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Market makers as information providers: The natural experiment of STAR

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ABSTRACT

Market makers are financial intermediaries who are supposed to provide additional liquidity, but do not have any information-related obligation. This paper studies the unique case of the Italian Stock Exchange, where market makers are also obliged to facilitate information disclosure about the firms they cover. We focus on a group of small/medium capitalization stocks (STAR) that are assigned a designated market maker (DMM) starting from 2001. We show that their liquidity requirements are not binding during the sample periods and that the main impact of DMMs' introduction is due to their obligations on information provision. We find that DMMs' activity as information providers reduces spread and price volatility, the probability of informed trading (PIN), and the adverse selection component of the spread. An event study provides evidence that the information released through DMMs is perceived as useful by market participants.

1. Introduction

In financial markets information on less traded stocks is generally supplied by firms or by analysts. This paper investigates an alternative channel of information disclosure by considering the role of market makers as information providers. Market makers are financial intermediaries that are supposed to provide additional liquidity but do not usually have any information-related obligation. We here study the unique trading environment of the Italian Stock Exchange, where market makers have obligations aimed at facilitating information disclosure of the listed firms.

In April 2001, Borsa Italiana (BIt from now on) started assigning a designated market maker (DMMs from now on) to a group of small-medium capitalization stocks, that were named STAR. The main novelty of this experiment is that DMMs have information disclosure requirements. Information obligations require DMMs to act as analysts on STAR stocks and to produce at least two detailed financial analyses per year; DMMs are also required to organize at least two yearly meetings, named roadshows, with professional investors. The purpose of the paper is to study how these information disclosure requirements affect market quality.

Generally in order driven markets DMMs who act as liquidity suppliers are required to comply only with liquidity requirements, the most relevant being the maximum quoted spread (Bessembinder et al., 2008). In the Italian case, instead, for the

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59 companies that were assigned a DMM between 2001 and 2005, the maximum spread requirement was not binding,[1] and this creates an ideal setting to focus on the effect of the information disclosure provided by DMMs.

We use high frequency data covering four sample periods, one before and three after the companies joined the STAR group. We find that after the assignment of the DMM, spread and volatility decrease for STAR stocks compared to a matched sample of control stocks, while volume does not change significantly. In the longer run, spread and volatility decrease substantially and volume increases significantly: we show that this improvement in market quality is associated with a decrease in information asymmetries (and, in turn, in adverse selection costs) induced by the DMMs' disclosure requirements. Accordingly, we find that information asymmetries, measured by the probability of informed trading (PIN) as in Easley et al. (1996), tend to decrease after the companies are assigned a DMM; furthermore, by estimating the model of Glosten and Harris (1988), we document that the component of the spread due to traders' inability to efficiently process information decreases. To verify that the short term reduction in the price impact is due to adverse selection costs and not to inventory adjustments, we estimate a VAR model similar to Hasbrouck (1991) and find evidence of a permanent decrease in adverse selection costs.

We show that these findings are consistent with a simple framework of asymmetric information and rational price formation in the spirit of Grossman and Stiglitz (1980) where information is disclosed to uninformed market participants. In order driven markets where both informed and uninformed traders can supply liquidity, this information disclosure reduces adverse selection costs for uninformed traders and hence makes them more willing to supply liquidity. Within this framework we show that when information is publicly disclosed the spread decreases. We also show that information disclosure has two opposite effects on volatility: it reduces the price impact component, and it increases the demand shock component.

An extensive literature exists that investigates whether the assignment of a market maker affects market quality. Numerous empirical papers[2] have shown advantages and disadvantages of moving from the NASDAQ dealer market (or from the OTC market) to the NYSE auction based specialist market, and at least as many papers have investigated how the specialist's activity can affect trading.[3]

By contrast, the experiment we study consists of a group of stocks listed on an order driven market organized as a limit order book that at a certain point in time, and all other things being equal, are assigned a DMM. The DMM has to meet the obligations imposed by Borsa Italiana, and does not monopolistically control the order book. This means that we depart from the literature comparing the virtues of NASDAQ vs. the NYSE for at least two main reasons. Firstly, the assignment of the DMM does not come with a change in market structure as in the NASDAQ vs. NYSE experiment. Secondly, the role of the DMM on the Italian stock market, as in any other stock market that works as an electronic limit order book, substantially differs from that of the specialist on the floor of the NYSE, who has an active and key role in managing the order book; by contrast, STAR DMMs act as limit order traders and have no privilege in the access to the order book.

The present paper is related to three recent empirical papers that study the effect on market quality[4] of the introduction of DMMs with only liquidity requirements. Venkataraman and Waisburd (2007) find that introducing DMMs in the Paris Bourse leads to an increase in liquidity for a sample of stocks traded through a call auction; their analysis also differs from ours as we consider DMMs trading in a limit order book. Anand et al. (2009) document an improvement in market quality after the introduction of DMMs in the limit order book of the Stockholm Stock Exchange; in this case, however, DMMs' maximum spread obligations are binding and, yet again, there are no requirements in terms of information disclosure. Menkveld and Wang (2009) study the introduction of DMMs in Euronext Amsterdam; they find that liquidity increases, stock prices increase and liquidity risk decreases after the event.

This analysis is also closely related to the field of research on the relation between analysts' activity and market liquidity. A vast body of literature examines the stock price reaction to analysts' forecasts (for a recent critical survey, see for example, Ramnath et al., 2008)[5] but little attention has been devoted to the effects of analysts' information on liquidity and adverse selection costs. Most previous papers, as Brennan and Subrahmanayam (1995), Roulstone (2003) and Kanagaretnam et al. (2005) find that liquidity is positively associated with analyst coverage; others (e.g. Chung et al., 1995) document a negative association. There is no consensus on whether analysts' activity fosters liquidity by reducing information asymmetries, or it is instead perceived as a signal of the presence of higher information asymmetries.

STAR DMMs differ from the analysts considered in previous research, because they are directly involved in trading on the same stocks about which they provide information.[6] Furthermore, previous studies are concerned with the contemporaneous

[1] Clearly, if the spread requirement is not binding the other liquidity requirements cannot be effective either.

[2] See among the many others Huang and Stoll (1996), Barclay et al. (1999), Kadlec and McConnell (1994), Christie and Huang (1994) and more recently Boehmer (2005).

[3] See for example Corwin (1999) and Kavajecz (1999).

[4] Theoretical literature also examines the role of market makers in providing liquidity and on how they compete with limit order books. Grossman and Miller (1988) show that market makers can increase liquidity by reducing temporary imbalances in the order flow. Seppi (1997) shows that a hybrid market structure (with a limit order book and specialists) can provide better liquidity than a pure limit order book depending on the order size, whereas Parlour and Seppi (2003) identify conditions under which a hybrid market Pareto-dominates a pure limit order book. Finally, Viswanathan and Wang (2002) show that introducing market makers in a limit order book can improve the customers' welfare.

[5] Following the classification proposed by Ramnath et al., 2008, two main research questions can be identified: some studies concentrate on whether stock prices efficiently reflect the information provided by analysts (e.g. Barber et al., 2001; Gleason and Lee, 2003, Irvine, 2003; Irvine, 2004; Mendenhall, 2004; Li, 2005; Sorescu and Subrahmanyam, 2006) and other papers investigate how analysts' forecasts explain inefficiencies in stock prices (e.g. Dechow et al., 1999; Shane and Brous, 2001; Teoh and Wong, 2002; Kadiyala and Rau, 2004, Purnanandam and Swaminathan, 2004, Jackson and Johnson, 2006).

[6] Some papers also examine the incentive that market makers have to provide research regarding the stocks they trade (e.g. Brennan and Hughes, 1991; Angel, 1997; Aggarawal and Angel, 1998).

association between analyst coverage and market quality; as a consequence, they cannot clearly identify the causal effect of analysts' activity on liquidity and other indicators of market quality. By contrast, we compare a period before the introduction of the DMMs to later periods and we are able to test the effect over time of the additional information provided to the market.

The remainder of this paper is organized as follows. Section 2 describes the dataset and the sample choice, Section 3 outlines a theoretical framework on which the empirical hypotheses are based, and Section 4 discusses the results on market quality. Section 5 focuses on information asymmetries and the market reaction to roadshows and financial analyses, and Section 6 concludes.

2. Dataset and samples

2.1. Institutional background: the Italian Stock Exchange and STAR stocks

STAR stocks have a capitalization lower than one billion euro and are traded in the Italian electronic limit order book, named MTA (Mercato Telematico Azionario); the peculiarity of these stocks, compared to the Blue Chips, is that they are assigned a DMM by BIt. Trading for STAR stocks takes place on a standard electronic platform which works as an order driven double auction market similar to Euronext or the English TradElect. There are four trading phases: an opening call auction, from 8:00 am to 9:10 am; a continuous phase, from 9:10 am to 5:25 pm, and a closing call auction, from 5:25 pm to 5:35 pm. Stocks can also be traded (on a voluntary basis) in the after-hours market from 6:00 pm to 8:30 pm. We examine data from the continuous auction, where all market participants submit orders, which are then matched by the centralized mechanism according to standard price and time priority rules. At the time examined, only STAR stocks had a DMM in BIt.

DMMs act as analysts for STAR stocks and have specific obligations of information disclosure. They have to produce at least two financial analyses each year, along with the presentation of the most recent available data, expectations about future economic results and a comparison with previous estimates. All the studies and research reports have to be timely transmitted to the stock exchange. In addition, DMMs have to organize at least twice per year meetings with professional investors which are referred to as roadshows. Even more importantly, DMMs interact with institutional and retail investors on a regular basis.

Borsa Italiana also assigns to the DMMs some liquidity obligations, namely to quote a maximum spread and to assure minimum depths and minimum trading volume. Yet, as shown in Section 2.3, these liquidity requirements are not binding. Following the rules set by BIt, DMMs are granted a lump sum payment by STAR firms, and their reward does not depend on trading activity.[7]

2.2. Sample stocks, control stocks and sample periods

DMMs were assigned to STAR stocks starting from April 2001; our sample includes the 59 stocks that were offered a DMM between April 2001 (when STAR stocks were created) and February 2006, and that were previously listed on BIt. Table 1 reports the dates corresponding to the beginning of the DMMs' activity. These dates are dispersed around the sample periods as a group of 31 stocks were assigned a DMM on four dates in 2001, one stock in 2002, another group of three stocks in 2004 and 24 stocks in 2005.

In order to control for confounding effects due to market elements not related to the DMMs' activity, we build a control sample of stocks with the same capitalization requirements as STAR stocks. Following the approach proposed by Huang and Stoll (1996), each STAR stock is matched to another stock that minimizes the score: $\sum_{i=1}^{5}\left(\frac{x_i^{STAR}-x_i^{control}}{\left(x_i^{STAR}+x_i^{control}\right)/2}\right)^2$; where x_i is either price, or market capitalization, trading volume, market-to-book ratio, or leverage.[8]

We consider four periods, one before and three after the stocks were assigned a DMM. The pre-STAR period goes from four to one month before the event and the post-STAR period goes from one to four months after the event; the post1-STAR and post2-STAR periods include the same months as the post-STAR, but one and two years ahead, respectively. The reason why we consider the post1 and post2-STAR periods is that we are especially interested in the longer run effects of the DMMs' activity.

BIt provided us with data on transaction prices and bid–ask quotes from November 2000 to February 2006 for each STAR stock except four companies.[9] Hence, for the pre and post periods we worked with a sample of 55 stocks; because three stocks were assigned a DMM in 2004 and 24 in 2005 (for some of these stocks the post1 and post2 periods would exceed February 2006), we ended up with a sample of 32 stocks for the post1 and of 30 stocks for the post2-period, respectively. For robustness, we ran all of our results on the 30 stocks that lasted until the post2-period for the pre, post, and post1 periods, so that all four periods had the same number of stocks in them; our results did not change.

2.3. Liquidity and information disclosure requirements

To investigate the effect of the information disclosure requirements on STAR stocks, first of all we have to check whether the liquidity requirements imposed by BIt on the DMMs are not actually binding during the sample period. To this end we compare the

[7] From informal conversations with DMMs on STAR stocks we learnt that this lump sum is in the range of 30,000 to 35,000 Euros.
[8] See Davies and Kim (2009) for a discussion on the optimal choice of a control sample.
[9] Centrale del Latte Torino, Cementir, Digital Bros., and It Ways.

Table 1
Sample and control stocks. This table presents the stocks in the sample and the corresponding control stocks. The sample contains all the stocks that entered STAR from November 2000 to February 2006. Because we did not receive complete data from BIt, we excluded four stocks (Centrale del latte Torino, Cementir, Digital Bros and IT Way). The table also reports the maximum spread required (as a percentage of the midquote) for DMMs at the time they started their market making activity, as well as the average spread in the *pre*-period and the binding spread time in the *pre*-period (this refers to the proportion of trading time during which the maximum spread required to the DMMs was lower than the spread observed in the market).

STAR stocks	Date of entry in STAR	Date of exit from STAR	Maximum spread required (%)	Average spread in the pre-period (%)	Binding spread time in the pre-period (%)	Control stocks
Fullsix	30/11/2005		3.50	0.58	0	Brioschi
Acotel Group	19/09/2005		4.50	0.65	0.00	Maffei
BB Biotech	19/09/2005		4.50	0.18	0	De Longhi
Buongiorno	19/09/2005		2.50	0.30	0.01	IMMSI
Cad It	19/09/2005		4.50	0.64	0	INTEK
Cairo Communication	19/09/2005		4.50	0.38	0	Viaggi Ventaglio
CDC	19/09/2005		4.50	0.49	0	Gewiss
DADA	19/09/2005		3.50	0.36	0	Linificio
Datalogic	19/09/2005		3.50	0.43	0	Acque potabili
Dea Capital	19/09/2005		2.50	0.32	0.01	Premafin
Digital Bros	19/09/2005		–	–		–
Dmail Group	19/09/2005		4.50	0.50	0.00	AS Roma
El.En.	19/09/2005		4.50	0.60	0.03	Caltagiorne
Engineering	19/09/2005		4.50	0.64	0.01	SOL
Esprinet	19/09/2005		3.00	0.35	0	Marcolin
Fidia	19/09/2005		4.50	0.83	0.57	CAM-FIN
I.Net	19/09/2005		3.50	0.48	0	Kaitech
IT Way	19/09/2005		–	–		–
Mondo TV	19/09/2005		4.50	0.56	0	Exprivia
Poligrafica S. Faustino	19/09/2005		4.50	0.43	0	KME
Prima Industrie	19/09/2005		4.50	0.68	0.12	Mittel
Reply	19/09/2005		4.50	0.61	0	Enertad
TAS	19/09/2005		4.50	0.69	0.12	Mediterranea Acque
TXT	19/09/2005		4.50	0.53	0	Sadi Servizi
Banca Ifis	29/11/2004		4.50	1.27	0.13	Gabetti
Actelios	20/09/2004		4.50	1.07	0.01	Zucchi
Sogefi	15/01/2004		3.50	0.63	0	Ratti
Gefran	27/05/2002		4.50	1.07	0.02	Finarte
Vittoria Assicurazioni	26/11/2001		4.50	2.85	0.22	Ciccolella
Aedes	24/09/2001		4.50	0.84	0	IPI
Amga	24/09/2001	01/11/2006	3.50	0.78	0.42	Eutelia
Cembre	24/09/2001		4.50	3.32	2.72	Filatura di Pollone
Cementir	24/09/2001	19/03/2007	–	–		–
Emak	24/09/2001		4.50	1.27	0	Grandi Viaggi
Stefanel	24/09/2001		4.50	1.29	0.61	Trevi
Banca Pop. Intra	01/07/2001		4.50	0.54	0	SNAI
Cremonini	01/07/2001		3.00	0.70	0.01	Beghelli
IMA	01/07/2001		4.50	1.59	0.74	Olidata
Jolly Hotels	01/07/2001	03/08/2007	4.50	0.94	0.00	Ricchetti
Meliorbanca	01/07/2001		3.50	0.59	0.04	Class Editori
Richard Ginori	01/07/2001		3.50	1.53	1.02	Bastogi
Banca Finnat	01/04/2001		3.00	2.10	2.66	Banca Profilo
BPEL	01/04/2001		4.50	0.95	0	Mediacontech
Brembo	01/04/2001		3.50	0.87	0.29	Aeroporto di Firenze
Centrale del latte Torino	01/04/2001		–	–	–	–
CSP International	01/04/2001	06/06/2005	4.50	1.13	0.04	Poligrafici Editoriale
Ducati	01/04/2001		2.50	0.50	0.08	Monrif
ERG	01/04/2001	19/12/2005	2.50	0.54	0.00	SNIA
Interpump	01/04/2001		3.50	0.70	0	Acegas
Irce	01/04/2001		4.50	2.07	0.84	Danieli
La Doria	01/04/2001		4.50	1.16	0	Basicnet
Manuli Rubber Industries	01/04/2001	29/01/2004	3.50	1.04	0.14	Pininfarina
Mariella Burani	01/04/2001		3.50	0.90	0.05	ACSM
Mirato	01/04/2001		4.50	0.84	0	Caltagirone Editore
Navigazione Montanari	01/04/2001		3.00	1.18	0.76	Schiapparelli
Reno De Medici	01/04/2001		3.50	0.91	0.08	Ergo Previdenza
Sabaf	01/04/2001		4.50	0.68	0	Permasteelisa
Saes Getters	01/04/2001		4.50	1.50	0.01	Data Service
Targetti Sankey	01/04/2001		3.50	1.76	0.91	FMR ART 'E'

average spread prevailing in the *pre*-period to the maximum spread required for the DMMs. As Table 1 shows, we find that, on average, the maximum spread is 5.8 times greater than the spread observed in the *pre*-period; and even by looking at any single stock in the sample, we find that the maximum spread required is greater than the spread observed in the *pre*-period.

Furthermore, as discussed in more detail in Section 4.2.1, we found that on average across stocks the maximum spread is not binding for 99.77% of the trading time. This means that the maximum spread rule is not binding, and therefore we are able to focus on the role of information disclosure requirements by comparing the period before the introduction of the DMMs to later periods.

3. Empirical hypotheses

To our knowledge, a micro-financial model that discusses the effectiveness of information disclosure by liquidity providers in limit order markets does not exist. One difficulty faced by the theoretical analysis is that if the existing models of limit order trading (e.g. Parlour, 1998) are extended to include asymmetric information among market participants, they do not provide a closed form solution for the equilibrium price function.[10] Hence, the closest theoretical framework we can use to derive empirical predictions for the effects of information disclosure in a market where both uninformed and informed investors act as liquidity providers, is a centralized auction model in the spirit of Grossman and Stiglitz (1980). We refer to this class of models and formulate testable hypotheses regarding the effects on market quality of the disclosure of information to uninformed traders.

When DMMs disclose public information about the company's value, uninformed investors become more informed and hence less uncertain about the future value of the asset. As a consequence, they also become less worried of paying adverse selection costs and offer liquidity at better prices. That better informed traders can be the best liquidity providers has been shown experimentally by Bloomfield, O'Hara and Saar (2005), and theoretically by Rindi (2008), and it is precisely to the latter framework that we refer to discuss the effects of the disclosure of information by DMMs on the firm's market quality.

Assume that in an order driven market three groups of traders are active: two groups of rational risk averse investors, n informed and m uninformed, and a group of z noise traders who submit $\phi \sim N(0,1)$. Assume also that the future value of the asset is equal to $s = q + e$ with q and e iid, zero mean, and variance 1 and σ_e^2 respectively. As the insiders directly observe q and the market price p offers a noisy signal of q, whatever the variance of e, the insiders' signal is always a sufficient statistic of p. Upon observing the signal q, informed traders demand $x_I = [aVar(s|q)]^{-1}(q-p)$, where a is the coefficient of risk aversion and $Var(s|q) = Var(e)$ is the residual variance after observing the signal q; uninformed traders instead submit $x_U = [aVar(s|p)]^{-1}(E(s|p)-p)$ as they use the market price to make inference on s.

It is straightforward to show that the rational expectation equilibrium price that solves the market clearing condition $mx_I + nx_U + z\phi = 0$ is equal to:

$$p = \varsigma\left(\frac{n}{\sigma_e^2}q + z\phi\right) \tag{1}$$

where $\zeta = \left[\frac{n}{\sigma_e^2} + \frac{m}{1 + \sigma_e^2 + \frac{12}{\sigma_e^2}}\right]^{-1}$ is the price impact parameter.

See Appendix.

From the equilibrium pricing function the following standard indicators of market quality can be derived: $PI = \left[\frac{\delta p}{\delta \phi}\right]^{-1} = \zeta^{-1}$, which is a measure of the price impact of a liquidity trader's order and $VOL = Var(p) = \varsigma^2\left[\frac{n^2}{\sigma_e^4} + z^2\right] = \varsigma^2\Omega$, which is a proxy of price volatility.

It is now possible to investigate the effects of information disclosure on these two measures. Assume that the DMM discloses the signal $\psi = q + \omega$ about the firm's fundamental value, with[11] $\sigma_e^2 < \sigma_\omega^2$. For simplicity, also assume that ψ is a sufficient statistic of the market price p and hence p', but not of the insiders' signal s. This means that neither the insiders nor the newly informed traders will use the market price to update their estimate of the fundamental value of the asset.

When investors use the signal ψ to update their inference on the future value of the asset, their new demand is equal to $x'_U = [aVar(s|\psi)]^{-1}(E(s|\psi)-p')$, and the firm equilibrium price is:

$$p' = \varsigma'[(3n + m)q + m\varepsilon + 3\phi) \text{ with } \zeta' = \left[\frac{n}{\sigma_e^2} + \frac{m\left(1 + \sigma_e^2\right)}{\sigma_e^2 + \sigma_\omega^2 + \sigma_e^2\sigma_\omega^2}\right]^{-1} \tag{2}$$

[10] Models of limit order book are still very few in number and each concentrates on a specific feature of the trading process. Parlour (1998) shows how the state of the two sides of the book influences the choice between limit and market orders. Goettler et al. (2008) introduce asymmetric information into Parlour's model and find a numerical solution for the equilibrium price function. Glosten (1994) and later Biais et al. (2000) model the discriminatory pricing function which governs the limit order book, but do not include the choice between limit and market orders, and also assume that liquidity providers are only uninformed. Foucault (1999) concentrates on the winner's course problem of a limit order trader who runs the risk of being picked off by scalpers when public information arrives, and, finally, both Foucault et al. (2005) and Rosu (2009) focus on liquidity provision in a model with patient and impatient traders without public and private information.

[11] Assuming that the noise of the insiders' signal is strictly smaller than that of the DMMs' greatly simplifies the computations as it rules out the case where the insiders have to make inference by using two signals.

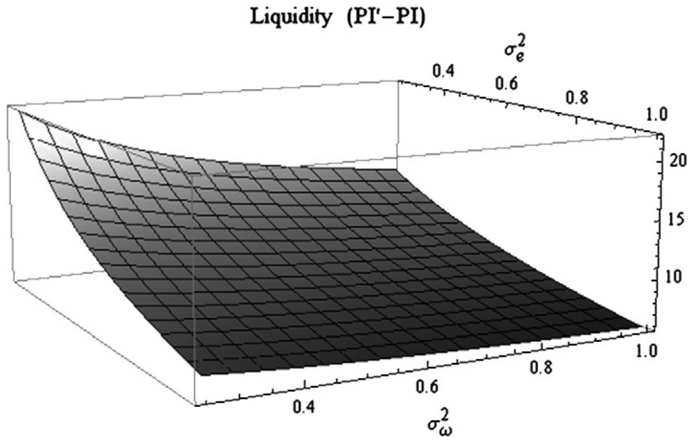

Fig. 1. Liquidity (PI′–PI). This figure reports the results of numerical simulations for the model described in Section 3. It plots the difference in liquidity between the regime with information disclosure and the benchmark regime for different values of the noise in the insiders' signal, σ_e^2, and in the new signal, σ_ω^2.

Hence, the new indicators of liquidity and volatility are respectively equal to:

$$PI' = \left[\frac{\delta p'}{\delta \phi}\right]^{-1} = \zeta'-1 \text{ and } VOL' = Var(p') = \varsigma'2\left[\frac{n^2}{\sigma_e^4}\left(1+\sigma_e^2\right) + \frac{m^2\left(1+\sigma_\varepsilon^2\right)}{\left(\sigma_e^2+\sigma_\omega^2+\sigma_e^2\sigma_\omega^2\right)^2} + z^2\right] = \varsigma'2\Omega'.$$

By comparing these values under the two regimes it is possible to show that the effects of DMMs' disclosure on market quality is to increase liquidity and reduce volatility.

In Fig. 1 the difference in the indicator of liquidity under the two regimes is plotted over a wide range of values for the noise of both the insiders' signal,σ_e^2, and the new signal, σ_ω^2, and it is shown that the price impact decreases with the release of new information. The graph clearly shows that as the new disclosed signal becomes more precise (σ_ω^2 decreases), the effect on the price impact is greater: the new informed traders, by becoming more informed, pay less adverse selection costs and supply better liquidity. Of course all the effects also depend on the precision of the insiders' signal: when insiders hold a very good signal (σ_e^2 is small), the effect is greater as there is more room to reduce adverse selection costs.

The intuition for this result is simple: in a market where both informed and uninformed traders supply liquidity, the release of new information makes uninformed traders more informed about the asset value, and therefore more willing to offer liquidity. This leads us to formulate our first hypothesis.

Hypothesis 1. The price impact and hence the bid–ask spread decrease after the introduction of DMMs with information disclosure requirements.

Fig. 2a shows that, following the information release, volatility decreases. To fully understand this result, one should consider, by looking at Eqs. (1) and (2), that information disclosure produces two opposite effects on volatility: it reduces the price impact, $\Delta\zeta^2 = \zeta'2-\zeta^2<0$, and it magnifies the demand shocks that are driven by information, captured by $\Delta\Omega^2 = \Omega'2-\Omega^2>0$. Fig. 2a illustrates that for a wide range of parameter values[12] the first effect outweighs the second, and overall volatility decreases; Fig. 2b and c also show that both effects are negatively related to σ_ω^2, which means that they get stronger with the precision of the information disclosed, as the residual variance of p', $Var(p'|\psi)$, decreases. This allows us to derive our second hypothesis:

Hypothesis 2. The effect of the introduction of DMMs with information disclosure requirements is a reduction of transaction price volatility.

So far we have derived predictions for liquidity and volatility. This simple model does not allow us to draw direct predictions for trading volume. However, if, following Admati and Pfeiderer (1988) we proxy trading volume by the variance of traders' demand, then we can derive indirect predictions on the effects of information disclosure on trading activity. As we have shown that the demand component of the transaction price variance increases, we can now express our third hypothesis.

Hypothesis 3. Trading volume increases after the introduction of DMMs with information disclosure requirements.

4. Empirical analysis: market quality

We focus on three measures of market quality: spread, volatility and trading volume. These measures are computed during the trading day from 11 am to 4 pm. We use this time interval as Kandel et al. (2008) show that it was not affected by the introduction

[12] In the simulations presented here we have assumed that $n=m=z=10$, but the results a robust to different values of these parameters.

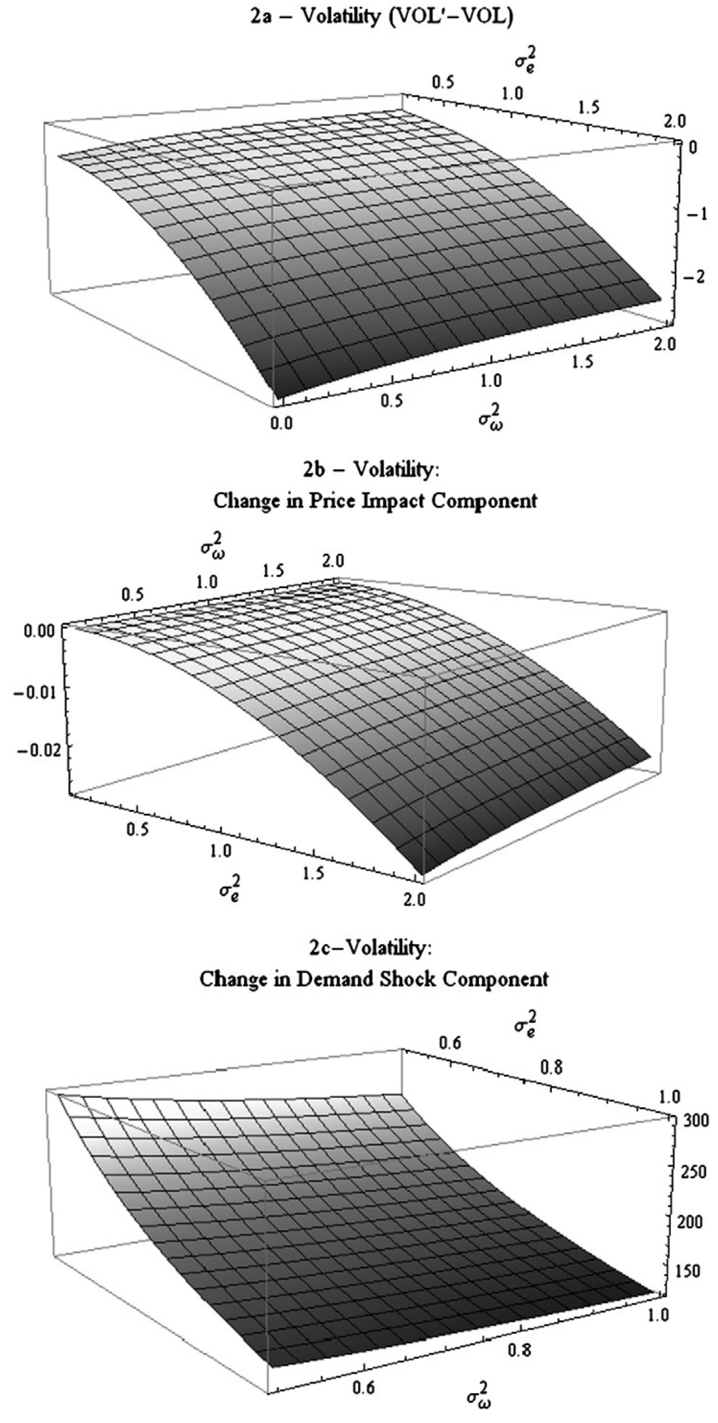

Fig. 2. Volatility (VOL′–VOL). Fig. 2a reports the results of numerical simulations for the model described in Section 3. It plots the overall difference in volatility between the regime with information disclosure and the benchmark regime for different values of the noise in the insiders' signal, σ_e^2, and the new signal, σ_ω^2. Panels b and c report numerical simulations for the two components of volatility: the price impact component and the demand shock component.

of the closing auction which took place during the sample period under analysis. However, we also replicated the analysis by considering the time interval from 9:30 am to 5 pm and we obtained qualitatively analogous results.

We use two measures of spread: the percentage quoted spread and the time-weighted percentage quoted spread. The percentage quoted spread is computed as the difference between the best ask and the best bid relative to the mid-quote. The time weighted

Table 2
Measures of market quality — descriptive statistics. This table reports descriptive statistics for the four measures of market quality considered (quoted spread in Panel A, time-weighted quoted spread in Panel B, volatility in Panel C, and trading volume in Panel D) in the four periods around the introduction of the DMMs.

STAR	pre	post	post1	post2	Control	pre	post	post1	post2
Panel A: Spread									
Average STAR	0.0092	0.0083	0.0103	0.0071	Average control	0.0102	0.0109	0.0141	0.0109
St. dev. STAR	0.0060	0.0042	0.0050	0.0039	St. dev. control	0.0093	0.0071	0.0100	0.0097
Panel B: Time-weighted spread									
Average STAR	0.0087	0.0079	0.0099	0.0069	Average Control	0.0095	0.0102	0.0132	0.0105
St. dev. STAR	0.0058	0.0041	0.0049	0.0039	St. dev. Control	0.0089	0.0069	0.0096	0.0106
Panel C: Volatility									
Average STAR	0.0306	0.0284	0.0369	0.0267	Average Control	0.0366	0.0375	0.0559	0.0401
St. dev. STAR	0.0124	0.0104	0.0104	0.0088	St. dev. Control	0.0147	0.0156	0.0193	0.0133
Panel D: Trading volume									
Average STAR	227,467	199,192	126,237	186,988	Average Control	264,519	249,433	165,326	244,616
St. dev. STAR	337,877	287,773	181,337	229,980	St. dev. Control	297,501	401,124	256,254	413,114

percentage quoted spread is computed by weighing each percentage quoted spread observation on the time between two subsequent quotes. We use the following weighted version of the realized volatility measure proposed by Andersen et al. (2003)[13]:

$$\sqrt{\frac{\frac{1}{N}\sum_{i=1}^{N} ln^2\left(\frac{p_i}{p_{i-1}}\right)}{\frac{(t_i - t_{i-1})}{T}}}$$

where p_i is the spread mid-quote at time t. The spread mid-points are used rather than transaction prices in order to control for the bid–ask bounce. N is the number of observations in the specific sample period and T is the number of seconds in the time interval considered. Because the dataset contains all quote revisions and, hence, the time between two subsequent observations is not constant, we weigh each observation by the duration (in seconds) between subsequent quote updates. Finally, Euro trading volume is defined as the sum of transaction volumes (in Euros) in the time interval considered.

Table 2 presents descriptive statistics for the measures of market quality considered. STAR stocks have higher levels of the bid–ask spread and volatility, whereas control stocks have higher volume levels. STAR stocks exhibit a decrease in the bid–ask spread and in volatility from the *pre* to the *post* and *post2* periods; in the *post1* period there is an increase, which is remarkably more pronounced for control stocks.

4.1. Measures of market quality: univariate analysis

Table 3 compares the average change in the three measures of market quality for STAR and control stocks in the different sub-periods under analysis. For each measure, y, we then concentrate on the difference in differences, defined as:

$$DID = [y_{STAR}(After) - y_{STAR}(Pre)] - [y_{Control}(After) - y_{Control}(Pre)]$$

where *Pre* and *After* refer to observations before and after the introduction of STAR. We compute a paired-sample t-test and a signed-rank Wilcoxon test for the null hypothesis that the average or the median of this difference is equal to zero.

Notice that only the 32 stocks that were in existence in the *post1*-period were used in the *pre*-period when calculating the *DID* results for the *post1*-period; and similarly, only the 30 stocks that were in existence in the *post2*-period were used in the *pre*-period when calculating the *DID* results for the *post2*-period. Accordingly, the numbers in Table 3 for the *pre* period do not match those in Table 2. We repeated all the analyses for the 30 stocks that lasted until the *post2*-period and we obtained qualitatively analogous results.

SPREAD — For treatment stocks the average quoted spread (Panel A) and the average time-weighted quoted spread (Panel B) decrease over the three sample periods; this difference is significantly greater (in absolute value) than the difference experienced by control stocks. It is important to notice that the spread reduction is three and four times larger in the *post1* and the *post2* periods. As expected, the DMMs' activity as information providers builds up over time.

VOLATILITY — Volatility (Panel C) for STAR stocks decreases in the *post* and *post2* periods, whereas it increases in the *post1*-period. However, volatility for STAR stocks significantly decreases across the three sample periods compared to control stocks; the reduction is smaller during the *post1*-period.

[13] This measure is computed by assuming that stock prices follow a brownian motion. In Andersen et al. (2003) volatility is not weighted on time because observations are equally distant.

Table 3
Measures of market quality — univariate tests (DID). This table compares the difference in the measures of market quality (quoted spread in Panel A, time-weighted quoted spread in Panel B, volatility in Panel C, and trading volume in Panel D) examined between the periods after the introduction of the DMMs and the *pre* period. The average difference for STAR (column STAR) and control (column Control) stocks are reported; in addition, the difference in differences (column STAR-Control), defined as *DID* in Section 4, is presented. In the *post1-pre* and *post2-pre* comparisons, we consider only the stocks for which the *post1* and *post2* periods exist, respectively. In panel A averages in the *pre*-period are compared. A *t*-test and a Wilcoxon signed-rank test for the null hypothesis that the average or the median of *DID* is equal to zero are presented. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	STAR	Control	STAR-Control	*t*-test	Wilcoxon
Panel A: Spread					
post–pre	−0.0009	0.0007	−0.0016	−2.6907***	−2.958***
post1–pre	−0.0016	0.0021	−0.0037	−3.2737***	−3.104***
post2–pre	−0.0049	−0.0008	−0.0041	−3.3436***	−3.096***
Panel B: Time-weighted spread					
post–pre	−0.0008	0.0007	−0.0015	−2.3833***	−2.765***
post1–pre	−0.0013	0.0019	−0.0032	−3.0686***	−2.805***
post2–pre	−0.0046	−0.0004	−0.0042	−3.2089***	−3.137***
Panel C: Volatility					
post–pre	−0.0022	0.0009	−0.0031	−1.9967*	−1.676*
post1–pre	0.0004	0.0135	−0.0131	−3.4537***	−2.805***
post2–pre	−0.0097	−0.0015	−0.0082	−2.2512***	−2.026**
Panel D: Trading volume					
post–pre	−28,275	−15,086	−13,189	−0.2146	0.900
post1–pre	−22,239	−93,491	71,252	1.1811	1.421
post2–pre	38,705	−37,396	76,101	0.8270	0.984

TRADING VOLUME — In none of the periods STAR stocks exhibit a significant change in volume compared to control stocks (Panel D).

We also computed the difference in differences in percentage terms, as follows:

$$\%DID = [y_{STAR}(After) - y_{STAR}(Pre)] \,/\, y_{STAR}(Pre) - [y_{Control}(After) - y_{Control}(Pre)] \,/\, y_{Control}(Pre)$$

The results (presented in Table 4) regarding the bid–ask spread and volume are analogous to the ones obtained with *DID*. As for volatility, we observe a significant decrease in *%DID* in the *post1* and *post2* periods, whereas the decrease in the *post*-period is not significantly different from zero.

The results of the univariate analysis support Hypothesis 1 and 2. Conversely, Hypothesis 3 cannot be confirmed.

Table 4
Measures of market quality — univariate tests (%DID). This table compares the percentage difference in the measures of market quality (quoted spread in Panel A, time-weighted quoted spread in Panel B, volatility in Panel C, and trading volume in Panel D) examined between the periods after the introduction of the DMMs and the *pre* period. The average percentage difference for STAR (column STAR) and control (column Control) stocks are reported; in addition, the difference in differences (column STAR–Control), defined as *DID* in Section 4, is presented. In the *post1–pre* and *post2–pre* comparisons, we consider only the stocks for which the *post1* and *post2* periods exist, respectively. A *t*-test and a Wilcoxon signed-rank test for the null hypothesis that the average or the median of *DID* is equal to zero are presented. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	STAR	Control	STAR–Control	*t*-test	Wilcoxon
Panel A: Spread					
post–pre	−0.0120	0.1438	−0.1558	−3.3591***	−3.184***
post1–pre	−0.0793	0.3183	−0.3976	−4.1393***	−3.553***
post2–pre	−0.3667	0.0308	−0.3975	−4.1448***	−3.486***
Panel B: Time-weighted spread					
post–pre	−0.0075	0.1518	−0.1593	−3.3797***	−3.100***
post1–pre	−0.0691	0.3239	−0.3930	−4.1397***	−3.385***
post2–pre	−0.3557	0.0760	−0.4317	−3.5931***	−3.445***
Panel C: Volatility					
post–pre	−0.0128	0.0427	−0.0555	−1.0967	−1.617
post1–pre	0.0994	0.4004	−0.3010	−3.0301***	−2.637***
post2–pre	−0.2102	0.0258	−0.2360	−2.933***	−2.520**
Panel D: Trading volume					
post–pre	−0.0104	−0.0313	0.0209	0.1182	1.020
post1–pre	−0.2748	−0.3675	0.0927	0.7786	1.548
post2–pre	0.2430	0.0540	0.1890	0.5236	0.457

4.2. Measures of market quality: multivariate analysis

In the univariate analysis we employ one observation for each stock in each sub-period. We also consider a multivariate approach, where we use one observation for each day in the sample period. As in the univariate analysis, in the *pre* vs. *post1* and in the *pre* vs. *post2* comparisons, we take only the stocks for which data in the *post1* and *post2* periods exist, respectively. Following Venkataraman and Waisburd (2007), for each market quality measure, *y*, we estimate the following model:

$$y_{i,t} = \beta_0 + \beta_1 Control_i + \beta_2 After_{i,t} + \beta_3 \left(After_{i,t} {*} Control_i\right) + \varepsilon_{i,t}$$

where *Control* is a dummy for control stocks and *After* is a dummy variable which is equal to 0 during the *pre*-period and 1 during the other sample periods. The interpretation of the model coefficients is straightforward and allows us to compare changes in the market quality measures both between the treatment and the control sample, and between the period before and the periods after the introduction of the DMMs. If β_1 is positive, it means that, all else equal, *y* is greater for control stocks than for STAR stocks. β_2 is positive if *y* increases after the introduction of the DMMs. More importantly, if β_3 is positive, the increase in the dependent variable is greater for control stocks than for STAR stocks. The model is estimated with three sets of data separately for each period after the DMMs introduction: *post*, *post1* and *post2*. To control for unobservable variables that might affect market quality firm-pair fixed effects have also been included into the regression.[14] Table 5 reports the results.

SPREAD — In the models for the quoted spread (Panel A) and for the time-weighted quoted spread (Table 5, Panel B), for the three period comparisons, β_2 is significant and negative, while β_3 is significant and positive. This confirms the findings of the univariate analysis and suggests that the introduction of the DMMs consistently decreases spread and time-weighted spread of STAR stocks relative to that of control stocks during the three sample periods. Even more interestingly, the decrease in spread more than doubles from the *post* to the *post1* period and it is more than three times greater in the *post2* period.[15]

VOLATILITY — The results for volatility (Table 5, Panel C) also confirm the univariate findings. β_2 is significant and negative in the *pre* vs. *post* and *pre* vs. *post2* comparisons, and it is negative but not significant in the *pre* vs. *post1* comparison. However, β_3 is significant and negative over the three period comparisons; this indicates that volatility for treatment stocks decreases more (and increases less in the *post1*-period) than for control stocks.

We also reran the analysis using the autocorrelation in intra-day returns as dependent variable. Return autocorrelation can be seen as a measure of short term volatility, which is due to temporary deviation of the transaction price from the fundamental value. We found (the results are not reported for brevity) that autocorrelation increases, i.e. it is less negative, after the introduction of the DMMs in the *post1* and *post2* periods. This result is consistent with our theoretical benchmark, which predicts that in the market with the DMMs uninformed traders can make a better inference of the fundamental value of the asset; as a consequence the deviation of the price from the fundamental value should decrease.

TRADING VOLUME — Volume (Panel D) is affected by the introduction of the DMMs. Right after the introduction of the DMMs (a month later) the variation in volume for STAR stocks is not significantly different from that of control stocks (β_3 is not significant). This result does not come unexpected as from informal conversations with professionals acting as DMMs on STAR stocks, we learnt that it takes time to build volume in fairly illiquid stocks, especially when spread requirements are not binding. In the *post1*-period the effects of DMMs on volume is positive as volume for STAR stocks performs better than volume for control stocks ($\beta_3 < 0$ and significant). Finally, STAR volume increases two years after the introduction of the DMMs and this increase is greater than for control stocks (in the *pre* vs. *post2* comparison $\beta_2 > 0$, $\beta_3 < 0$, and both parameters are significantly different from zero).

Furthermore, we include in the regression for all our measures of market quality three variables that control for other possible cross-sectional differences; we consider market capitalization, market to book ratio and leverage. Table 6 shows the results, which confirm our findings from the more parsimonious specification.[16]

To summarize, the findings of the multivariate analysis confirm Hypothesis 1 and 2; Hypothesis 3 can only be confirmed for the *post1* and *post2* periods.

4.2.1. Measures of market quality: further investigations

In this section we consider two extensions of the multivariate analysis that firstly address the issue of a possible endogeneity bias and secondly consider the proportion of time during which the maximum spread was effectively binding in the *pre*-period.

[14] The results obtained from the regression without fixed effects are unchanged.

[15] We also replicated the analysis using the quoted spread not standardized on the midquote. The results from this model show that spreads significantly decrease in the *post1* and *post2* periods; we also observe a decrease in the *post* period, which is not significantly different from zero.

[16] The results are also robust to a 97.5% level winsorization, to the inclusion of dummy variables for the groups of stocks that were assigned a DMM at the same date, and to the inclusion of time effects. Furthermore, the same models have been estimated using only the stocks for which the *post2*-period exists and qualitatively analogous results have been obtained. To economize on space these results are not included here and are available from the authors upon request.

Table 5
Measures of market quality — Multivariate analysis. This table reports the results of the regression: $y_{i,t}=\beta_0+\beta_1 Control_i+\beta_2 After_{i,t}+\beta_3(After_{i,t}*Control_i)+\varepsilon_i$; where the subscript *i* refers to stock *i*, the subscript *t* refers to day *t*, *Control* is a dummy variable for the control stocks, *After* is a dummy variable for the period after the introduction of STAR; *y* is either the quoted spread (Panel A), or the time-weighted quoted spread (Panel B), or volatility (Panel C), or trading volume (Panel D). The model is estimated using data from the periods *pre* and *post* (column *pre* vs. *post*), or from the periods *pre* and *post1* (columns *pre* vs. *post1*) or from the periods *pre* and *post2* (column *pre* vs. *post2*). In the *post1–pre* and *post2–pre* comparisons, we consider only the stocks for which the *post1* and *post2* periods exist. *T*-tests are reported in brackets.***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	pre vs. post	pre vs. post1	pre vs. post2
Panel A: Spread			
Constant	0.0090***	0.0116***	0.0113***
	(73.88)	(56.30)	(67.76)
Control	0.0012***	0.0007**	−0.0014***
	(−7.20)	(−2.28)	(−6.06)
After	−0.0008***	−0.0014***	−0.0043***
	(−4.42)	(−4.98)	(−18.42)
(Control)*(After)	0.0015***	0.0035***	0.0042***
	(6.03)	(8.63)	(12.77)
R^2	0.0121	0.0145	0.0389
Panel B: Time-weighted spread			
Constant	0.0084***	0.0108***	0.0107***
	(73.60)	(55.19)	(67.76)
Control	0.0012***	0.0008***	−0.0013***
	(−7.44)	(−2.79)	(−5.94)
After	−0.0006***	−0.0011***	−0.0039***
	(−3.79)	(−4.01)	(−17.95)
(Control)*(After)	0.0011***	0.0027***	0.0038***
	(4.68)	(6.96)	(12.16)
R^2	0.0103	0.0100	0.0367
Panel C: Volatility			
Constant	0.0307***	0.0372***	0.0356***
	(48.21)	(32.55)	(36.59)
Control	0.0063***	0.0057***	0.0034**
	(−6.97)	(−3.52)	(−2.46)
After	−0.0022**	−0.0001	−0.0087***
	(−2.52)	(−0.04)	(−6.42)
(Control)*(After)	0.0033***	0.0132***	0.0103***
	(2.61)	(5.87)	(5.38)
R^2	0.0103	0.0220	0.0172
Panel D: Trading volume			
Constant	232945.80***	157420.00***	161335.50***
	(20.50)	(14.83)	(10.34)
Control	26989.18*	103935.70***	119897.00***
	(−1.67)	(−6.88)	(−5.42)
After	−27657.50*	−22891.40	38044.96*
	(−1.73)	(−1.55)	(−1.76)
(Control)*(After)	22393.03	−73357.80***	−70710.10**
	(0.99)	(−3.50)	(−2.31)
R^2	0.0011	0.0109	0.0053

4.2.1.1. Endogeneity. As the choice of being assigned a DMM is on the side of the firm, to control for a potential endogeneity bias, we consider here a treatments-effect model (Maddala, 1983) where the multivariate model is simultaneously estimated with a new probit model relating the probability of entering STAR to the firm-specific characteristics. Hence we estimate the two following equations:

$$y_{i,t} = \beta_0 + \beta_1 Control_i + \beta_2 After_{i,t} + \beta_3\left(After_{i,t}{*}Control_i\right) + \varepsilon_{i,t}$$
$$Control_i^* = \alpha_0 + \alpha_1 Cap_{i,t} + \alpha_2 MTB_{i,t} + \alpha_3 LEV_{i,t} + \alpha_4 Price_{i,t} + u_{i,t}$$

where $Control^*$ is a latent variable that we assume to be linearly related to market capitalization (*CAP*), market to book ratio (*MTB*), leverage (*LEV*) and price (*Price*). $Control^*$ is related to the observed dummy variable for control stocks as follows:

$$Control_i = \begin{cases} 1, \text{if } Control_i^* > 0 \\ 0, \quad \text{otherwise} \end{cases}$$

Table 6

Measures of market quality — further cross-sectional differences. This table reports the results of the regression: $y_{i,t} = \beta_0 + \beta_1 Control_i + \beta_2 After_{i,t} + \beta_3 (After_{i,t} * Control_i) + CV_{i,t} + \varepsilon_i$; where the subscript *i* refers to stock *i*, the subscript *t* refers to day *t*, *Control* is a dummy variable for the control stocks, *After* is a dummy variable for the period after the introduction of STAR; *y* is either the quoted spread (Panel A), or the time-weighted quoted spread (Panel B), or volatility (Panel C), or trading volume (Panel D); *CV* indicates a set of additional control variables i.e. market capitalization, market to book ratio (MTB) and leverage. In the regression in Panel D MTB and Leverage are multiplied by 1000. The model is estimated using data from the periods *pre* and *post* (column *pre* vs. *post*), or from the periods *pre* and *post1* (columns *pre* vs. *post1*) or from the periods *pre* and *post2* (column *pre* vs. *post2*). In the *post1*–*pre* and *post2*–*pre* comparisons, we consider only the stocks for which the *post1* and *post2* periods exist. *T*-tests are reported in brackets. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	pre vs. post	pre vs. post1	pre vs. post2
Panel A: Spread			
Constant	0.0139***	0.0168***	0.0173***
	(40.86)	(30.18)	(40.72)
Control	0.0018***	0.0028***	−0.0017***
	(−9.86)	(−7.43)	(−5.62)
After	−0.0006***	−0.0014***	−0.0046***
	(−3.86)	(−5.25)	(−19.56)
(Control) * (After)	0.0013***	0.0037***	0.0048***
	(5.81)	(9.29)	(14.55)
Capitalization	−0.0014***	−0.0018***	−0.0020***
	(−17.86)	(−13.98)	(−18.55)
MTB	−0.2918***	−0.4613***	−0.1049***
	(−10.32)	(−10.98)	(−3.32)
Leverage	0.0003	0.0029***	−0.0032***
	(0.67)	(2.68)	(−4.13)
R^2	0.0307	0.0220	0.0977
Panel B: Time-weighted spread			
Constant	0.0135***	0.0167***	0.0183***
	(41.96)	(30.19)	(46.04)
Control	0.0018***	0.0028***	−0.0017***
	(−9.86)	(−7.43)	(−5.62)
After	−0.0006***	−0.0014***	−0.0046***
	(−3.86)	(−5.25)	(−19.56)
(Control) * (After)	0.0011***	0.0029***	0.0046***
	(5.26)	(7.63)	(15.39)
Capitalization	−0.0014***	−0.0018***	−0.0024***
	(−19.12)	(−14.74)	(−23.85)
MTB	−0.2730***	−0.3999***	0.0253
	(−10.26)	(−9.73)	(0.86)
Leverage	−0.0001	0.0010	−0.0057***
	(−0.30)	(1.02)	(−7.87)
R^2	0.0290	0.0254	0.1050
Panel C: Volatility			
Constant	0.0336***	0.0495***	0.0448***
	(18.17)	(14.84)	(17.22)
Control	0.0061***	0.0066***	0.0022
	(−5.77)	(−2.74)	(−1.18)
After	−0.0008	0.0029*	−0.0082***
	(−0.88)	(−1.77)	(−5.77)
(Control) * (After)	0.0029**	0.0110***	0.0105***
	(2.20)	(4.72)	(5.32)
Capitalization	−0.0012***	−0.0035***	−0.0031***
	(−2.75)	(−4.53)	(−4.78)
MTB	−0.1719	−0.4884*	−0.1265
	(−1.11)	(−1.93)	(−0.66)
Leverage	0.0014	−0.0098	−0.0045
	(0.49)	(−1.52)	(−0.95)
R^2	0.0189	0.0191	0.0165
Panel D: Trading volume			
Constant	149628.50***	83779.95***	46189.98
	(4.39)	(2.74)	(1.10)
Control	52472.82***	206079.50***	196015.40***
	(−2.72)	(−9.02)	(−6.23)
After	−34777.34**	−51108.70***	88685.33***
	(−2.04)	(−3.25)	(−3.84)
(Control) * (After)	24570.09	−44002.37**	−113437.20***
	(1.02)	(−2.02)	(−3.53)
Capitalization	966.37***	651.65***	1052.01***
	(11.69)	(9.02)	(9.90)
MTB	−7896.37***	−13300.00***	−11200.00***

Table 6 (*continued*)

	pre vs. post	pre vs. post1	pre vs. post2
Panel D: Trading volume			
	(−2.79)	(−5.60)	(−3.62)
Leverage	−210.25***	−61.45	−219.25***
	(−4.00)	(−1.03)	(−2.85)
R^2	0.0110	0.0356	0.0230

Following Maddala (1983), we estimate the model through maximum likelihood by assuming that the error terms of the two equations are bivariate normally distributed. The results for the coefficient β_3, which are not reported for brevity, are qualitatively analogous to the ones previously obtained. We conclude that, after controlling for the potential endogeneity bias, the introduction of the DMMs leads to the documented improvement in market quality.

4.2.1.2. Binding maximum spread. If we compare the spread prevailing before the introduction of the DMMs with the maximum spread required to market makers, we notice that the latter is on average never binding during the *pre*-period. As shown in Table 1, the maximum spread is on average 5.8 times greater than the prevailing spread in the *pre*-period. This is the reason why we believe that liquidity requirements are not effective. We also computed the proportion of time in the *pre*-period during which the maximum spread was effectively binding (Table 1) and found that the maximum spread required to DMMs was not effectively binding (average across stocks) for the 99.77% of the trading time considered; this corresponds to an average of 41 s/day during which the spread required was effectively binding. Notice also that for 22 stocks the maximum spread required was strictly non binding. Professionals acting as DMMs on STAR stocks confirmed us that the reward offered for their activity would not be adequate to compensate them for the risk of posting a binding spreads.

To further check the robustness of our results, we included in the general model a control term indicating the daily percentage of time during which the spread required was binding, and found that the sign and the significance levels of the interaction terms (which measure the effect of the introduction of the DMMs on market quality) are qualitatively analogous to the ones described before (Table 7).

This suggests that in this case the improvement in market quality documented after the introduction of the DMMs cannot be attributed to the minimum liquidity guarantee granted by the maximum spread requirement.

5. Empirical analysis: information disclosure, asymmetric information and probability of informed trading

The results in Section 4 show that after the introduction of the DMMs spread and volatility significantly decrease. If this improvement is due to the information disclosure requirements imposed on the DMMs, we expect information asymmetries to decrease.

We study how information asymmetries, measured by the probability of informed trading, vary for STAR stocks in the four sub-periods under analysis. Accordingly, we investigate the pattern of the informational component of the bid–ask spread by estimating the standard Glosten and Harris (1988) model, which relates price changes to the order flow; following Hasbrouck (1991), we also study the long run price impact of trades in the context of a VAR model. Finally, to further inquire into the effect of disclosure, we examine the market reaction to the information released both in roadshows and in DMMs' financial reports.

5.1. Information asymmetries and the probability of informed trading

We measure information asymmetries by estimating the probability of informed trading (PIN) as it is derived in the model of Easley et al. (1996). This method to studying information asymmetries has been extensively used in market microstructure, corporate finance, asset pricing and financial accounting. The model considers a market for a single risky asset, where a competitive market maker receives orders from informed and uninformed traders.[17] The market game is repeated over T days. At the beginning of each day an information event occurs with probability α, and it is good news with probability $(1-\delta)$ and bad news with probability δ. Orders from informed traders (who know whether the event is good or bad news) and uninformed traders (who trade for liquidity reasons) follow a Poisson process with daily intensity μ and ε, respectively. The probability of observing B buys and S sells on day t, conditional on the parameters of the model ($\Theta \equiv [\mu, \varepsilon, \beta, \delta]$), can be derived as:

$$Pr[y_t = (B,S)\,|\,\Theta] = \alpha(1-\delta)e^{-(\mu+2\varepsilon)}\frac{(\mu-\varepsilon)^B\varepsilon^S}{B!S!} + \alpha\delta e^{-(\mu+2\varepsilon)}\frac{(\mu+\varepsilon)^S\varepsilon^B}{B!S!} + (1-\alpha)e^{-2\varepsilon}\frac{\varepsilon^{B+S}}{B!S!}$$

where y_t contains the number of buys and sells on day t.

[17] The model has been applied to both quote driven and order driven markets. An example of application to order driven markets is Atkas et al. (2007), in which PIN is estimated using data from the electronic limit order book of Euronext.

Table 7

Measures of market quality — control for binding maximum spread. This table reports the results of the regression: $y_{i,t} = \beta_0 + \beta_1 Control_i + \beta_2 After_{i,t} + \beta_3 (After_{i,t} * Control_i) + EP_{i,t} + \varepsilon_s$; where the subscript *i* refers to stock *i*, the subscript *t* refers to day *t*, *Control* is a dummy variable for the control stocks, *After* is a dummy variable for the period after the introduction of STAR; *EP* is the proportion of time during which the maximum spread required to DMMs is binding during the day; *y* is either the quoted spread (Panel A), or the time-weighted quoted spread (Panel B), or volatility (Panel C), or trading volume (Panel D). The model is estimated using data from the periods *pre* and *post* (column *pre* vs. *post*), or from the periods *pre* and *post1* (columns *pre* vs. *post1*) or from the periods *pre* and *post2* (column *pre* vs. *post2*). In the *post1–pre* and *post2–pre* comparisons, we consider only the stocks for which the *post1* and *post2* periods exist, respectively. *T*-tests are reported in brackets. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	pre vs. post	pre vs. post1	pre vs. post2
Panel A: Spread			
Constant	0.0087***	0.0112***	0.0109***
	(−73.27)	(−55.53)	(−67.49)
Control	0.0014***	0.0009***	−0.0011***
	(−8.27)	(−3.26)	(−4.90)
After	−0.0005***	−0.0011***	−0.0039***
	(−3.47)	(−4.06)	(−17.54)
(Control) * (After)	0.0012***	0.0032***	0.0038***
	(−5.39)	(−8.05)	(−12.15)
EP	0.0903***	0.0933***	0.0934***
	(−19.45)	(−15.38)	(−20.29)
R^2	0.0327	0.0352	0.0860
Panel B: Time-weighted spread			
Constant	0.0083***	0.0106***	0.0104***
	(72.91)	(54.40)	(67.17)
Control	0.0013***	0.0009***	−0.0011***
	(−8.27)	(−3.56)	(−5.00)
After	−0.0004***	−0.0008***	−0.0036***
	(−3.01)	(−3.27)	(−17.15)
(Control) * (After)	0.0009***	0.0024***	0.0035***
	(4.15)	(6.47)	(11.60)
EP	0.0678***	0.0695***	0.0697***
	(15.39)	(11.93)	(15.88)
R^2	0.0240	0.0231	0.0669
Panel C: Volatility			
Constant	0.0293***	0.0350***	0.0331***
	(47.51)	(31.53)	(35.90)
Control	0.0076***	0.0078***	0.0058***
	(−8.69)	(−4.98)	(−4.43)
After	−0.0008	0.0020	−0.0062***
	(−1.04)	(−1.36)	(−4.89)
(Control) * (After)	0.0020*	0.0110***	0.0078***
	(1.67)	(5.05)	(4.34)
EP	0.7729***	0.7976***	0.8005***
	(30.78)	(22.82)	(29.03)
R^2	0.0701	0.0803	0.1189
Panel D: Trading volume			
Constant	233128.70***	158207.90***	162613.20***
	(20.46)	(14.85)	(10.38)
Control	26807.30*	103149.00***	118626.90***
	(−1.66)	(−6.82)	(−5.36)
After	−27841.10*	−23681.50	36753.10*
	(−1.74)	(−1.60)	(−1.69)
(Control) * (After)	22575.40	−72570.40***	−69424.90**
	(0.99)	(−3.46)	(−2.27)
EP	−97096.20	−260180.60	−381602.50
	(−0.22)	(−0.83)	(−0.87)
R^2	0.0011	0.0110	0.0053

The likelihood function is then computed by assuming that $\{y_t\}_{t=1}^{T}$ are i.i.d. We use the reformulated log-likelihood proposed by Easley et al. (2002):

$$L\left(\{y_t\}_{t=1}^{T} | \Theta\right) = \sum_{t=1}^{T} \left[-2\varepsilon + M\ln(x) + (B-S)\ln(\mu+\varepsilon)\right] + \sum_{t=1}^{T} \ln\left[\alpha(1-\delta)e^{-\mu}x^{S-M} + \alpha\delta e^{-\mu}x^{B-M} + (1-\alpha)x^{B+S-M}\right]$$

where $M = \min(B,S) + \max(B,S)/2$, and $x = \frac{\varepsilon}{\mu+\varepsilon}$.

Table 8
Probability of informed trading (PIN). This table presents the results of the estimation of the probability of informed trading (PIN), following Easley et al. (1996). Panel A reports descriptive statistics for PIN in the four periods around the introduction of the DMMs. Panel B compares the average difference in PIN between the periods after the assignment of the DMMs and the *pre*-period for STAR (column *STAR*) and control stocks (column *Control*). In the *post1–pre* and *post2–pre* comparisons, we consider only the stocks for which the *post1* and *post2* periods exist. A paired-sample *t*-test and a Wilcoxon signed-rank test for the null hypothesis that the average or the median difference in differences (defined as *DID* in Section 4 and reported in column *STAR–Control*) is equal to zero are presented. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

STAR	pre	post	post1	post2	Control	pre	post	post1	post2
Panel A: PIN — descriptive statistics									
Average STAR	0.2499	0.2328	0.2303	0.2320	Average control	0.2305	0.2514	0.2364	0.2560
St. dev. STAR	0.0738	0.0684	0.0691	0.0419	St. dev. control	0.0771	0.0902	0.0722	0.1089

	STAR	Control	STAR–Control	*t*-test	Wilcoxon
Panel B: Variation in PIN					
post–pre	−0.0171	0.0209	−0.0380	−1.5062	−1.129
post1–pre	−0.0358	0.0127	−0.0485	−1.7922*	−1.721*
post2–pre	−0.0275	0.0525	−0.0800	−1.9583*	−1.932*

The probability of informed trading is defined as the ratio of the arrival rate of informed orders to the arrival rate of all orders:

$$PIN = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon}$$

To obtain the estimate of *PIN*, we only need the number of buys and sells in each day in the sample.[18] To classify trades as buys or sells we use the algorithm proposed by Lee and Ready (1991). A trade is classified as a buy if its execution price is above the previous midquote and it is classified as a sell if its execution price is below; if the execution price is equal to the previous midquote, then it is compared to the price of the previous trade and the trade is classified as a buy (sell) if there has been an upward (downward) price change. In the comparison between the execution price and the previous midquote, we require the midquote to be 5 s older than the trade.[19]

RESULTS — Table 8 compares the estimates of PIN for STAR and control stocks in the different sample periods. We concentrate again on the difference in differences (DID), defined as in Section 4.1 The results show that moving from the pre to the post-period, the change in the STAR stocks' PIN is not significantly different from that experienced by control stocks; comparing, instead, the pre with the post1 and post2 periods, we find that PIN significantly decreases relatively to the control sample, even though the results should be interpreted with caution as the significance is at the 10% level.

5.2. The informational component of the bid–ask spread

The observed decrease in information asymmetry suggests that the concurrent improvement in liquidity can be related to the different degree of information disclosure characterizing STAR stocks before and after the assignment of the DMMs.

Indeed, DMMs have the objective of improving and speeding up the dissemination of the companies' information. Hence, we expect the outcome of this disclosure activity to be the general improvement of traders' ability to process information about STAR stocks. This has the effect of reducing the impact of traders' orders on stock prices, thus making it difficult to obtain profits out of the companies' information disclosure. If market participants are generally more informed, they are no longer able to move prices when submitting their orders, and the adverse selection component of the spread due to traders' inability to efficiently exploit information, becomes significantly smaller.

We interpret the reduction in the probability of informed trading observed in the data as evidence of increased informational efficiency of STAR stocks. We verify this conjecture by using the Glosten and Harris (1988) model, which relates price changes to order flow.[20]

[18] We maximize the likelihood function numerically by using the Nelder–Mead method; the computation is performed through a Matlab routine. We exclude the sub-periods with less than ten trades on average. The maximization converges for 94.6% of the stock/periods. Moreover, we compute the hessian of the parameters of the model by using the Newton–Rhapson–Simpson method and we derive the standard errors. According to the corresponding *z*-tests, the estimates of the parameters are significantly different from zero at the 10% level.

[19] We apply the five-second adjustment because we were advised by BIt that there could be small delays in quote reporting. We also examined the classification of trades without any time adjustment and for a one, three and ten second time delay; the resulting average number of trades classified as buyer or seller initiated is not significantly different than the one reported.

[20] Doran et al. (2009) point out that the existence of serial correlation in the order flow might affect the estimate of adverse selection costs when it is evaluated using the Glosten and Harris (1988) model. Thus, we also computed the serial correlation in the order flow, measured as the first order serial correlation of trade direction. In none of the period comparisons the variation in serial correlation for STAR stocks is significantly different than the one exhibited by control stocks. Therefore, in this sample considered, the results are not subject to this criticism.

Table 9
Informational component of the bid–ask spread. This table presents the results of the estimation of the model of Glosten and Harris (1988), used to identify the adverse selection component of the bid–ask spread, as described in Section 5. We estimate the model separately for each stock/period in the sample. We use ordinary least squares and we compute Newey–West standard errors. We restrict the coefficients related to size to be equal to zero and we consider the following specification: $\Delta P_t = c_0 \Delta Q_t + z_0 Q_t + u_t$, where $\Delta P_t = P_t - P_{t-1}$ is the price change, Q_t is the transaction sign (it is equal to 1 for buyer-initiated trades and it is equal to -1 for seller-initiated trades), and $\Delta Q_t = Q_t - Q_{t-1}$ is the transaction sign change. Panel A summarizes the average estimates (in parentheses, the proportion of coefficients significantly different from zero at the 10% level according to a *t*-test are reported). Panel B and C compare the average estimates of c_0 and z_0 between the periods after the assignment of the DMMs and the *pre*-period for STAR (column *STAR*) and control stocks (column *Control*). In the *post1–pre* and *post2–pre* comparisons, we consider only the stocks for which the *post1* and *post2* periods exist. A paired-sample *t*-test and a Wilcoxon signed-rank test for the null hypothesis that the average or the median difference in differences (defined as *DID* in Section 4 and reported in column *STAR–Control*) is equal to zero are presented. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

STAR	pre	post	post1	post2	Control	pre	post	post1	post2
Panel A: Summary of estimates									
Average c_0	0.0189	0.0166	0.0091	0.0067	Average c_0	0.0102	0.0121	0.0138	0.0082
	(100%)	(100%)	(100%)	(100%)		(100%)	(100%)	(96.88%)	(96.67%)
Average z_0	0.0053	0.0054	0.0027	0.0023	Average z_0	0.0025	0.0041	0.0053	0.0031
	(100%)	(100%)	(100%)	(100%)		(97.83%)	(100%)	(96.88%)	(96.67%)

	STAR	Control	STAR–Control	*t*-test	Wilcoxon
Panel B: Variation in c_0					
post–pre	−0.0023	0.0019	−0.0042	−2.4066**	−1.425
post1–pre	−0.0034	−0.0006	−0.0028	−0.9371	−0.729
post2–pre	−0.0065	−0.0066	0.0001	0.0552	−0.524
Panel C: Variation in z_0					
post–pre	0.0001	0.0016	−0.0015	−2.249**	−1.675*
post1–pre	−0.0009	0.0020	−0.0029	−2.4817**	−3.029***
post2–pre	−0.0013	−0.0002	−0.0011	−2.2143**	−2.376**

The reduced form of the model is the following:

$$\Delta P_t = c_0 \Delta Q_t + c_1 \Delta x_t + z_0 Q_t + z_1 x_t + u_t$$

where $\Delta P_t = P_t - P_{t-1}$ is the price change, Q_t is the transaction sign (it is equal to $+(-)1$ for buyer(seller)-initiated trades), x_t is the size of the trade multiplied by its sign, $\Delta Q_t = Q_t - Q_{t-1}$ is the transaction sign change, $\Delta x_t = x_t - x_{t-1}$ is the change in the signed trade size, and finally u_t is a white noise error term.

We interpret the coefficients c_0 and c_1 as standard measures of order processing costs, with the latter relating fixed costs to order size. The relative interpretation of the coefficients z_0 and z_1 is more intricate. z_1 captures the adverse selection component of the spread due to order size, that is traditionally related to insider trading; following Easley and O'Hara (1987), in fact, large orders are generally considered as vehicle of private information. z_0, instead, indicates the effect on price changes of all the orders, independently of their size. It is precisely this adverse selection component that we expect to decrease after the introduction of the STAR DMMs. We expect z_0 to fall more than z_1 as the DMMs' activity influences the informativeness of all market participants, not only of those submitting large orders. In addition, STAR stocks are of small-medium capitalization, and their average trade size is fairly small, with little size variability. Hence, we expect that when traders on these stocks become more informed, it will be the generality of the orders rather than those of large size that will reveal better informational efficiency.

To determine the sign of the transaction, we use again the Lee and Ready (1991) algorithm. We estimate the model for each stock and each period with ordinary least squares, and compute Newey–West standard errors to take serial correlation into account. For most of the stocks in the sample we find that c_1 and z_1 are not significantly different from zero. According to *t*-tests, c_1 and z_1 are significantly different from zero at the 10% level only for 28.05% and 18.98% of the stock/periods, respectively; according to *F*-tests both coefficients are not significantly different from zero for 62.43% of the stock/periods; on the contrary, c_0 and z_0 are significantly different from zero for all the sample stocks. The results imply that for these small-cap stocks trade size contributes to explain a negligible part of the variation in price.[21]

Therefore, we estimate the model by restricting c_1 and z_1 to be equal to zero. Table 9 reports the difference in differences (DID) concerning c_0 and z_0. Order processing costs are not affected by the introduction of the DMMs. c_0 decreases for STAR stocks and for control stocks, but the two average variations are not significantly different. As conjectured, we find that z_0 significantly decreases for STAR stocks more than for control stocks in the post, post1 and post2 periods.[22]

[21] Van den Bongard and Klar (2007) estimate the Glosten and Harris (1988) model using data from Xetra, the German equity market; they also find that for small stocks trade size has a negligible impact on price variation.

[22] As a robustness check, we also estimated the model by including among the regressors daily volatility measured as described in Section 4, and obtained analogous results.

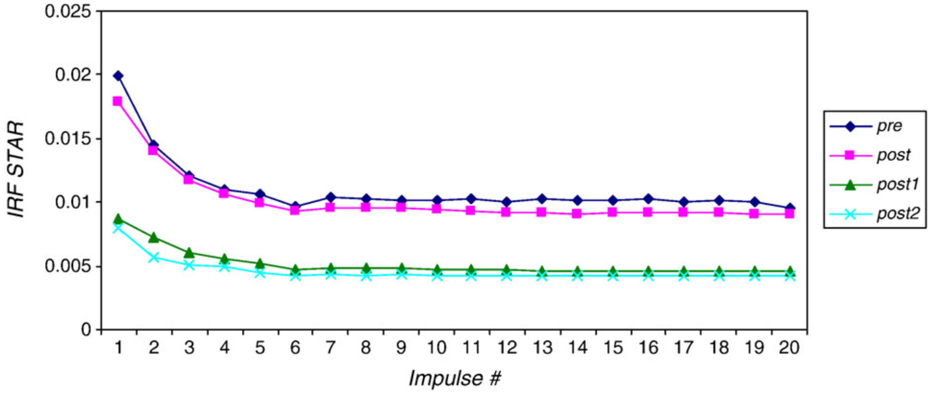

Fig. 3. Cumulative impulse response function of transaction sign on price changes — STAR stocks. This figure reports the cumulative impulse response function (IRF) of transaction sign on price changes corresponding to the VAR model described in Section 5. Precisely, it depicts the average cumulative IRF across all STAR stocks for the four sample periods considered. The *x*-axis indicates the time-step (step 1 is the contemporaneous impulse), the *y*-axis indicates the cumulative IRF.

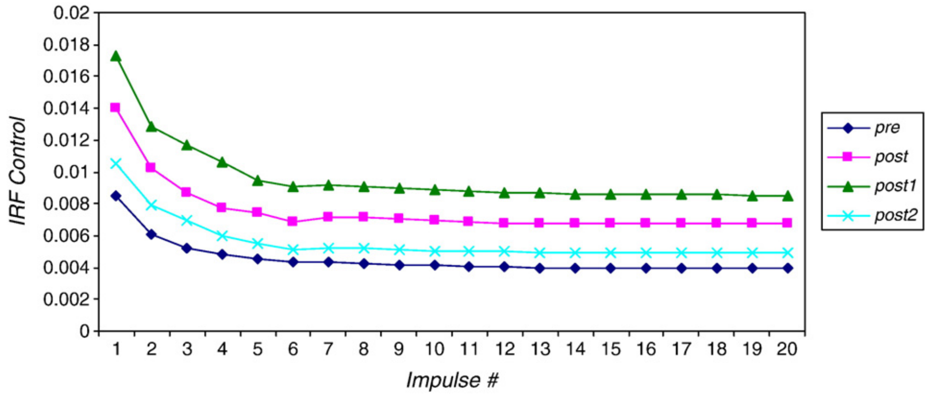

Fig. 4. Cumulative impulse response function of transaction sign on price changes — Control stocks. This figure reports the cumulative impulse response function (IRF) of transaction sign on price changes corresponding to the VAR model described in Section 5. Precisely, it depicts the average cumulative IRF across all control stocks for the four sample periods considered. The *x*-axis indicates the time-step (step 1 is the contemporaneous impulse), the *y*-axis indicates the cumulative IRF.

5.3. A VAR approach to model information asymmetries

The results of the Glosten and Harris (1988) model indicate that the price impact of trades decreases after the introduction of the DMMs. This can be interpreted as a reduction in both inventory and/or adverse selections costs. In our case, it is unlikely that the advent of the DMMs reduces inventory costs; however, to attribute the observed price impact reduction to adverse selection costs we have to investigate its longer run pattern. In fact, theory predicts that the price impact due to inventory costs is transitory, and only the price impact due to adverse selection costs is permanent.

In markets where traders actively manage their inventory, prices reverse back to their fundamental in the absence of new information.

Hasbrouck (1991) proposes a straightforward methodology to evaluate the longer run impact of trades on price changes by estimating a structural VAR model. The VAR also allows one to take into account serial correlation in the order flow and the feedback effect of price changes on the order flow. We consider the following specification:

$$\begin{cases} \Delta P_t = a_0 Q_t + a_1 Q_{t-1} + \ldots + a_5 Q_{t-5} + b_1 \Delta P_{t-1} + \ldots + b_5 \Delta P_{t-5} + \varepsilon_{1,t} \\ Q_t = c_1 Q_{t-1} + \ldots + c_5 Q_{t-5} + d_1 \Delta P_{t-1} + \ldots + d_5 \Delta P_{t-5} + \varepsilon_{2,t} \end{cases}$$

where $\Delta P_t = P_t - P_{t-1}$ is the price change, Q_t is the transaction sign (it is equal to $+(-)1$ for buyer(seller)-initiated trades), and $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are white noise uncorrelated error terms. Notice that to identify the model it is assumed that price changes have no contemporaneous effect on order flow changes; this is a natural assumption in markets that work as limit order books where trades are done at prices available before the trade. As in the previous analysis, we use the Lee and Ready (1991) algorithm to determine transaction signs.

Table 10
Cumulative impulse response function of transaction sign on price changes. This table reports the cumulative impulse response function (IRF) of transaction sign on price changes corresponding to the VAR model described in Section 5. Panel A presents the average cumulative IRF across control stocks for the four sample periods considered. Notice that step 1 is the contemporaneous impulse. Panels B and C compare the average difference in the cumulative IRF between the periods after the assignment of the DMMs and the *pre*-period for STAR (column *STAR*) and control stocks (column *Control*). In the *post1–pre* and *post2–pre* comparisons, we consider only the stocks for which the *post1* and *post2* periods exist. A paired-sample *t*-test and a Wilcoxon signed-rank test for the null hypothesis that the average or the median difference in differences (defined as *DID* in Section 4 and reported in column *STAR-Control*) is equal to zero are presented. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

STAR	*pre*	*post*	*post1*	*post2*	*Control*	*pre*	*post*	*post1*	*post2*
Panel A: Summary of estimates									
step 1 (cont.)	0.0199	0.0179	0.0087	0.0080	*step 1 (cont.)*	0.0085	0.0140	0.0173	0.0105
step 20	0.0096	0.0090	0.0046	0.0042	*step 20*	0.0040	0.0068	0.0085	0.0049

	STAR	Control	STAR–Control	*t*-test	Wilcoxon
Panel B: Variation at impulse 1					
post–pre	−0.0020	0.0055	−0.0075	2.5464**	2.359**
post1–pre	−0.0049	0.0065	−0.0114	2.7849***	3.279***
post2–pre	−0.0059	−0.0004	−0.0055	2.5196**	2.811***
Panel C: Variation at impulse 20					
post–pre	−0.0006	0.0028	−0.0034	2.7478***	2.75***
post1–pre	−0.0012	0.0034	−0.0046	2.5712**	3.279***
post2–pre	−0.0017	−0.0003	−0.0014	1.8905*	1.778*

Within this framework, the long run impact of trades on returns can be captured by the impulse response function (IRF) of order flow on price changes, which can be obtained by the VMA representation of the structural model.[23] We take step 20 as the limit point of the system because the prevalence of the adjustment is complete approximately after step 10.

Figs. 3 and 4 present the cumulative IRF for STAR and control stocks. For STAR stocks the IRF gradually moves downwards and it has a marked shift in the *post1*-period. For control stocks the pattern is different. The IRF goes up in the *post*-period and it moves downwards only in the *post2*-period.

Table 10 reports the cumulative IRF at step one (the contemporaneous) and 20. The difference in differences (*DID*) is always negative and significantly different from zero, indicating that the IRF decreases more for STAR stocks than for control stocks in the three period-comparisons at both step one and 20. The results regarding the contemporaneous effect are consistent with those obtained estimating the Glosten and Harris (1988) model. The results concerning step 20 can be interpreted as a longer-run reduction in the price impact of trades and therefore suggest a reduction in adverse selection costs.

5.4. Market reaction to the release of information: roadshows and DMMs' reports

Disclosure requirements for STAR stocks prescribe that DMMs organize meetings, called roadshows, with professional investors. At least two roadshows per year must be held: in the period examined one takes place in Milan and the others in London or in New York. Additionally, DMMs are required to publish no less than two financial analyses per year. To analyze the market reaction to roadshows and to financial analyses we use a standard event study approach.[24]

We examine two metrics of market reaction commonly used in the literature on the usefulness of accounting information[25]: abnormal returns and abnormal trading volume. Abnormal returns (AR) are computed as the residuals from the market model:

$$AR_{it} = R_{it} - \left(\hat{a}_i + \hat{b}_i R_{mt}\right)$$

where $\hat{a}$ and $\hat{b}$ are the estimated parameters, R_m is the return on the MIBTEL index,[26] whereas R_i is the return on stock *i*. Because we are not able to distinguish between good and bad news, we examine an absolute response metric, ABRET.

[23] The structural model can be written as vector autoregression: $\begin{pmatrix} 1 & b_0 \\ 0 & 1 \end{pmatrix}\begin{pmatrix} \Delta p_t \\ Q_t \end{pmatrix} = \sum_{k=1}^{5}\begin{pmatrix} a_k & b_k \\ c_k & d_k \end{pmatrix}\begin{pmatrix} \Delta p_{t-k} \\ Q_{t-k} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{pmatrix}$. The impulse response function can then be computed from the VMA representation of the model: $\begin{pmatrix} \Delta p_t \\ Q_t \end{pmatrix} = \sum_{k=0}^{5}\begin{pmatrix} a_k^* & b_k^* \\ c_k^* & d_k^* \end{pmatrix}\begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{pmatrix}$.

[24] We consider all the roadshows organized and all the DMMs' financial reports published on the Borsa Italiana website from April 2001 to December 2007.

[25] See Kothari (2001) for a critical survey of this literature.

[26] The MIBTEL is the benchmark all-share index of the Italian stock market. We also replicated the analysis using the ALLSTARS index, which is a market-cap weighted index measuring the performance of all the firms belonging to the STAR group; the results are analogous.

Table 11
Event study around roadshows. This table reports the mean absolute abnormal returns and abnormal volume in the days around roadshows. Absolute abnormal returns and abnormal volume are defined in Section 5. Day 0 refers to the day of the roadshow. *T*-tests for the null hypothesis that the average absolute abnormal returns or that average abnormal volume are equal to zero are also presented. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Day	Absolute abnormal returns		Abnormal volume	
	Average	*T*-test	Average	*T*-test
−20	−0.0239	−0.5194	0.0345	0.7046
−19	−0.0450	−0.9801	0.0052	0.0942
−18	0.0296	0.5836	0.0235	0.4210
−17	−0.0486	−1.2288	0.0446	0.9007
−16	−0.0696*	−1.8850	0.0374	0.8692
−15	−0.0567	−1.5466	0.0366	0.8185
−14	−0.0586	−1.5631	−0.0359	−0.7538
−13	−0.0633	−1.6239	−0.0136	−0.3433
−12	0.0041	0.0989	0.0260	0.6477
−11	−0.0070	−0.1556	0.0590	1.2464
−10	0.0316	0.7089	0.0483	1.2035
−9	0.0018	0.0426	0.0421	0.8912
−8	0.0079	0.1873	0.0844*	1.7245
−7	0.0396	0.9432	0.0839*	1.7506
−6	0.0879	1.5539	0.1145**	2.3574
−5	0.0808*	1.8597	0.0910*	1.8252
−4	0.0370	0.7548	0.1579**	2.5489
−3	0.1614**	2.4128	0.1787***	3.1695
−2	0.0599	1.2756	0.1650***	2.9786
−1	0.1588***	2.8156	0.1626***	3.7867
0	0.2674***	4.1559	0.2503***	4.1516
1	0.2385***	3.9365	0.2771***	5.0908
2	0.2298***	4.0286	0.1905***	3.5931
3	0.2068***	4.0110	0.0605	1.5570
4	0.1185**	2.3669	0.1485***	2.8341
5	0.1045	1.5645	0.1774***	3.3331
6	0.1114**	2.0572	0.1473**	2.4301
7	0.1102*	1.8737	0.1471**	2.4962
8	0.0645	1.2704	0.1921***	2.6827
9	0.0112	0.2547	0.0577	1.2731
10	0.0414	0.8559	0.0690	1.5705
11	0.0611	1.2068	0.0605	1.2876
12	0.0654	1.2956	0.1211	1.4843
13	0.0790	1.5757	0.1207	1.4871
14	0.0251	0.5325	0.1055	1.6184
15	−0.0574	−1.3779	0.0651	1.5908
16	−0.0090	−0.1808	0.0708	1.3762
17	0.0168	0.3378	0.0013	0.0297
18	0.0000	−0.0010	0.0276	0.6724
19	−0.0296	−0.6822	0.0460	1.0043
20	−0.0478	−1.1141	0.0486	0.9533

Following Cready and Hurtt (2002), we define absolute abnormal returns (ABRET) as:

$$ABRET_{it} = [|AR_{it}| - E(|AR_i|)] / \sigma(|AR_i|)$$

where $E(|AR_i|)$ and $\sigma(|AR_i|)$ are the mean and the standard deviation of $|AR_i|$ over the estimation period respectively.

Furthermore, we define abnormal trading volume (AVOL) as in a number of papers that build on Beaver (1968):

$$AVOL_{it} = [V_{it} - E(V_i)] / \sigma(V_i)$$

where V_{it} is trading volume of stock *i* on day *t*, standardized on the number of outstanding shares, and $E(V_i)$ and $\sigma(V_i)$ are the mean and the standard deviation of trading volume over the estimation period, respectively.

For the computation of both abnormal returns and abnormal trading volume we take the 345 days before the roadshows and the analysts' reports publications as the estimation period. We also checked for the date of the quarterly earnings announcements and verified that the disclosure events do not overlap.

RESULTS — Table 11 presents the mean absolute abnormal returns and the mean abnormal volume around roadshows; Table 12 (Figs. 5 and 6) present the same statistics for the financial analyses. Notice that there is a peak right around the information disclosure date, being abnormal returns significantly different from zero from day −1 to +4 for roadshows and from day −3 to +3 for financial analyses. The impact of disclosure on trading volume persists for a wider window: abnormal volume is

Table 12
Event study around analysts' reports. This table reports the mean absolute abnormal returns and abnormal volume in the days around the disclosure of analysts' reports. Absolute abnormal returns and abnormal volume are defined in Section 5. Day 0 refers to the day of the roadshow. *T*-tests for the null hypothesis that the average absolute abnormal returns or that average abnormal volume are equal to zero are also presented. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Day	Absolute abnormal returns		Abnormal volume	
	Average	*T*-test	Average	*T*-test
−20	−0.0239	−0.5194	0.0345	0.8454
−19	−0.0450	−0.9801	−0.0444	−0.9842
−18	−0.0583	−1.3970	0.0512	1.1670
−17	−0.0486	−1.2288	−0.0651	−1.3355
−16	−0.0528	−1.3312	0.0174	0.3996
−15	−0.0567	−1.5466	0.0006	0.0137
−14	−0.0456	−1.1670	0.0047	0.1004
−13	−0.0254	−0.6207	0.0562	1.1981
−12	0.0041	0.0989	0.0635	1.2641
−11	−0.0070	−0.1556	0.0311	0.7395
−10	0.0316	0.7089	0.0678	1.4452
−9	0.0018	0.0426	0.0328	0.7821
−8	0.0079	0.1873	0.0439	1.2983
−7	0.0396	0.9432	0.0729	1.5372
−6	0.0796	1.4081	0.0999**	2.0810
−5	0.0625	1.4374	0.1308***	2.8226
−4	0.0370	0.7548	0.1101***	2.5183
−3	0.1451**	2.1514	0.2065***	3.6986
−2	0.0599	1.2756	0.2220***	4.1481
−1	0.1811***	3.0642	0.3251***	5.7609
0	0.3155***	4.8818	0.6440***	4.8088
1	0.2330***	3.7951	0.5722***	4.5748
2	0.1867***	3.1807	0.3240***	2.7041
3	0.1342**	2.3715	0.3657***	2.9388
4	0.0741	1.4193	0.3319***	3.6270
5	0.1045	1.5645	0.2705***	3.2840
6	0.0697	1.2023	0.0848**	2.0913
7	0.0766	1.1795	0.0665	1.4292
8	0.0351	0.6308	0.0134	0.3636
9	0.0112	0.2547	0.0809	1.5262
10	0.0414	0.8559	0.0422	0.8799
11	0.0684	1.2532	0.1320	1.4833
12	0.0537	0.9660	0.0832	1.5475
13	0.0507	0.9258	0.0743	1.5788
14	0.0251	0.5325	0.0594	1.2749
15	−0.0574	−1.3779	−0.0314	−0.6516
16	−0.0090	−0.1808	0.0196	0.4481
17	0.0168	0.3378	0.0587	1.1173
18	0.0000	−0.0010	0.0523	0.9481
19	−0.0296	−0.6822	0.0671	0.9103
20	−0.0478	−1.1141	0.0357	0.7452

significantly different from zero from day −8 to +8 for roadshows and from day −6 to +6 for financial analyses. This is probably evidence of some information leakage close to the disclosure dates. Overall, we can interpret this result as evidence that market participants perceive the information released both in the roadshows and in the financial analyses as useful for investment decisions. These findings confirm our conjecture that information disclosure has a driving role in the performance of STAR stocks.

Finally, we also related the variation in our market quality measures to the size of the market response to roadshows and financial reports. Specifically, for each pair of stocks and in each period comparison, we regressed the difference in differences on the average absolute abnormal returns and abnormal volume on roadshow and financial report days. We found (the results are not reported for brevity) that the difference in differences in the spread and in the time-weighted spread for the *pre* vs. *post1* and *pre* vs. *post2* comparisons is significantly negatively associated to the market reaction to roadshows and financial reports. Thus, the greater the market reaction to roadshows and financial reports, the larger the improvement in liquidity. The results regarding volatility, volume, and in general, the *pre* vs. *post* comparison, are instead not significant.

6. Conclusions

Pre-trade transparency is a timely issue in financial market design and regulation. The amount and precision of the information disclosed to market participants before trading has been at the center of a wide empirical and theoretical literature. Little research instead has so far investigated possible channels of information disclosure other than firms and analysts. This paper raises a new question: should information be disclosed by firms and analysts, or by intermediaries? To our knowledge, there is no evidence on

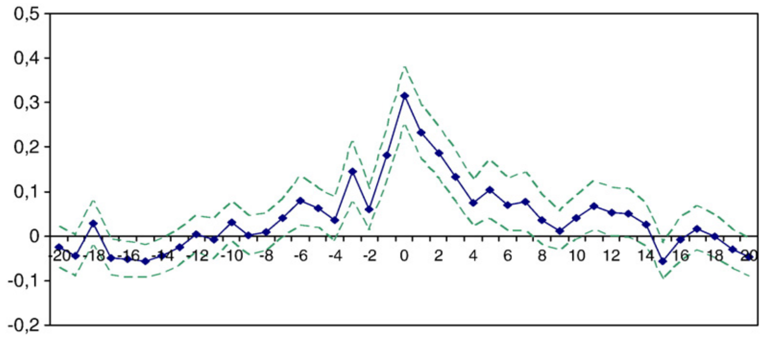

Fig. 5. Absolute abnormal returns DMMs' reports. This figure reports (solid line) the mean absolute abnormal returns, defined as in Section 5, in the days around the disclosure of DMMs' financial reports. Day 0 corresponds to the disclosure date. The *x*-axis indicates the day, the y-axis indicates the mean absolute abnormal returns. A two-standard error confidence interval (dashed lines) is also reported.

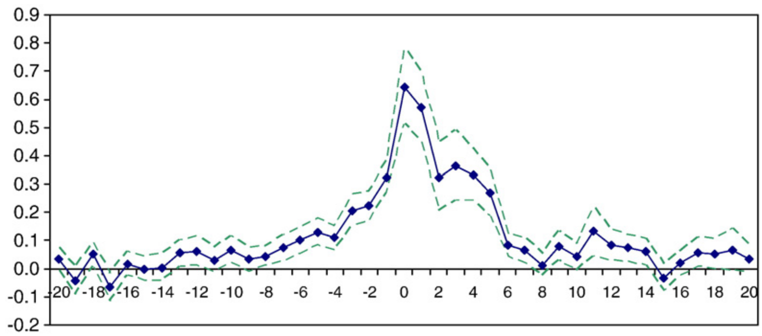

Fig. 6. Abnormal volume around DMMs' reports. This figure reports (solid line) the mean absolute abnormal volume, defined as in Section 5, in the days around the disclosure of DMMs' financial reports The *x*-axis indicates the day, the *y*-axis indicates the mean abnormal volume. A two-standard error confidence interval (dashed lines) is also reported.

the effects of information disclosure by dealers. The concern of conflict of interest prevents regulators from introducing this disclosure vehicle. However, our results show that information disclosure by designated market makers (DMMs) can improve market quality and hence suggest that reputational concerns might prevent front-running and adverse selection costs.[27]

We here study the effect on market quality of the introduction of DMMs in STAR, a group of small-medium capitalization stocks listed on the limit order book of Borsa Italiana. The peculiarity of STAR is that DMMs have information disclosure requirements: precisely, they are required to provide financial analyses on the stocks and to interact with institutional and retail investors on a regular basis. Because liquidity requirements were not binding during the periods examined, we are able to focus on the effect of disclosure requirements and, thus, on the role of market makers as information providers.

We find that, after the introduction of DMMs, spreads and volatility decrease relatively to a matched sample of control stocks. More interestingly, these changes get stronger as time passes. We also find a decreasing trend in information asymmetries, measured by the probability of informed trading (PIN) which is weakly significant but interestingly consistent with the significant decrease in the adverse selection component of the spread, captured by the Glosten and Harris (1988) model and by a VAR model in the spirit of Hasbrouck (1991). Finally, following an event study approach, we show that the information released with the help of DMMs is perceived as useful for investment decisions.

We show that the decrease in information asymmetries observed after the introduction of DMMs is due to an improvement in the degree of information disclosure. As DMMs have the objective of improving and fastening the dissemination of the companies' information, the outcome of this disclosure activity is the general improvement of traders' ability to process information about STAR stocks. This reduces the impact of traders' orders on stock prices and, hence, the adverse selection component of the spread. Analogously, the decrease in the price impact reduces price variations around the fundamental, and volatility can decrease.

In this paper we concentrate on a unique trading environment and we show how relevant can be the disclosure requirements implemented by an exchange to improve market quality for small-medium size stocks. It follows that regulators may find this

[27] A recent intervention of STAR regulators is concerned with the consequences of information disclosure requirements for DMMs. BIt limit order book is anonymous, i.e. traders' identities are not visible; in an exception to the general rule, starting from the migration of the Italian platform on TradeElect 2008 (London Stock Exchange) DMMs' identity codes are publicly visible. The introduction of this new trading feature aims at reassuring counterparties that DMMs do not use the information they hold opportunistically. Such intervention recognizes the function of DMMs as information providers. See, for a thorough discussion of market makers´ trading behavior in anonymous and transparent settings, Reiss and Werner (2004).

information dissemination mechanism preferable when firm-specific incentives for disclosure are not effective. Future research can tackle the issue of how to optimally design and regulate the contracts among DMMs, companies and customers.

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Appendix

Eq. (1) for the equilibrium rational expectation price under the initial regime with only one signal can be easily derived by considering the updating process by investors who do not hold private information. Each uninformed trader updates his/her expectation and variance of the future value of the asset by making firstly a conjecture on the other uninformed traders' demand function, $x_{-U}=-Gp$, secondly by deriving the market price from the market clearing condition, and finally by extracting from this price the signal R.

To obtain R, one should plug x, $x_{-U}=-Gp$ and x_U into the market clearing condition $nx_I+mx_U+z\phi=0:n[\sigma_e^2]^{-1}(q-p)-(m-1)Gp+x_u+z\phi=0$; solve for p, and then extract the signal $R=p\left(1+\frac{\sigma_e^2}{n}(m-1)G\right)-\frac{\sigma_e^2}{n}x_U=q+\frac{\sigma_e^2}{n}x\phi=r$, where r is the realization of the random variable R that uninformed traders extract from the market price. Finally, one should use the signal to compute:

$$E(s|R)=\left(1+\frac{\sigma_e^4 z^2}{n^2}\right)^{-2}\left[p\left(1+\frac{\sigma_e^2}{n}(m-1)G\right)-\frac{\sigma_e^2}{n}x_U\right]$$

and $Var(s|R)=1+\sigma_e^2-\left(1+\frac{\sigma_e^4 z^2}{n^2}\right)^{-2}$, plug these values into x_U and solve for the rational expectation equilibrium value of $G^*=\left[1+\sigma_e^2+\frac{11}{\sigma_e^2}\right]^{-1}$, where for simplicity here $n=m=z=10$. Numerical simulations show that the results hold for a wide range of values for n, m and z.

Now the equilibrium price (1) can be obtained by substituting both the insiders' demand and the RE equilibrium demands ($x_U^*=-G^*p$) of the uninformed traders into the market clearing condition, and solving for p'.

The solution for p' can be simply derived by computing $E(s|\psi)$ and $Var(s|\psi)$, substituting into the market clearing condition, and solving for p'.

Straightforward algebra allows us to show that:

$$PI'-PI=\frac{10\left(\sigma_e^2+11\left(1+\sigma_\omega^2\right)\right)}{(11+\sigma_e^2+\sigma_e^4)(\sigma_e^2+\sigma_\omega^2+\sigma_e^2\sigma_\omega^2)}>0$$

Inspection of Fig. 2a shows that for a wide range of parameter values:

$$VOL'-VOL=\frac{1+\frac{1+\sigma_e^2}{\sigma_e^4}+\frac{1+\sigma_e^2}{(\sigma_e^2+\sigma_\omega^2+\sigma_e^2\sigma_\omega^2)^2}}{\left(\frac{1}{\sigma_e^2}+\frac{1+\sigma_\omega^2}{\sigma_e^2+\sigma_\omega^2+\sigma_e^2\sigma_\omega^2}\right)^2}-\frac{100\left(1+\sigma_e^2\right)\left(11+\sigma_e^2+\sigma_e^4\right)^2}{(110+10\sigma_e^2+11\sigma_e^4)^2}<0$$

References

Atkas, N., de Bodt, E., Declerck, F., Van Oppens, H., 2007. The PIN anomaly around M&A announcements. Journal of Financial Markets 10, 169–191.
Admati, A., Pfeiderer, P., 1988. A theory of intraday patterns: volume and price variability. Review of Financial Studies 1, 3–40.
Aggarawal, R., Angel, J., 1998. Optimal Listing Strategy: Why Microsoft and Intel Do Not List on the NYSE. Available at SSRN: http://ssrn.com/abstract=7712.
Anand, A., Tanggaard, C., Weaver, D., 2009. Paying for market quality. Journal of Financial and Quantitative Analysis 44, 1427–1457.
Angel, J., 1997. Tick size, share prices and stock splits. Journal of Finance 52, 655–681.
Andersen, T., Bollerslev, T., Diebold, F.X., Labys, P., 2003. Modeling and forecasting realized volatility. Econometrica 71, 529–626.
Bessembinder, H., Hao, J., Lemmon, M.L., 2008. Why designate market makers? Affirmative obligations and market quality. Working paper. University of Utah.
Barclay, M.J., Christie, W.G., Harris, J.H., Kandel, E., Schultz, P.H., 1999. The effects of market reform on the trading costs and depth of NASDAQ stocks. Journal of Finance 54, 1–34.
Barber, B., Lehavy, R., McNichols, M., Trueman, B., 2001. Can investors profit from the prophets? Security analyst recommendations and stock returns. Journal of Finance 56, 531–563.
Beaver, W.H., 1968. The information content of annual earnings announcements. Journal of Accounting Research (supplement) 6, 67–92.

Bloomfield, R., O'Hara, M., Saar, G., 2005. The make or take decision in an electronic market: evidence on the evolution of liquidity. Journal of Financial Economics 75, 165–199.
Brennan, M.J., Hughes, P., 1991. Stock prices and the supply of information. Journal of Finance 46, 1665–1692.
Brennan, M.J., Subrahmanayam, A., 1995. Investment analysis and price formation in securities markets. Journal of Financial Economics 38, 361–381.
Biais, B., Martimort, D., Rochet, J.C., 2000. Competing mechanisms in a common value environment. Econometrica 68, 799–837.
Boehmer, E., 2005. Dimension of execution quality: recent evidence from US equity markets. Journal of Financial Economics 78, 553–582.
Christie, W., Huang, R., 1994. Market structures and liquidity: a transactions data study of exchange listings. Journal of Financial Intermediation 3 300-26.
Chung, K.H., McInish, T.H., Wood, R.A., Whyowski, D.J., 1995. Production of information, information asymmetry, and the bid–ask spread: empirical evidence from analysts' forecasts. Journal of Banking and Finance 19, 1025–1046.
Corwin, S., 1999. Differences in trading behaviours across NYSE Specialist Firms. Journal of Finance 2 (1999), 721–745.
Cready, W.M., Hurtt, D.N., 2002. Assessing investor response to information events using return and volume metrics. Accounting Review 77, 891–909.
Davies, R.J., Kim, S.S., 2009. Using matched samples to test for differences in trade execution costs. Journal of Financial Markets 12, 173–202.
Dechow, P., Hutton, A., Sloan, R., 1999. An empirical assessment of the residual income valuation model. Journal of Accounting and Economics 26, 1–34.
Doran, L., Goldstein, M., Golubeva, E., Hughson, E., 2009. Tick size and adverse selection: spurious effects arising from serial correlation. Working paperGeorgetown University.
Easley, D., Kiefer, N.M., O'Hara, M., Paperman, J., 1996. Liquidity, information and infrequently traded stocks. Journal of Finance 51, 1405–1436.
Easley, D., Engle, R.F., O'Hara, M., Wu, L., 2002. Time-varying arrival rates of informed and uninformed trades. Working paper. Cornell Univeristy.
Easley, D., O'Hara, M., 1987. Price, trade size, and information in securities markets. Journal of Financial Economics 19, 69–90.
Foucault, T., 1999. Order flow composition and trading costs in a dynamic limit order market. Journal of Financial Markets 2, 99–134.
Foucault, T., Kadan, O., Kandel, E., 2005. Limit order book as a market for liquidity. Review of Financial Studies 18, 1171–1217.
Gleason, C., Lee, C., 2003. Analyst forecast revisions and market price discovery. Accounting Review 78, 193–225.
Glosten, L., 1994. Is the electronic open limit order book inevitable? Journal of Finance 49, 1127–1161.
Glosten, L., Harris, L.E., 1988. Estimating the components of the bid–ask spread. Journal of Financial Economics 21, 123–142.
Goettler, R.L., Parlour, C., Rajan, U., 2008. Equilibrium in a dynamic limit order market. Working paper. Carnegie Mellon University.
Grossman, S., Miller, M.H., 1988. Liquidity and market structure. Journal of Finance 43, 617–633.
Grossman, S., Stiglitz, J., 1980. On the impossibility of informational efficient markets. American Economic Review 70, 398–408.
Hasbrouck, J., 1991. Measuring the information content of stock trades. Journal of Finance 46, 179–207.
Huang, R.D., Stoll, H.R., 1996. Dealer versus auction markets: a paired comparison of execution costs on NASDAQ and the NYSE. Journal of Financial Economics 41, 313–357.
Irvine, P., 2003. The incremental impact of analyst initiation coverage. Journal of Corporate Finance 9, 431–451.
Irvine, P., 2004. Analysts' forecasts and brokerage-firm trading. Accounting Review 79, 125–149.
Jackson, A., Johnson, T., 2006. Unifying underreaction anomalies. Journal of Business 79, 75–114.
Kadiyala, P., Rau, P., 2004. Investor reaction to corporate event announcements: underreaction or overreaction? Journal of Business 77, 357–386.
Kanagaretnam, K., Lobo, G.J., Whalen, D.J., 2005. Relationship between analyst forecast properties and equity bid–ask spreads and depths around quarterly earnings announcements. Journal of Business Finance and Accounting 32, 1773–1799.
Kadlec, G.B., McConnell, J.J., 1994. The effect of market segmentation and illiquidity on asset prices: evidence from exchange listings. Journal of Finance 49, 611–636.
Kandel, E., Rindi, B., Bosetti, L., 2008. The impact of a closing call auction on prices and trading strategies. Working paper. Bocconi University.
Kavajecz, K., 1999. A specialist's quoted depth and the limit order book. Journal of Finance 2 (747), 771.
Kothari, S.P., 2001. Capital market research in accounting. Journal of Accounting and Economics 31, 105–231.
Lee, C., Ready, M.A., 1991. Inferring trade direction from intraday data. Journal of Finance 46, 733–746.
Li, X., 2005. The persistence of relative performance in stock recommendations of sell-side financial analysts. Journal of Accounting and Economics 40, 129–152.
Maddala, G.S., 1983. Limited-Dependent and Qualitative Variables in Econometrics. Cambridge University Press, Cambridge, UK.
Mendenhall, R., 2004. Arbitrage risk and post-earnings-announcement drift. Journal of Business 77, 875–894.
Menkveld, A.J., Wang, T., 2009. How do designated market makers create value for small-cap stocks. Working paper. University of Tilburg.
Parlour, C., 1998. Price dynamics in limit order markets. Review of Financial Studies 11, 789–816.
Parlour, C., Seppi, D., 2003. Liquidity-based competition for order flow. Review of Financial Studies 16, 301–343.
Purnanandam, A., Swaminathan, B., 2004. Are IPOs really underpriced? Review of Financial Studies 17, 811–848.
Ramnath, S., Rock, S., Shane, P., 2008. The financial analyst forecasting literature: a taxonomy with suggestions for further research. International Journal of Forecasting 24, 34–75.
Reiss, P., Werner, I., 2004. Anonymity, adverse selection, and the sorting of interdealer trades. Review of Financial Studies 17, 599–636.
Rindi, B., 2008. Informed traders as liquidity providers: anonymity, liquidity and price formation. Review of Finance 12, 497–532.
Roulstone, D.T., 2003. Analyst following and market liquidity. Contemporary Accounting Research 20, 551–578.
Rosu, I., 2009. A dynamic model of the limit order book. Review of Financial Studies 22, 4601–4641.
Seppi, D., 1997. Liquidity provision with limit orders and a strategic specialist. Review of Financial Studies 10, 103–150.
Shane, P., Brous, P., 2001. Investor and (Value Line) analyst underreaction to information about future earnings: the corrective role of non-earnings-surprise information. Journal of Accounting Research 39, 387–404.
Sorescu, S., Subrahmanyam, A., 2006. The cross section of analyst recommendations. Journal of Financial and Quantitative Analysis 41, 139–168.
Teoh, S., Wong, T., 2002. Why new issues and high-accrual firms underperform: the role of analysts' credulity. Review of Financial Studies 15, 869–900.
Van den Bongard, I., Klar, J., 2007. Determinants of the bid–ask spread and the role of designated sponsors: evidence from Xetra. Working paper. University of Bonn.
Venkataraman, S., Waisburd, A.C., 2007. The value of the designated market maker. Journal of Financial and Quantitative Analysis 42, 735–758.
Viswanathan, S., Wang, J., 2002. Market architecture: limit-order books versus dealership markets. Journal of Finance 44, 115–134.