 2006-2014. Descriptive statistics and firm characteristics are reported in **Table II**. In the sample, many companies do not pay dividends to shareholders and set a disclosed dividend yield to zero, accordingly. The disclosed dividend yield has an average of 0.9% which is below the average dividend yield (1.3%). So companies tend to under-report the dividend yield, on average. Our sample has the following characteristics: The mean (median) Tobin's Q is at 2.01 (1.67). The total Tobin's Q is smaller on average (1.19) but above with the median (0.83). The one-year-ahead growth in dividends represents 3.5¢ by unit of shares outstanding on average. Our measure of operating risk is represents 0.045% of total assets, on average. However, this measure exhibits a large cross-sectional dispersion, with a 5% (95%) percentile at -3.87% (5.10%). In particular, the median value (-0.25%) shows that more than 50% of firms have experienced a worsening in cash-flow stability, likely driven by the financial crisis. The total number of analysts producing EPS forecasts is 13 on average. Less than 5% (5%) of our sample has 3 or less (30 or more) analysts following the stocks. The proportion of independent members is actually very high: 50% of the firm-year observations have their whole board composed with only independent members. Finally, the audit fee amount represents 0.18% of total asset on average, with the 5th (95th) percentile of 0.02% (0.53%).

Summary statistics on the report accuracy are provided in **Table III**. Our approach returns a large area under which the disclose dividend yield is fairly measured: 90.7% of the firm-year observations in our sample report a yield between the bounds. Only 4.3% underreport while 5.0% overreport. The average disclosed dividend yields are 1%, 0.8% and 2.5% for category 1, 2 and 3, respectively. Reporting a null FDY when no dividend are paid to shareholders is common in the sample and we also report the summary statistics when these observations are excluded. It turns out that the trend found in the data is not modified: 83.2% of firm-year observations report a fair an accurate estimate of the FDY based on our methodology. Only the proportion of companies overreporting is affected, switching from 5.0% to 10.6%. However, sample means move to 1.5%, 2% and 2.5% when non-dividend payers are removed from the sample. "Persistence" refers to the proportion of firms that remains in the same category over two consecutive years. On average, 35.7% (30.8%) of firms that underreport (overreport) the FDY one year underreport (overreport) the yield the next year, too. It shows that around two thirds of the observations switch between the area of fair report and the area of biased report while one third of the firms persistently state a biased report over years.

Because 90% of our sample report a FDY classified into the second category, it might be interesting to see how the report accuracy spreads within the bounds. For instance, if the majority of FDYs are concentrated inside the bounds but very close to the lower bound, it might be the sign that our categorical approach is missing something and that our report accuracy variable does not capture well the heterogeneity of reporting behaviors. On **Figure I**, the space between the lower and upper bounds is divided into ten intervals and we calculate the total number of FDY falling into a specific interval. Actually, we find no wide dispersion across the intervals, 283 firm-year FDY observations belong to the first interval, then this number decreases slowly along the intervals up to the 7th one (185) and then starts to increase again to reach 216 in the 10th category.

4.5 Results

4.5.1 Evidence from time series analysis

Table IV shows the coefficients obtained by estimating equation (1). Some firm characteristics are introduced in (3) and (4) as extra-regressors. They should capture some dispersion in the panel of one-year-ahead dividend yields. **Appendix A** provides the definitions of these variables. The FDY is positive and significant at 1% in both univariate and multivariate settings, with an estimated coefficient of 0.85, 0.62, 0.58 and 0.78 for columns 1 to 4. This is clear evidence that the FDY bring useful information to predict the next-year dividend yield. **Table IV** shows the output from several regressions of the one-year-ahead dividend growth over a predictor derived from time-series regression (DVT_HAT), various control variables and the FDY stripped of the effective dividend yield (DVT_GAP). DVT_HAT is derived using individual stock time-series. A summary table with coefficients and t-stat is provided in **Appendix C.I**. Globally, our results are similar to Grullon and Michaely (2002). We find that DVT_GAP is able to predict the dividend growth. The coefficient associated to this variable lies within 0.35 and 0.76

across specifications and is always significant at 1%. From regression (4), one can see that if the difference between the dividend amount implied by the FDY[26] and the true amount paid to shareholders increased by 8¢ per share, there will be an increase by 4.67¢ per share of the dividend amount paid to shareholders between t and $t+1$.

4.5.2 Report accuracy and forward-looking information

4.5.2.1 Private information proxy

Figure II shows variable magnitudes across report accuracy types (1, 2 or 3). Kruskal-Wallis tests for significant differences across report accuracy type are reported in **Table VI**. One can observe that the DVT_PROJ and O_RISK varies a lot across report accuracy. DVT_PROJ is low (high) for firms that overreport (0.08 for $i = 3$ against 0.01 for $i = 1$) and the differences across report types are significant at 1%. O_RISK is high (low) for firms that underreport (overreport) (-0.321 for $i = 1$ against -0.21 for $i = 2$ and -0.56 for $i = 3$). Hence, the report accuracy seems to be connected to cross-sectional variations in the one-year-ahead dividend growth and variations in the operating risk. **Table VII** shows the results of the multinomial logit regressions. There are two sets of estimates for each specification. The column denoted (a) stands for equation (5) while (b) stands for (6). We find that the coefficient associated to O_RISK is negative ($= -0.06$) and significant at 10% in 5b and keeps this significance at 5% ($= -0.10$) in 12b, when all variables are introduced simultaneously. The coefficient is not significant in the first equation of the pair regression. It shows that when the variability of future cash flow, adjusted from past fluctuations, goes down (i.e. less variability anticipated), the relative likelihood of overreporting over fair reporting goes up, and there is no influence on the relative likelihood of underreporting over fair reporting. About dividend projection (DVT_PROJ), we find that the coefficient of the pair regression is positive, while the second coefficient of the pair regression is negative. An increase of the dividend projection lower the likelihood to underreport against fair reporting but increase the likelihood of

[26] FDY multiplied by the market value of equity gives a dividend raw amount implied by the footnote information.

overreporting against fair reporting. This is consistent with the theory. However, no coefficient is significant.

4.5.2.2 Growth opportunity proxy

Companies that underreport the dividend yield seems to have a lower Tobin's Q (1.54 for $i = 1$ against 1.67 for $i = 2$, on average) while those which overreport experience more growth opportunity (1.81 for $i = 3$). The differences across report types is significant at 1%. TOT_TOBIN confirms this trend with 0.69 for $i = 1$, 0.84 for $i = 2$ and 0.96 for $i = 3$. This is significant at 1%, too. In **Table VII**, the coefficient associated to $TOBIN$ is negative and significant in 1a (= −0.32) at 1% and the TOT_TOBIN is also negative and significant in 2a (= −0.31), 5a (= −0.35) and 12a (= −0.57) at 1%. However, we find no significant coefficient in 1b, 2b, 5b and 12b. All together, these results show that when the variables reflecting proxies for private information or growth opportunity go up, the likelihood of underreporting versus fair reporting goes down and there is no effect on the overreporting likelihood.

4.5.3 Report accuracy, analyst exposure and managerial opportunism

The analysts coverage is higher among firm-year observations that bias the disclosed dividend yield (14 for $i = 1$, 11 for $i = 2$ and 16 for $i = 3$). The Kruskal-Wallis test shows that these differences are statistically different at 1%. Apparently, a wide exposure to analyst coverage does not work as a disciplinary effect. Rather, companies that bias their FDY are the ones that actually have the largest amount stock analysts. In **Table VII**, regressions 6a, 6b, 8a and 8b show positive and significant coefficients associated to $COVE$, lying between 0.02 and 0.06. However, 13b show a non-significant coefficient (= −0.01). When all variables are introduced in the regression, the relationship between analyst coverage and the relative likelihood of overreporting against fair reporting vanished. In addition, one can observe that the coefficients in equations 6a, 8a and 12a are larger in magnitude than coefficients in equations 6b, 8b and 12b, respectively. Overal, these results suggest that exposure to analyst's scrutiny works as an incentive in favor of downward FDY manipulation. An underlying explanation could be that the fear that analysts interpret the DFY as an implied commitment forces the managerial team to be prudent and to report a low dividend yield.

A summary of CEO compensation regression is provided in **Appendix C.II.** The coefficients, in sign and magnitude, are in line with what has been found in previous researches. A stock-year excessive compensation measure is built with the residuals of this regression. Hypothesis 2 states that if the compensation of the CEO is excessive, the dividend yield should be overreported by executives that seek to hide ESO values. However, we find no evidence that favors such behavior. In **Table VI**, The Kruskal-Wallis returns a p-value at 0.31, showing that one cannot reject the null hypothesis that sample medians are not statistically different. In Table VIII, the coefficient associated to EXC_REM in 7a ($= -0.26$) and 8a ($= -0.54$) are significant at 5% and the one in 7b ($= -0.22$) is significant at 10%. However, the significance completely disappears in 12a and 12b. The interaction term COV_DHF times EXC_REM is only significant in 8b ($= -0.025$). The coefficients linking EXC_REM to $REPORT\_ACC$ in 7a, 8a and 12a are greater in magnitude than the ones in 7b, 8b and 12b, suggesting a larger impact of EXC_REM on the relative likelihood of underreport over fair report than on the relative likelihood of overreport over fair report. But no coefficient turns out to be significant. Hypothesis 2 does not hold in data.

4.5.4 Report accuracy and disciplinary mechanisms

Companies that report a fair dividend yield have a board full of independent directors, in median. For the observations that underreport or overreport, the median is around 0.9. This difference is significant at 1%. **Table VII** shows coefficients significant at 99% confidence level in 9a ($= -1.71$) , 11a ($= -1.80$) and 12a ($= -2.59$) and non significant in 9b ($= -0.06$), 11b ($= -0.03$) and 12b ($= -0.27$). Hence, the proportion of independent members of the board is clearly connected to the likelihood of underreporting but not overreporting. It shows that firms characterized by a weaker corporate governance have a greater risk of reporting a FDY downwardly bias. In terms of economical magnitude, result from 12a shows that when there is one more independent member on the board, the probability of being in category 2 (fair report) compared to being in category 1 (underreport) increases by around 0.08% ($\approx \exp(-2.58)$).

Consistent with hypothesis 4, the amount of audit fees is larger for observations that report a fair FDY with respect that observations that do not. The median audit fee amount is 0.07% of total assets for $i = 1$, 0.12% for $i = 2$ and 0.06% for $i = 3$. These differences are statistically different at 1%. For the regression part, we obtain that the coefficients from 10a to 11b have the negative sign as expected, but are not significant. However, in 12b, this is large ($= -5.93$) and significant at 1%. An increase in total audit fees decreases the relative likelihood of overreporting over report fairly. Like the corporate governance quality proxy, the variable reflecting audit process cost influences downwardly the likelihood of biased report. However, while the proportion of independent is connected to underreporting, the audit fee amount is connected to overreporting.

4.6 Conclusion

In this paper, we analyze the reporting accuracy of the dividend yield reported in the 10-K financial statements footnotes. Three mechanisms are proposed to explain why the FDY can deviate from a range of acceptable values determined regarding the FASB guidance. The *information revelation hypothesis* establishes a positive link between private information on ex-post performance and the FDY as well as a positive link between ex-ante growth opportunities and the FDY. The *managerial opportunism hypothesis* states that biasing the FDY should be connected to coverage and CEO excessive compensation. The *disciplinary effect hypothesis* posits that the likelihood of reporting a fair FDY is connected to the audit quality and to the corporate governance quality. We propose a new methodology to identify underreport, fair report and overreport. This method is based on public information, the financial statements 10-K and 10-Q, and can be easily replicated. Our method accommodates well the flexibility given by the authoritative guidance, as more than 90% of our firm-year observation sample report a DFY that classified as fair.

First, underreporting is negatively associated with a proxy for operating risk and two proxies for growth opportunities. Moreover, variation in the operating risk is able to explain the relative likelihood of overreporting against fair report. This is consistent with the idea that some firms use discretion over footnotes to convey superior information about future cash flow variability and the quality of future prospects. This result contrasts with Choudhary (2011) that rejects the information revelation hypothesis. Second, underreporting is significantly connected to the magnitude of analysts' coverage but not connected to the excessiveness of executive compensation. Third, more independent directors on the board are associated to less underreport while an expensive audit process is associated to less overreport. All together, our findings suggest that information revelation objective and disciplinary effects are all in our firm-year panel, and influences the relative likelihood of underreporting over a fair report of the FDY. The managerial opportunism hypothesis receives mitigated evidence.

4.7 References

[1] Aboody, D., Barth, M., Kasnik, R., 2003, "Firms' voluntary recognition of stock-based compensation expense", Journal of Accounting Research, Vol. 42, pp. 123-150

[2] Aboody, D., Barth, M., Kasznik, R., 2006, "Do firms understate stock option-based compensation disclosed under SFAS 123?", Review of Accounting Studies, Vol. 11, pp. 429-461

[3] Amemiya, T., 1985, "Advanced Econometrics", Cambrige, Harvard University Press

[4] Andres, C., Doumet, M., Fernau, E., Theissen, E., 2015, "The Lintner model revisited: Dividends versus total payouts", Journal of Banking and Finance, Vol. 55, pp. 56-69

[5] Armstrong, C., Core, J., Guay, W., 2014, "Do independent directors cause improvements in firm transparency?", Vol. 113, pp. 383-403

[6] Babiak, H., Fama, E., 1968, "Dividend policy: An empirical analysis", Journal of the American Statistical Association, Vol. 63, pp. 1132-1161

[7] Baker, T., 1999, "Options reporting and the political costs of CEO pay", Journal of Accounting, Auditing and Finance, Vol. 14, pp. 125-145

[8] Bartov, E., Mohanram, P., Nissim, D., 2007, "Managerial discretion and the economic determinants of the disclosed volatility parameter for valuing ESOs", Review of Accounting Studies, Vol. 12, pp. 155-179

[9] Bebchuk, L., Fried, J., 2004, "Pay without performance: The unfulfilled promise of executive compensation", Harvard University Press

[10] Bechmann, K., Hjortshoj, T., 2009, "Disclosed values of option-based compensation: Incompetence, deliberate underreporting or the use of expected option life?", European Accounting Review, Vol. 18, No. 3, pp. 475-513

[11] Becker, C., Defond, M., Jiambalvo, J., Subramanyam, K., 1998, "The effect of audit quality on earnings management", Contemporary Accounting Research, Vol. 15, pp. 1-24

[12] Bhattacharya, S., 1979, "Imperfect information, dividend policy, and "the bird in the hand" fallacy", Bell Journal of Economics, Vol. 10, pp. 259-270

[13] Blacconiere, W., Frederickson, J., Johnson, M., Lewis, M., 2011, "Are voluntary disclosures that disavow the reliability of mandated fair value information informative or opportunistic?", Journal of Accounting and Economics, Vol. 52, pp. 235-251

[14] Black, F., Scholes, M., 1973, "The pricing of options and corporate liabilities", Journal of Political Economy, Vol. 81, No. 3, pp. 637-654

[15] Bratten, B., Jennings, R., Schwab, C., 2016, "The accuracy of disclosures for complex estimates: Evidence from reported stock option fair values", Accounting, Organizations and Society, Vol. 52, pp. 32-49

[16] Cameron, C., Gelbach, J., Miller, D., 2011, "Robust inference with multiway clustering", Journal of Business and Economic Statistics, Vol. 29, pp. 238-249

[17] Choudhary, P., Rajgopal, S., Venkatachalam, M., 2007, « Accelerated vesting of employee stock options in anticipation of FAS 123-R », Journal of Accounting Research, Vol. 47, No. 1, pp. 105-146

[18] Choudhary, P., 2011, "Evidence on differences between recognition and disclosure: A comparison of inputs to estimate fair values of employee stock options", Journal of Accounting and Economics, Vol. 51, pp. 77-94

[19] Core, J., Holthausen, R., Larcker, D., 1999, "Corporate governance, chief executive office compensation, and firm performance", 1999, Journal of Financial Economics, Vol. 51, pp. 371-406

[20] Core, J., Guay, W., Larcker, D., 2008, "The power of the pen and executive compensation", Journal of Financial Economics, Vol. 88, pp. 1-25

[21] DeAngelo, H., DeAngelo, L., Skinner, D., 2004, "Are dividends disappearing? Dividends concentration and the consolidation of earnings", Vol. 72, pp. 425-456

[22] Fields, T., Lys, T., Vincent, L., 2001, "Empirical research on accounting choice", Journal of Accounting and Economics, Vol. 31, pp. 255-307

[23] Financial Accounting Standard Board, 2004, "Statement of financial accounting standards No. 123 (revised 2004)"

[24] Gaver, J., Gaver, K., Austin, J., 1995, "Additional evidence on bonus plans and income management, Journal of Accounting and Economics, Vol. 19, pp. 3-28

[25] Gow, I., Ormazabal, G., Taylor, D., 2010, "Correcting for cross-sectional and time-series dependence in accounting research", Accounting Review, Vol. 85, pp. 483-512

[26] Grullon, G., Michaely, R., 2002, "Dividends, share repurchase, and the substitution hypothesis", Journal of Finance, Vol. 57, pp. 1649-1684

[27] Guidry, F., Leone, A., Rock, S., 1999, "Earnings-based bonus plans and earnings management by business-unit managers", Journal of Accounting and Economics, Vol. 26, pp. 113-142

[28] Hayes, R., Lemmon, M., Qiu, M., 2012, "Stock options and managerial incentives for risk taking: Evidence from SFAS 123R", Journal of Financial Economics, Vol. 105, pp. 174-190

[29] Healy, P., 1985, "The effect of bonus schemes on accounting decisions", Journal of Accounting and Economics, Vol. 7, pp. 85-107

[30] Hirshleifer, D., Teoh, S., 2003, "Limited attention, information disclosure, and financial reporting", Journal of Accounting and Economics, Vol. 36, pp. 337-386

[31] Hodder, L., Mayew, W., McAnally, M., Weaver, C., 2006, "Employee stock option fair-value estimates: Do managerial discretion and incentives explain accuracy?", Contemporary Accounting Research, Vol. 23, No. 4, pp. 933-975

[32] Holthausen, R., Larcker, D., Sloan, R., 1995, "Annual bonus schemes and the manipulation of earnings", Journal of Accounting and Economics, Vol. 19, pp. 29-74

[33] Ikäheimo, S., Kuosa, N., Puttonen, V., 2006, "The true and fair view of executive stock option valuation", European Accounting Review, Vol. 15, No. 3, pp. 351-366

[34] Jensen, M., Murphy, K., 1990, "Performance pay and top-management incentives", Journal of Political Economy, Vol. 98, pp. 225-264

[35] Johnston, D., 2006, "Managing stock option expense: The manipulation of option-pricing model assumptions", Contemporary Accounting Research, Vol. 23, pp. 395-425

[36] Kothari, S., Leone, A., Wasley, C., 2005, "Performance matched discretionary accrual measures", Journal of Accounting and Economics, Vol. 39, pp. 136-197

[37] Kuhnen, C., Niessen, A., 2012, "Public opinion and executive compensation", Management Science, Vol. 58, pp. 1249-1272

[38] Lintner, J., 1956, "Distribution of incomes of corporations among dividends, retained earnings, and taxes", American Economic Review, Vol. 46, pp. 97-113

[39] Murphy, K., 1999, "Chapter 38 Executive Compensation", Handbook of Labor Economics, Vol. 3, pp. 2485-2563

[40] Nguyen, B., Nielsen, K., 2010, "The value of independent directors: Evidence from sudden deaths", Vol. 98, pp. 550-567

[41] Peters, R., Taylor L., 2016, "Intangible capital and the investment-q relation", Journal of Financial Economics, Forthcoming

[42] Petersen, M., 2009, "Estimating standard errors in financial panel data sets: Comparing approaches", Review of Financial Studies, Vol. 22, pp. 435-480

[43] Rees, L., Gill, S., Gore, R., 1996, "An investigation of asset write-downs and concurrent abnormal accruals", Journal of Accounting Research, Vol. 34, pp. 157-169

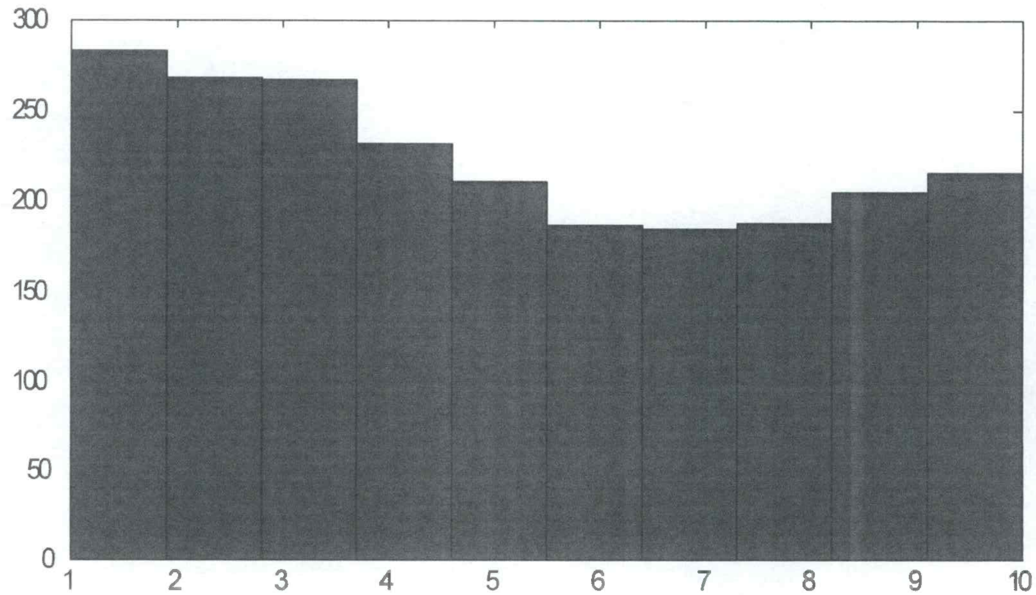
[44] Thompson, S., 2011, "Simple formulas for standard errors that cluster by both firm and time", Journal of Financial Economics, Vol. 99, pp. 1-10

[45] Yermack, D., 1998, "Companies' modest claims about the value of CEO stock option awards", Review of Quantitative Finance and Accounting, Vol. 10, pp. 207-226

[46] Weisbach, M., 2007, "Optimal executive compensation versus managerial power: A review of Lucian Bebchuk and Jesse Fried's pay without performance: The unfulfilled promise of executive compensation", Journal of Economic Literature, Vol. 45, pp. 419-428

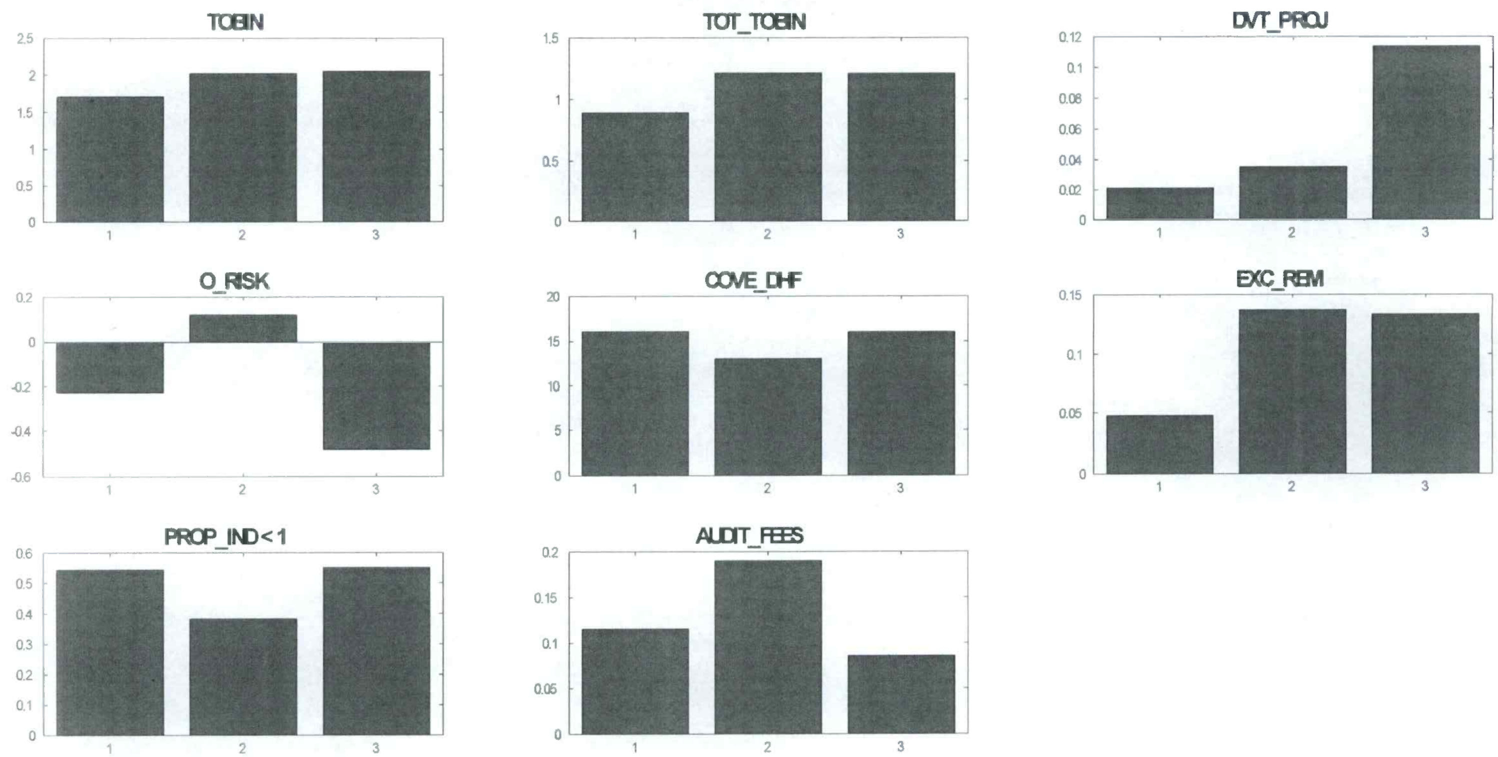
4.8 Figures

Figure I: Distribution of report accuracy within the fair report category



For each firm-year observation of our sample, the footnote dividend yield is classified to be underreported, fairly reported or overreported. See Appendix A for methodological details. This histogram provides a focus on the companies that report a fair FDY. It shows the distribution of the report accuracy within the fair report ($i = 2$) area. We proceed as follows: For each company-year observation, the distance between the low bound and the high bound is split into 10 intervals equally sized. This is the x-axis. The y-axis gives the count of footnote dividend yields per interval. Companies with no dividend policy are excluded (low bound = 0) to avoid a leverage effect of the first decile in the graph.

Figure II: Sample means by report accuracy level



For each firm-year observation of our sample, the footnote dividend yield is classified to be underreported (=1 in the x-axis), fairly reported (=2) or overreported (=3). See Appendix A for methodological details. Each figure indicates the average of a specific variable by report accuracy level. Variables are defined Appendix B. "PROP_IND<1" stands for the proportion of firms whose the board is not full of independent members.

4.9 Tables

Table I: Sample of footnotes

Company Name	Rank	ESO grants	Dividend input rate	Note number	Pricing Method	Comments
Altria	17	No	3.99%	Note 13	B-S	Empty[2]
AT&T	1	Yes	6,61%	Note 12	B-S	Empty[2]
Abbott Laboratories	19	Yes	3,20%	Note 8	B-S	"Dividend yield is based on the option's exercise price and annual dividend rate at the time of grant."
Bristol-Myers	21	Yes	5,80%	Note 22	B-S	"Expected dividend yield is based on historical dividend payments."
Chevron	8	Yes	3,90%	Note 20	B-S	Empty[1]
Coca-Cola	7	Yes	2,90%	Note 12	B-S	"The dividend yield is the calculated yield on the Company's stock at the time of the grant."
ConocoPhilips	16	Yes	4.00%	Note 19	B-S	Empty[1]
Eli Lilly	22	Yes	4,50%	Note 9	M-C	"Similarly, the dividend yield is based on historical experience and our estimate of future dividend yields."
ExxonMobil	15	No	N.A.	N.A	N.A	Empty[2]
General Electric	6	Yes	3,90%	Note 16	B-S	"Expected dividend yields presume a set dividend rate. For stock options granted in 2010, 2009 and the fourth quarter of 2008, we used a historical five-year average for the dividend yield."
Home Depot	25	Yes	3.90%	SSAP	B-S	Empty[2]
IBM	11	No	N.A.	Note T	B-S	"Estimates of fair value are not intended to predict actual future events or the value ultimately realized by employees who receive equity awards, and subsequent events are not indicative of the reasonableness of the original estimates of fair value made by the company."

In the footnotes of the consolidated financial statement (10-K), the disclosure of input values for ESO pricing (dividend yield, volatility rate, option's life and risk-free rate) is often accompanied with sentences that provide additional details about each inputs. For instance, if the company adopts a historical avèrage to defined the disclosed dividend yield, the window length or data type (quarter or year) may be given in these statements. We select the 25 largest dividend payers among public companies in 2010 and report the sentences that inform about the way the dividend yield is derived. "ESO grants" indicates if the company has granted stock options to employee or executive through the fiscal year 2010. "Rank" refers to the rank in terms of cash dividend amounts paid to shareholders For Ford and Verizon, A Black and Scholes (1973) formula on a non dividend-paying stock has been adopted as the pricing methodology, although these companies pay dividends to shareholders. For Johnson and Johnson, "SC Table" and "SSAP" stands for Summary compensation table and Summary of Significant Accounting Policy, respectively. In column (4), "B-S" refers to the Black and Scholes (1973) valuation formula, as advised by the FASB in the SFAS 123(R). "MC" stands for Monte-Carlo simulation.

[1]: There is no sentence about the dividend yield input.

[2]: There is no sentence regarding inputs at all.

Table I (continued)

Company Name	Rank	ESO grants	Dividend input rate	Note number	Pricing Method	Comments
Intel	5	Yes	2,60%	Note 24	B-S	Empty[2]
Johnson and Johnson	4	Yes	3,30%	SC Table	B-S	Empty[2]
Kraft Foods	23	Yes	4.14%	Note 10	B-S	"Dividend yield is estimated over the expected life of the options based on our stated dividend policy."
McDonald's	20	Yes	3.50%	SSAP Table	B-S	"The expected dividend yield is based on the company's most recent annual dividend payout."
Merck & Co.	3	Yes	4,10%	Note 14	B-S	"The expected dividend yield is based on historical patterns of dividend payments."
Microsoft	10	Yes	N.A	Note 20	N.A	Empty[2]
Pepsico	18	Yes	2.80%	Note 6	B-S	"Dividend yield is estimated over the expected life based on our stated dividend policy and forecasts of net income, share repurchases and stock price."
Pfizer	14	Yes	4,00%	Note 15	B-S	"Determined using a constant dividend yield during the expected term of the option."
Philip Morris	9	No	4.07%	Note 9	B-S	Empty[2]
Procter and Gamble	2	Yes	2,20%	Note 7	Lattice	Empty[1]
UPS	24	Yes	2.70%	Note 10		"The expected dividend yield is based on the recent historical dividend yields for our stock, taking into account changes in dividend policy."
Wal-Mart	13	Yes	2,10%	Note 10	B-S	"The expected dividend yield over the vesting period is based on the expected dividend yield rate over the life of the grant."

Table II: Descriptive statistics

Variable	N	Mean	Std. Dev.	Percentile				
				5%	25%	50%	75%	95%
Dividend yields reported and effective								
DIS_DIV_YLD	7400	0.009	0.013	0.000	0.000	0.000	0.017	0.036
DIV_YLD	7400	0.013	0.040	0.000	0.000	0.001	0.017	0.041
Variables used to test the hypothesis 1 (Informational objective)								
TOBIN	7400	2.005	1.127	0.951	1.289	1.666	2.326	4.328
TOT_TOBIN	7400	1.193	1.330	0.025	0.478	0.833	1.436	3.557
DIV_PROJ	7400	0.035	0.743	-0.073	0.000	0.000	0.048	0.277
O_RISK	7400	0.046	3.221	-3.869	-1.557	-0.245	0.954	5.106
Variables used to test the hypotheses 2a, 2b and 2c (Managerial objective)								
COVE	7400	13.170	8.303	3.000	7.000	11.000	18.000	30.000
EXC_REM	7400	0.125	0.596	-0.852	-0.181	0.145	0.452	1.075
Variables used to test the hypotheses 3 and 4 (Disiplinary objective)								
P_IND	7400	0.929	0.104	0.714	0.889	1.000	1.000	1.000
AUDIT_FEES	7400	0.183	0.251	0.022	0.057	0.116	0.219	0.531

This table provides some descriptive statistics for the main variables that are connected to the report accuracy of the footnote dividend yield. Our sample spans all companies over 1996-2014 observations that grant stock options to their executives. These variables are winsorized at 2.5% and 97.5%. See **Appendix B** for variable definitions.

Table III: Report type statistics

	All observations			$DIS\_DVT\_YLD > 0$		
$REPORT\_ACC$	N	%	DIS_DVT_YLD	N	%	DIS_DVT_YLD
Underreport ($i = 1$)	278	0.043	0.010	185	0.062	0.015
Fair report ($i = 2$)	5,831	0.907	0.008	2,496	0.832	0.020
Overreport ($i = 3$)	319	0.050	0.025	319	0.106	0.025
Bounds	Mean			Mean		
Low bound	0.006			0.013		
High bound	0.027			0.035		
High - Low	0.021			0.022		
Persistence ($i = 1$)	0.357			0.242		
Persistence ($i = 2$)	0.776			0.734		
Persistence ($i = 3$)	0.308			0.308		

For each firm-year observation, the 10-K footnote disclosed dividend yield (DIS_DVT_YLD) is compared to 13 yields that could serve as acceptable values by auditors or analysts, regarding the guidelines provided by SFAS 123(r). We generate a categorical variable ($i = 1, 2, 3$) that captures the report accuracy: If the disclosed dividend yield is strictly below the minimum (low bound) of the computed yields, then the company underreports ($i = 1$). If this is between the minimum and the maximum, the company fairly reports ($i = 2$). If this is strictly above the maximum (high bound), then the company overreports ($i = 3$). See Appendix A for the methodological details. This table presents some descriptive statistics are reported for this variable and the bounds. Unreported statistics show that there is no statistically significant differences across years or industries in $REPORT\_ACC$. "Persistence" refers to the average proportion of firms that remains in the same category over two consecutive years. "All observations" includes ESO providers that disclose a null dividend yield, while "$DIS\_DVT\_YLD > 0$" excludes these firm-year observations.

Table IV: One–year-ahead dividend yield

	DIV_YLD			
	(1)	(2)	(3)	(4)
INTERCEPT	0.005***	0.004***	0.005***	0.002
	(0.001)	(0.001)	(0.001)	(0.003)
DIS_DIV_YLD	0.850***	0.618***	0.579***	0.782***
	(0.041)	(0.161)	(0.145)	(0.060)
DIV_YLD		0.262*	0.295**	0.060*
		(0.142)	(0.127)	(0.035)
LEV			-0.001	0.008
			(0.003)	(0.006)
TOBIN			-0.000	-0.002***
			(0.001)	(0.001)
ROA			-0.007	0.014
			(0.006)	(0.012)
OCF_STD			0.010	0.059*
			(0.013)	(0.035)
RD_ASSET			-0.017***	0.003
			(0.006)	(0.003)
PFDA				-0.006
				(0.005)
N	6492	6492	5922	2113
Adjusted R^2	0.137	0.257	0.280	0.253

The one-year-ahead dividend payment (DIV_YLD_A) is regressed over the dividend yield reported in the financial statement footnotes (DIS_DIV_YLD) plus a set of control variables. The contemporaneous and one-year-ahead dividend amounts are scaled by market capitalization. See Appendix B for variable definitions. The sample is made with companies that have a dividend payout policy ($DVT > 0$) and that grant stock options to executives. Company-year observations with option-based award plans are identified as follows: From the Execucomp table, we identify a firm as ESO granters if the total value of options granted across executive is non-null. Then, the 10-K disclosed dividend yield is retrieved from the Compustat table. It must be either positive or null, but not blank. See Section III for a description of the methodology. The period of analysis is 2006-2014, i.e. post-SFAS 123(r). Standard errors are clustered by firm and industry, where industry is defined with two-digit SIC codes. All industries are covered except the sector "Finance, Insurance & Real Estate".

* Significance at the 10% level

** Significance at the 5% level

*** Significance at the 1% level

Table V: One-year-ahead dividend growth

	DVT_GROWTH						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
INTERCEPT	0.003***	0.001***	0.001***	0.003	0.003	0.000	-0.001
	(0.001)	(0.000)	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)
DVT_GAP	0.756***	0.348***	0.384***	0.584***	0.602***	0.372***	0.384***
	(0.138)	(0.079)	(0.063)	(0.078)	(0.078)	(0.049)	(0.065)
DVT_HAT		0.136***		0.064**		0.706**	
		(0.028)		(0.025)		(0.306)	
DVT_HAT_M			0.080***		0.015		0.753**
			(0.020)		(0.016)		(0.322)
LEV				0.002	0.002	0.001	-0.001
				(0.003)	(0.003)	(0.003)	(0.003)
TOBIN				-0.003***	-0.004***	-0.001	-0.000
				(0.001)	(0.001)	(0.001)	(0.000)
ROA				0.044***	0.053***	0.013	0.009
				(0.012)	(0.014)	(0.011)	(0.011)
OCF_STD				0.042	0.037	-0.006	0.012
				(0.031)	(0.029)	(0.009)	(0.016)
RD_ASSET				-0.022	-0.022	-0.001	0.002
				(0.016)	(0.016)	(0.010)	(0.014)
ACCRUALS						-0.003	-0.004***
						(0.002)	(0.001)
N	8090	1933	1933	1785	1785	813	813
Adjusted R^2	0.565	0.211	0.192	0.347	0.342	0.285	0.264

The one-year-ahead dividend change is regressed over the footnote dividend yield (FDY) minus the realized dividend yield (*DIS_DIV_GAP*), a dividend growth forecast derived following the Lintner's model (1956) (*DIV_HAT*) and a set of control variables. Variables are scaled by market capitalization. This adjustment reduces heteroscedasticity in data. See Appendix B for variable definitions. The sample is made with companies that were dividend payers over 1975-2014 and that grant stock options to executives over 2006-2014. The Lintner's model is estimated with the time-series of dividend payment over 1975-2005. Then, a projection of the dividend growth is derived for 2006-2014, given the beta estimated from the time-series regressions. This "best" dividend growth forecast is plugged into our panel regression. Company-year observations with option-based award plans are identified as follows: From the Execucomp table, we identify a firm as ESO granters if the total value of options granted across executive is non-null. Then, the 10-K disclosed dividend yield is retrieved from the Compustat table. It must be either positive or null, but not blank. See Section III for a description of the methodology. The period of analysis is 2006-2014, i.e. post-SFAS 123(r). All industries are covered except the sector "Finance, Insurance & Real Estate". Standard errors are clustered by firm and industry, where industry is defined with the two-digit SIC code.

* Significance at the 10% level

** Significance at the 5% level

*** Significance at the 1% level

Table VI: Non parametric tests

	N			Median			Kruskal-Wallis test
	$i=1$	$i=2$	$i=3$	$i=1$	$i=2$	$i=3$	P-value
TOBIN	247	5407	296	1.545	1.665	1.809	0.000
TOT_TOBIN	276	5820	318	0.689	0.835	0.960	0.000
DVT_PROJ	248	5137	274	0.010	0.000	0.083	0.000
O_RISK	270	5591	312	-0.308	-0.214	-0.563	0.007
COVE	245	4945	288	14.000	11.000	16.000	0.000
EXC_REM	196	4242	267	0.111	0.154	0.147	0.311
PROP_IND	267	5594	314	0.917	1.000	0.926	0.000
AUDIT_FEES	256	5379	302	0.071	0.120	0.058	0.000

For each firm-year observation, the disclosed dividend yield is compared to 13 yields that could serve as acceptable values by auditors or analysts, regarding the guidelines provided by SFAS 123(r). We generate a categorical variable ($i = 1, 2, 3$) that captures the report accuracy: If the disclosed dividend yield is strictly below the minimum (low bound) of the computed yields, then the company underreports ($i = 1$). If this is between the minimum and the maximum, the company fairly reports ($i = 2$). If this is strictly above the maximum (high bound), then the company overreports ($i = 3$). See Appendix A for methodological details. This table gives the sample median of our main variables, per report accuracy level. Variables are defined Appendix B. The p-value of the Kruskal-Wallis test is reported over the last column. Under the null hypothesis, the three sample median are equals. Kruskal-Wallis is less affected than the classical ANOVA by changes in a small portion of the data. It is more robust to any leverage effects induced by fat tails.

* Significance at the 10% level

** Significance at the 5% level

*** Significance at the 1% level

Table VII: Multinomial logistic regression

Variable	Predictice Sign	1a	1b	2a	2b	3a	3b	4a	4b
		Dependent variable: *REPORT_ACC*							
TOBIN	-	-0.323*** (0.103)	-0.056 (0.082)						
TOT_TOBIN	-			-0.306*** (0.089)	-0.090 (0.063)				
O_RISK	+					-0.306*** (0.089)	-0.090 (0.063)		
DVT_PROJ	-							-0.043 (0.082)	0.069 (0.082)
COVE	-								
EXC_REM	-								
COVE × *EXC_REM*	?								
PROP_IND	-								
AUDIT_FEES	-								

Above are reported the results of multinomial logit regressions for various specifications. The dependent variable is based on the categorical variable *REPORT_ACC* that returns the accuracy level of the footnote dividend yield. $REPORT\_ACC = 1$ refers to firm-year observations (N_1) for which the FDY is bias downwardly, $REPORT\_ACC = 2$ refers to observations (N_2) for which the report is consistent with the flexibility given by authoritative guidance. $REPORT\_ACC = 3$ refers to observations (N_3) that bias upwardly the yield. See **Appendix A** for methodological details. Each model has two equations estimated. In (a), the dependent variable is the relative likelihood of an underreport of the FDY versus a fair report, that is $P\{REPORT\_ACC = 1\}/P\{REPORT\_ACC = 2\}$. In (b), the dependent variable is the likelihood of an overreport of the FDY versus a fair report, that is $P\{REPORT\_ACC = 3\}/P\{REPORT\_ACC = 2\}$. All variables are defined **Appendix B**. The intercepts are not reported for space purpose and an underlying dispersion parameter set to one is assumed in all regressions. Unreported statistics show that the dispersion parameter takes values closed to one once it is set free.

* Significance at the 10% level

** Significance at the 5% level

*** Significance at the 1% level

Table VII (Continued)

Dependent variable: *REPORT_ACC*

Variable	Predictice Sign	1a	1b	2a	2b	3a	3b	4a	4b
SIZE	-	0.452***	0.602***	0.412***	0.604***	0.411***	0.599***	0.433***	0.601***
		(0.052)	(0.049)	(0.049)	(0.048)	(0.050)	(0.049)	(0.051)	(0.051)
LEV	+	1.081***	-0.290	0.950**	-0.216	0.943***	-0.158	1.099***	-0.016
		(0.394)	(0.405)	(0.370)	(0.392)	(0.360)	(0.393)	(0.375)	(0.415)
ROA	-	0.325	5.882***	0.091	5.402***	-0.868	5.315***	-0.683	5.297***
		(0.873)	(1.393)	(0.773)	(1.283)	(0.663)	(1.179)	(0.688)	(1.218)
FCF_STD	+	0.087***	0.023	0.061**	0.018	0.041	-0.011	0.056*	0.013
		(0.031)	(0.036)	(0.028)	(0.034)	(0.029)	(0.037)	(0.029)	(0.036)
NB_OPT_AW	?	-0.250***	-0.157**	-0.206***	-0.163***	-0.228***	-0.165***	-0.214***	-0.116*
		(0.063)	(0.063)	(0.060)	(0.062)	(0.060)	(0.063)	(0.063)	(0.066)
OPTLIFE	?	0.088	0.254***	0.122**	0.267***	0.107*	0.269***	0.086	0.271***
		(0.058)	(0.055)	(0.055)	(0.053)	(0.056)	(0.053)	(0.058)	(0.057)
	?								
N_bias		245	291	274	313	270	308	270	308
N_unbias		5354		5766		5555		5555	

Table VII (Continued)

Dependent variable: *REPORT_ACC*

	5a	5b	6a	6b	7a	7b	8a	8b
TOBIN								
TOT_TOBIN	-0.350***	-0.058						
	(0.099)	(0.068)						
O_RISK	0.004	-0.062*						
	(0.027)	(0.034)						
DVT_PROJ	-0.046	0.065						
	(0.083)	(0.081)						
COVE			0.042***	0.022***			0.056***	0.023***
			(0.008)	(0.008)			(0.009)	(0.009)
EXC_REM					-0.264**	-0.220*	-0.535**	0.190
					(0.127)	(0.112)	(0.263)	(0.235)
COVE × *EXC_REM*							0.017	-0.025**
							(0.013)	(0.012)
PROP_IND								
AUDIT_FEES								
SIZE	0.411***	0.583***			1.620***	0.311		
	(0.053)	(0.052)			(0.396)	(0.373)		
LEV	1.157***	0.002	1.385***	0.356	1.705	4.936***	1.775***	0.197
	(0.391)	(0.419)	(0.348)	(0.350)	(1.696)	(1.433)	(0.428)	(0.396)
ROA	0.737	6.073***	-0.097	5.351***	-0.049	-0.072*	1.192	4.955***
	(0.870)	(1.399)	(0.689)	(1.066)	(0.042)	(0.037)	(1.906)	(1.561)
FCF_STD	0.073**	-0.003	-0.019	-0.082**	-0.010	0.341***	-0.053	-0.066
	(0.031)	(0.038)	(0.029)	(0.034)	(0.070)	(0.062)	(0.047)	(0.040)
NB_OPT_AW	-0.204***	-0.110	-0.052	0.203***	0.180***	0.360***	-0.131*	0.299***
	(0.067)	(0.068)	(0.065)	(0.062)	(0.062)	(0.055)	(0.078)	(0.072)
OPTLIFE	0.101*	0.275***	0.206***	0.389***	0.023	-0.275	0.206***	0.366***
	(0.059)	(0.057)	(0.057)	(0.052)	(0.304)	(0.258)	(0.066)	(0.058)
N_bias	244	270	244	284	196	263	176	238
N_unbias	5081		4902		4211		3668	

Table VII (Continued)

Dependent variable: *REPORT_ACC*

	9a	9b	10a	10b	11a	11b	12a	12b
TOBIN								
TOT_TOBIN							-0.573***	-0.118
							(0.143)	(0.081)
O_RISK							-0.056	-0.100**
							(0.046)	(0.042)
DVT_PROJ							0.050	0.123
							(0.143)	(0.112)
COVE							0.054***	-0.011
							(0.011)	(0.011)
EXC_REM							-0.322	0.238
							(0.304)	(0.281)
COVE ×							0.013	-0.024*
EXC_REM							(0.015)	(0.014)
PROP_IND	-1.705***	-0.055			-1.797***	-0.033	-2.244***	0.019
	(0.534)	(0.588)			(0.546)	(0.599)	(0.724)	(0.753)
AUDIT_FEES			-0.202	0.190	0.131	0.117	-0.300	-5.932***
			(0.577)	(0.687)	(0.434)	(0.707)	(0.905)	(1.316)
SIZE	0.427***	0.627***	0.494***	0.621***	0.446***	0.622***	2.325***	-0.378
	(0.050)	(0.049)	(0.061)	(0.060)	(0.056)	(0.060)	(0.488)	(0.492)
LEV	0.657*	-0.248	0.969**	-0.361	0.786**	-0.276	6.197***	7.315***
	(0.365)	(0.392)	(0.403)	(0.418)	(0.375)	(0.403)	(2.263)	(2.003)
ROA	-0.968	4.732***	-0.584	5.829***	-0.921	5.010***	-0.040	-0.034
	(0.672)	(1.138)	(0.794)	(1.221)	(0.704)	(1.165)	(0.053)	(0.047)
FCF_STD	0.050*	0.017	0.074**	0.022	0.061**	0.019	-0.167*	0.318***
	(0.028)	(0.034)	(0.031)	(0.036)	(0.029)	(0.035)	(0.086)	(0.082)
NB_OPT_AW	-0.237***	-0.185***	-0.273***	-0.179***	-0.221***	-0.184***	0.146**	0.336***
	(0.060)	(0.062)	(0.065)	(0.065)	(0.062)	(0.064)	(0.072)	(0.064)
OPTLIFE	0.092	0.250***	0.066	0.239***	0.082	0.245***	-0.130	-0.331
	(0.056)	(0.054)	(0.061)	(0.057)	(0.058)	(0.055)	(0.362)	(0.292)
N_bias	265	309	245	291	250	298	150	195
N_unbias	5542		5354		5220		2966	

4.10 Appendix

4.10.1 Appendix A: Report accuracy definition

Table A.I: Methodology

Literature	
Yermack (1998)	*"The dividend yield (d) is estimated as four times the quarterly dividend declared nearest to the date of stock option award, divided by the company's stock price on the award date, with this quotient compounded continuously."*
Aboody et al. (2006)	*"Historical dividend yield for the most recent year. "*
Hodder et al. (2006)	*"Annualized dividend yield as of the prior fiscal year-end month."*
Johnston (2006)	*"The firm's dividend yield in the previous fiscal year."*
Choudhary (2011)	*"I estimate the dividend benchmark as four times the sum of dividends paid per share over the last quarter, divided by the average monthly price per share."*
Bratten et al. (2016)	Undefined
Our approach	
$EST\_YLD_1=$	$\frac{4 \times DVQ_t}{K_t \times CSHOQ_t}$
$EST\_YLD_2=$	$\frac{4 \times DVQ_{t-1}}{PRCCQ_{t-1} \times CSHOQ_{t-1}}$
$EST\_YLD_3=$	$\frac{1}{4}\sum_{i=0}^{3}\frac{4 \times DVQ_{t-i}}{PRCCQ_{t-i} \times CSHOQ_{t-i}}$
$EST\_YLD_4=$	$\frac{1}{8}\sum_{i=0}^{7}\frac{4 \times DVQ_{t-i}}{PRCCQ_{t-i} \times CSHOQ_{t-i}}$
$EST\_YLD_5=$	$\frac{1}{12}\sum_{i=0}^{11}\frac{4 \times DVQ_{t-i}}{PRCCQ_{t-i} \times CSHOQ_{t-i}}$
$EST\_YLD_6=$	$\frac{1}{16}\sum_{i=0}^{15}\frac{4 \times DVQ_{t-i}}{PRCCQ_{t-i} \times CSHOQ_{t-i}}$
$EST\_YLD_7=$	$\frac{1}{20}\sum_{i=0}^{19}\frac{4 \times DVQ_{t-i}}{PRCCQ_{t-i} \times CSHOQ_{t-i}}$

EST_YLD_i with $i = 1, ..., 7$ is from Compustat quarterly file while EST_YLD_i with $i = 8, ..., 13$ is from Compustat Annual file. For companies that grant options one time per year, for all executive simultaneously, we have $\min(EST\_YLD_i) = \max(EST\_YLD_i)$

Table A.I (Continued)

$EST\_YLD_8 =$		$\frac{DVT_t}{PRCC\_F_t \times CSHO_t}$
$EST\_YLD_9 =$		$\frac{DVT_{t-1}}{PRCC\_F_{t-1} \times CSHO_{t-1}}$
$EST\_YLD_{10} =$		$\frac{1}{2}\sum_{j=0}^{1}\frac{DVT_{t-j}}{PRCC\_F_{t-j} \times CSHO_{t-j}}$
$EST\_YLD_{11} =$		$\frac{1}{3}\sum_{j=0}^{2}\frac{DVT_{t-j}}{PRCC\_F_{t-j} \times CSHO_{t-j}}$
$EST\_YLD_{12} =$		$\frac{1}{4}\sum_{j=0}^{3}\frac{DVT_{t-j}}{PRCC\_F_{t-j} \times CSHO_{t-j}}$
$EST\_YLD_{13} =$		$\frac{1}{5}\sum_{j=0}^{4}\frac{DVT_{t-j}}{PRCC\_F_{t-j} \times CSHO_{t-j}}$
$REPORT\_ACC =$	1	if $DIS\_DIV\_YLD < \min\{\min(EST\_YLD_1), ..., \min(EST\_YLD_{13})\}$
	2	if $\min\{\min(EST\_YLD_1), ..., \min(EST\_YLD_{13})\} \leq DIS\_DIV\_YLD \leq \max\{\max(EST\_YLD_1), ..., \max(EST\_YLD_{13})\}$
	3	if $DIS\_DIV\_YLD > \max\{\max(EST\_YLD_1), ..., \max(EST\_YLD_{13})\}$

4.10.2 Appendix B: Variable definitions

1. Variables related to the information revelation hypothesis

Dividend Projection (DVT_PROJ)
The one-year ahead dividend amount growth, divided by common share outstanding (item CSHO)
Source: Compustat - Fundamental Annual File -

Operational Risk (O_RISK)
Standard deviation of scaled free cash flow computed over the next year quarters minus the same measure over the last eight quarters. Data are from the Compustat Fundamental Quarterly table. Scaled free cash-flow are operating cash-flow (item OANCFY) divided by total assets (item ATQ).
Source: Compustat - Fundamental Quarterly File -

Tobin's Q ($TOBIN$)
Total assets (item AT) plus the market value of equity (MVE) minus the common shareholders' interest in the company (item CEQ) plus the book value of deferred taxes (item TXDB). This sum is divided by total assets. This definition is from Kedia and Mozumdar (2002).
Source: Compustat - Fundamental Annual File -

Total Tobin's Q (TOT_TOBIN)
New version of the Tobin's Q that takes intangible capital into account. The new formula has been proposed by Peters and Taylor (2016) who claim that it is a superior proxy for both physical and intangible investment opportunities.

2. Variables related to the managerial objective hypothesis

Coverage ($COVE$)
Total number of analysts that disclose an earning per share forecast, per stock and per fiscal year. Each analysts (item ANALYS) have usually several updates by stock, for a given forecast period end (item FPEDATS). We keep the last forecast update by analyst. This forecast must occur at least two quarters before the quarter where the forecast period end falls. The forecast count for a given firm-year observations is the coverage measure. This dataset is merged with Compustat on the CUSIP and the end-of-fiscal year month.
Source: I/B/E/S - Detail History file -

CEO Excess Compensation (EXC_REM)
Following Aboody et al. (2006), we regress the log value of total compensation over the log value of sales, sales growth ($\Delta SALE$), book-to-market (BM), return on assets (ROA), the one-year stock returns and the one-year stock return volatility. The model also includes industry and year dummies. Regression residuals are proxies for the "excessiveness" compensation. Total compensation is defined as the sum of salary, bonus, total value of restricted stock granted, total value of stock options granted, long term incentives payouts and other annual (item TDC1). One-year stock volatility is derived with the one-day stock return (item RET). CRSP is merged to Compustat with CUSIPs. **Appendix C.II** exhibits the regression coefficients, standard errors, t-stat and P-values.
Source: Compustat - Fundamental Annual File -
merge with Execucomp - Annual Compensation -
merge with and CRSP - Daily Stock File -

4. Variables related to the disciplinary hypothesis

Audit Fees ($AUDIT\_FEES$)
Sum of audit fees and related audit fees, by company by year, divided by total assets (AT).
Source: AuditAnalytics - Audit Fees -

Proportion of Independent ($PROP\_IND$)
Number of independent board (item BOARDROLE) divided by the board size.
Source: Boardex - Board and Director Committees -

5. Yields

One-Year-Ahead Dividend Yield (DIV_YLD_A)
Total amount of dividends, other than stock dividends, declared on all equity capital of the company, based on the current year's net income (item DVT), scaled by lagged market value of equity (MVE).
Source: Compustat - Fundamental Annual File -

Dividend growth (DVT_GROWTH)
One-year-ahead dividend amount minus dividend amount, scaled by market value of equity (MVE).
Source: Compustat - Fundamental Annual File -

Dividend gap (DVT_GAP)
Disclosed dividend yield in the 10-K footnotes (DIS_DVT_YLD) minus the effective dividend yield (DVT/MVE).
Source: Compustat - Fundamental Annual File -

10-K Footnote reported dividend yield (DIS_DVT_YLD)
Rate disclosed by the company in the footnotes of its consolidated financial statement, and used to compute the fair value of ESOs as mandated by SFAS 123(R), using a Black and Scholes (1973) model or a lattice approach. (item OPTDR). We multiply it by 100 and then by the contemporaneous market value of equity (MVE) to obtain the variable.
Source: Compustat - Fundamental Annual File -

6. Other variables

Book-to-market (BM)
this is defined as total asset (item AT) minus total liabilities (item LT) plus deferred taxes (item TXDB) plus investment tax credit (item ITCB) minus preferred stock convertible (item PSTKC). This is divided by market value of equity (MVE). This definition comes from Kenneth French's website.
Source: Compustat - Fundamental Annual File -

Leverage (LEV)
Long-term debt (item DLTT) plus debt in current liabilities (item DLC) divided by total assets (item AT).
Source: Compustat - Fundamental Annual File -

Market Value of Equity (MVE)
Fiscal year-end close price (item PRCC_F) times the number of common shares outstanding (item CSHO).
Source: Compustat - Fundamental Annual File -

Relative Performance (OCF_STD)

The standard deviation of the operating cash flow, where operating cash-flow is defined as the net change in cash from all items classified in operating activities (item OANCFY). The standard deviation is computing using the last 8 quarters (including the most contemporaneous one) and scaled by total assets (Item ATQ) recorded over the last quarter.
Source: Compustat - Fundamental Quarterly File -

Return on Assets (ROA)
Net income (item IB) divided by total assets (item AT).
Source: Compustat - Fundamental Annual File -

Sales ($SALE$)
The company's sales (Item SALE)
Source: Compustat - Fundamental Annual File -

Size ($SIZE$)
Logarithm of total assets (item AT).
Source: Compustat - Fundamental Annual File -

EPS forecasts dispersion (EPS_STD)
This is the same way to proceed than for building COVE. This variable is the standard deviation of forecasts (item VALUE).
Source: I/B/E/S - Detail History file -

Performance-matched discretionary accruals ($PMDA$)
We follow the approach of Khotari et al. (2005). Total accruals (TA) is defined as the sum of cash, including inventories and receivables (item ACT) and debt in current liabilities, minus cash and short-term investment (item CHE), minus current liabilities (item LCT), minus depreciation and amortization (item DP). In a first step, TA is regressed over an the inverse of total assets, one-year growth in sales (ΔSALE) and property, plant and equipment (item PPE). The regression is performed every year, by industry (two-digit SIC code) for the whole Compustat universe. In a second step, each firm-year observation classified as ESO granters group is matched with an observation not classified as ESO granters. To match, the two companies must belong to the same industry and their ROAs must be the closest among all possible matches within the industry. In a third step, the regression residual from the matching firm is subtracted to the residual of the ESO granter observation. This difference represents the performance-matched discretionary accrual measure. According to Subrahmanyam (1996), dividend growth is significantly related to accrual levels. To control for this potential link between the two variables, PMDA is used as an extra regressor in the last column of **Table III** and **Table IV**.
Source: Compustat - Fundamental Annual File -

4.10.3 Appendix C: Additional exhibits

Table C.I: Lintner's type regression

	INTERCEPT		*EARN*		*DVT*		Adj. R-squared
	beta	t-stat	beta	t-stat	beta	t-stat	
Standard Lintner model							
5th	-0.007	-2.414	0.001	0.025	-0.435	-5.267	0.004
25th	-0.001	-0.541	0.027	1.668	-0.239	-3.037	0.182
50th	0.001	0.624	0.051	2.951	-0.124	-1.774	0.374
75th	0.005	1.667	0.083	4.520	-0.035	-0.512	0.539
95th	0.012	3.112	0.185	7.232	0.101	1.618	0.741
Modified Lintner model							
5th			0.006	0.400	-0.324	-5.272	0.034
25th			0.031	2.131	-0.164	-3.075	0.285
50th			0.056	3.313	-0.088	-1.759	0.493
75th			0.087	4.988	-0.025	-0.555	0.665
95th			0.182	7.872	0.066	1.428	0.831

Above are reported the main statistics for the time-series Lintner (1956) regression performed over 1975-2005. A minimum of 24 non-null dividend amounts is required to perform the regression. The time-series starts the year a first dividend payment occur and ends the year the last dividend payment occurs. Years with dividend omission must not exceed 10% of the time series. After filtering, the sample represents 1,024 dividend-payer companies. *EARN* and *DVT* stand for net income and dividend payments, respectively, scaled by market value of equity. The modified Lintner model excludes the intercept, following Fama and Babiak (1968). We find that the beta associated to scaled earnings is always positive (median = 0.051, median t-stat = 2.951) while the coefficients associated to scaled dividend payments are negative in more than 75% of the sample (median = -0.124, median t-stat = -1.774). The median R^2 is 37.4%. These findings are fairly in line with Grullon and Michaely (2002).

Table C.II: Estimation of CEO excessive compensation

	INTERCEPT	*SALE_LOG*	*SALE_GROWTH*	*BM*	*ROA*	*RETURNS*	*HIST_VOL*
			Our Sample				
Sign	+	+	-	+	+		-
Beta	5.163	0.419	-0.037	0.022	0.300	0.000	-0.184
Std. Err	0.317	0.007	0.034	0.009	0.157	0.000	0.055
T-stat	16.311	59.302	-1.079	2.352	1.906	0.900	-3.347
P-value	0.000	0.000	0.281	0.019	0.057	0.368	0.001
			Yermack (1998)				
Sign		+				+	
			Core et al. (1999)				
Sign		+			+	+	-
			Aboody et al. (2006)				
Sign		+	+	-	+	+	+

Above are reported coefficients, standard errors, t-stats and p-values of the CEO compensation regression model. Following Aboody et al. (2006), the CEO total compensation is regressed over a set of explaining variables: Sales, sale growth, book-to-market ratio, return-on-assets, one-year return and one-year stock return volatility. Variables are presented **Appendix B**. Standard errors are clustered by industry and years, following Gow et al. (2010). Two-digit SIC codes are used for industry classification.

5

Conclusion

In the first paper of our thesis, we develop a model that disentangles the informed-based trading activity into a sector-specific (type S) and a firm-specific (type I) component, like in Albuquerque et al. (2008). Our model reflects an underlying trading game between market-makers, uninformed traders, traders informed on the sector-specific risk and traders informed on the firm-specific risk. The introduction of the State Street SPDR Select Sectors ETFs in December 1998 is an ideal laboratory to study how the two components of the sophisticating trading change following tradable index introductions. The specialists of the industry risk are expected to migrate to the ETF markets while the specialists of the firm-specific risk can use these ETFs as an hedging instrument against sector-specific innovations. To conduct our empirical analysis, we create nine buckets of 10 stocks, each bucket reflecting a two-digit GICS sector and containing the largest, most liquid companies of their respective sectors. This aims at reflecting the presumed underlying holdings of the ETF sponsorship. We estimate structural parameters by maximum likelihood over the stock-quarter panel of intraday data, before and after ETF introductions.

By performing non-parametric tests over the trading activity related to sector-specific information and firm-specific information separately, we find strong evidence in favor of the migration hypothesis. This finding is robust to the choice of the trade classification algorithm and to the exclusion of stocks from the IT sector. To rule out the possibility that something different than ETF inception is responsible for our findings, we conduct the same event study on a control sample. We find no significant change in the S-informed and the I-informed trading intensity around the event. In the 3 months post-introduction the Select Sector ETFs are characterized by a highly level of sophisticated trading compared to what experienced other popular ETFs in the aftermath of their launch. In addition, it seems that there is a positive relationship between the loss of S-informed traders on an industry and the magnitude of sophisticated trading on the corresponding ETF. This provides additional evidence in favor of a migration effect. We find no evidence in favor of the hedging hypothesis. An increase in the trading activity of type I is actually observed but this is small and non-significant at 5%. Trading costs (expense ratios, short-sell costs) may play a role to explain why the I-informed traders do not use the ETFs as hedging instrument.

In our second paper, we develop a theoretical model of market microstructure adapted to accommodate multimarket trading, in the spirit of Easley et al. (1998), John et al. (2003) and Hu et al. (2015). There are two types of investors. Informed traders observe signal on the price direction and seek to maximize expected returns from trading while non-informed traders negotiate for reasons exogenous to asset payoff. They trade with numerous market-makers a single asset through the equity or the option market. The pool of informed traders split between markets when expected payoffs are equal in the stock and option markets. Under this assumption, we derive the Nash equilibrium and the magnitude of option informed trading.

By calibrating margin parameters to the CBOE margin requirements and other parameter to recent empirical studies, we find that the split is likely to emerge. Then, we study the relative allocation of informed trading across markets and across moneyness. In the benchmark case, 14% of informed traders negotiate the option when signals are low and 23% negotiate the option when signal are high. Option informed trading (OIT) can reach 50% when the relative liquidity favors the option. Our findings give some support to Chakravarty et al. (2004) and Rourke (2013). The OIT magnitude is fairly close to their measure of the contribution of the option market to the price discovery process. Moreover, our results give echoes to Lakonishok et al. (2006) who find that nonmarket-maker written option positions account for a wider part of the trading volume than purchased positions. In our model, the equilibrium OIT when informed traders take a short position on the put is always greater than the one derived with long position. The asymmetry between long put and short put margin requirements is responsible for this difference in OIT magnitude.

In our third paper, the accuracy of the dividend yield reported in the 10-K financial statements footnotes is assessed. A new methodology to identify underreport, fair report and overreport is proposed. This method is based on public information and can be easily replicated. Our method accommodates well the flexibility given by the authoritative guidance, and more than 90% of companies in our sample actually report a DFY that seems fair. For the remaining 10%, three mechanisms are proposed to explain why the FDY deviates from our range of acceptable values. The information revelation hypothesis establishes a positive link between private information on the firm performance and the FDY. Under the managerial opportunism hypothesis, biasing the FDY comes from a will to hide CEO excessive compensation. The disciplinary effect hypothesis posits that the likelihood of reporting a fair FDY is connected to the audit quality and the corporate governance quality.

First, underreporting is negatively associated with a proxy for operating risk and proxies for growth opportunities. Moreover, variation in the operating risk is able to explain the relative likelihood of overreporting against fair report. This is consistent with the idea that some firms use discretion over footnotes to convey superior information about future cash flow variability and the quality of future prospects. This result contrasts with Choudhary (2011) that rejects the information revelation hypothesis. Second, overreporting is not connected to the excessiveness of executive compensation so that we reject the managerial opportunism hypothesis. However, we find that underreporting is significantly negatively connected to analyst coverage. Third, an expensive audit process is correlated to less overreporting. Our findings suggest that information revelation objective, disciplinary effects and to a lesser extent, managerial opportunism, are present in our panel, and influence the relative likelihood of underreporting and overreporting over a fair report of the FDY.

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