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"Subscribing to Transparency"

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Subscribing to Transparency

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Abstract

The paper empirically explores how more trade transparency affects market liquidity. The analysis takes advantage of a unique setting in which the Shanghai Stock Exchange offered more trade transparency to market participants subscribing to a new software package. First, the results show that the additional data disclosure increased trading activity, but also increased transactions costs through wider bid-ask spreads. Thus, in contrast to popular policy belief, the paper finds that more transparency need not improve market liquidity. Second, the paper finds a particularly strong immediate liquidity impact accompanied by altered trading behavior, which suggests a significant impact on institutional traders subscribing relatively early. Lastly, since the effective level of market transparency is bound to depend on how many traders are subscribing to the data, the study can empirically establish the functional form between market-wide transparency and liquidity. The relationship is non-monotonic, which can explain the lack of consensus in the existing literature where each empirical study is naturally confined to specific parts of the transparency domain.

JEL classification: G14, G28

Keywords: transparency, liquidity, market microstructure, market design

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1 Introduction

Transparency discussions have exacerbated following the financial crisis, making world leaders repeatedly call out for more transparency in financial markets.[1] However, it has not yet been established that increased transparency necessarily improves market outcomes. This paper examines the extent to which increased pre- and post-trade transparency improves liquidity.

In August 2006 the Shanghai Stock Exchange introduced a policy change that increased the pre- and post-trade information available to market participants. The additional market information was provided to any market participant who subscribed to a new computer software package named Level II. The paper investigates the effects of this change on trading activity (measured by turnover) and trading costs (measured by bid-ask spreads).

First, the paper quantifies a significant liquidity impact of the one-time increase in pre- and post-trade disclosure. The results show that the additional data disclosure increased trading activity, but also increased transaction costs through wider bid-ask spreads. The detrimental effect directly contrasts the widespread policy view that 'more is better' when it comes to trade transparency. Instead, the results conform to a more multivariate approach to transparency design, which ultimately depends on the level of transparency already in place in the individual setting.

Second, it is of specific interest to examine what impact the transparency change has had on major institutional traders, who not only have the most at stake but are presumably also the most responsive to any alterations in market conditions and day-to-day trading operations. As major traders are relatively more invested and active in the marketplace, it is reasonable to presume that institutional traders are among the first group of subscribers. Consistently, an empirical evaluation reveals that the bulk of the liquidity impact is immediate and accompanied by altered trading behavior, which conforms to major traders being relatively more affected and responding more strongly to the transparency change compared to other market players.

Third, the paper studies the overall liquidity dynamics as the software subscription level rises over the sample period. As the effective level of market transparency is bound to depend on how many traders can actually access the data, the number of traders having access to the transparency enhancing information (a measure provided to us directly from the Shanghai Stock Exchange) acts as a time-varying proxy for the implicit level of market-wide transparency. Exploiting this time dimension creates a unique possibility to estimate the functional form between trade

[1] For example, the European Union finance ministers have agreed on an overhaul of financial system (endorsed by the European Parliament) and the European Commission has introduced rules that will force more disclosure on financial markets (The Economist, 2010; Wall Street Journal, 2010). In the U.S. the Dodd-Frank act was passed in July 2010, which aims to promote financial stability by e.g. increasing transparency of the financial system.

transparency and liquidity, which has not been possible in existing studies naturally constrained to only discrete one-time shifts in transparency. The results show that although the overall liquidity impact is clear-cut (higher turnover and wider spreads), the dynamics of such a change are non-monotonic. This means that the liquidity impact of additional software subscribers can change depending on how many market participants already have access. In other words, the same transparency change can have different – and even opposite – liquidity outcomes depending on effective transparency level already in place.

This has several implications. First, it reinforces the result that increased transparency may not be uniformly welfare improving across all settings, in sharp contrast to prevailing perceptions. Second, as markets in general differ in their level and access to market information, this implies that any wide reaching policy recommendations on trade transparency cannot be assumed to uniformly affect different markets. To take an example, a transparency policy implemented across all EU countries can have markedly different liquidity outcomes across member states – both in terms of sign and size. Finally, the result that liquidity outcomes vary across pre-existing transparency levels can help explain the contrasting results in the existing literature. Namely, as each empirical study is bound to evaluate the effect of a transparency change relative to pre-existing market conditions, the empirical results of the literature may differ because the effective transparency level already in place differs across each market being studied – i.e. each study is naturally confined to specific parts of the non-monotonic transparency domain.

Lastly, through a series of attractive features in both the data set and the empirical setting, this study improves upon the extent and accuracy to which these relationships can be examined. First, the study takes advantage of a ‘near-randomized’ treatment vs. control group allocation. Specifically, the transparency effect on Shanghai listed firms is evaluated in relation to a control group of Shenzhen listed firms, which were not subject to the policy change. The randomization comes from the fact that before September 2000 the Chinese authorities unilaterally allocated firms to list at either the Shanghai or Shenzhen stock exchange. This implies that firms cannot self-select onto the exchanges. Thus, after controlling for firm location, the absence of a systematic mechanism to prescribe firms to either exchange creates an ideal setting, which allows for a robust comparison of firm outcomes across exchanges. Second, the Shanghai policy change was directly targeted to increase pre- and post-trade transparency and as such it was not accompanied by any other market change. The study therefore naturally circumvents challenges faced by several existing studies, where numerous (potentially counteracting) policy changes occur simultaneously.[2] As detailed further in the next section, this offers a 'cleaner' estimate of the increased transparency effect on liquidity.

The paper proceeds by providing some background information on the existing literature (2.1), the exact transparency changes under study (2.2) and the Chinese stock market structure (2.3). Section 3 first introduces the data and sample choice (3.1), followed by a presentation of the empirical results showing the overall liquidity results (3.2), the immediate impact associated with early subscribers (3.3) and the liquidity dynamics as the subscription level gradually rises (3.4). The paper finally establishes the robustness of the results (3.5) and section 4 concludes.

2 Background information

2.1 Literature review

The academic literature generally agrees that changed pre- or post-transparency will alter market outcomes by changing the behavior of market participants (e.g., Boehmer, Saar and Yu, 2005; Porter and Weaver, 1998; Bloomfield, O'Hara and Saar, 2011). However, there is less agreement on the direction of the effect, i.e. whether increased transparency improves or deteriorates market quality. For example, both positive and negative effects have been demonstrated theoretically in several transparency studies (see e.g. Madhavan, 1995, 1996; Naik, Neuberger and Viswanathan, 1999; Baruch, 2005).

On the empirical side, a handful of studies document a positive link between increased transparency and market outcomes. Swan and Westerholm (2006) empirically study 33 major stock exchanges and analyze which transparency features and market designs are associated with desirable market outcomes, such as high liquidity. They conclude that market designs that favor greater (pre- or post-trade) transparency typically outperform more opaque market structures. This is in line with a series of recent papers concluding that increased trade transparency will increase liquidity (Boehmer, Saar and Yu, 2005; Zhao and Chung, 2007), improve price discovery (Hendershott and Jones, 2005), lower volatility (Chung and Chuwonganant, 2007) and ameliorate various other market outcomes (Eom, Ok and Park, 2007).

But despite widespread belief – in particular among policy makers[3] – that increasing transparency leads to a fairer and informatively more efficient market, there are empirical studies

[2] As an example, Eom, Ok and Park (2007) study transparency increases on the Korean stock exchange that are accompanied by an event which reduces disclosure, which may contaminate any transparency estimates, as is openly acknowledged by the authors.

that contrast this (see e.g. Madhavan, Porter and Weaver, 2005). This is particularly true in the debate on broker anonymity, where the case against increased pre-trade transparency is prevalent (Foucault, Moinas and Theissen, 2007; Simaan, Weaver and Whitcomb, 2003; Comerton-Forde, Frino and Mollica, 2005; Desgranges and Foucault, 2005; Rindi, 2008). The benefits of increased post-trade transparency have similarly been questioned in several studies that do not find that changes in the data publication regime – such as changed timing of reporting – leads to liquidity improvements (Gemmill, 1996; Saporta, Trebeschi and Vila, 1999; Board and Sutcliffe, 1995).

In short, there is no clear consensus in the existing literature on the exact liquidity impact of increased pre- and post-trade transparency. However, it is possible that the lack of consensus results from strictly examining discrete events, which can produce different outcomes due to inevitably different transparency levels within each empirical setting. As previously described, this study addresses this issue by introducing a time-varying proxy for the effective level of transparency (number of data users), which allows for an evaluation of how liquidity improves or deteriorates for a range of different transparency levels.

2.2 Transparency changes

The Level II data package introduces five pre- and post-trade transparency changes on the Shanghai Stock Exchange. These are detailed in Table 1, where the most significant pre-transparency change is listed first (volume *individually* detailed) and the most notable post-transparency change is listed last (*every* transaction documented). More specifically, the primary Level II change in pre-trade transparency is to break down the total volume available at the top bid and ask quotes. This means that rather than only displaying total volume (the depth of the order book at the best quote), now the total number and the average size of requests/offers at the best bid/ask are reported. Moreover, the individual volume of the first 50 requests/offers to arrive at the best bid/ask (which coincides with the execution order) are detailed with Level II. This level of volume requested/offered by individual traders can be argued to reveal some of their characteristics; in particular, it helps to infer whether they are small (retail) or big (institutional) market participants. Thus, this implies a lower degree of anonymity.[4] Second, the Level II

[3] For example, both the United States Securities and Exchange Commission (SEC, 1994) and the Office of Fair Trading in the UK (Carsberg, 1994) have repeatedly through time called for increases in transparency as a way to improve market quality.

[4] This is explicitly argued by the suppliers of the software in their commercial leaflets for Level II, i.e. that one may use this detailed information on volume to infer if a trader is an institutional/big investor or an individual/small investor. In particular, small traders are typically thought of as relatively uninformed investors, whereas big (institutional) traders are classified as informed. Thus, although the Level II software does not explicitly provide traders' identities, it nevertheless reduces the degree of anonymity. See for example the website of the largest Level II

software increases the number of bid and ask quotes reported to market participants. Instead of only the best 5 bid/ask quotes formerly being available, the best 10 bid/ask quotes become visible to subscribers of the Level II data software. Thus the depth of reporting increases. Third, bid/ask withdrawals are now reported for the 10 stocks that experience the highest number of such withdrawals. Before Level II, no such cancellation data was reported.

The Level II data also introduces two post-trade transparency changes. First, trading information is now updated more frequently, i.e. trading data is now updated every 3 seconds instead of every 6 seconds. This lowers the time arrival uncertainty faced by traders on submitted orders. Specifically, when placing a market order at the prevailing price, this change reduces the time until the realized transaction price is revealed. In modern automated markets such changes may have considerable effects on market outcomes.[5] Last but not least, with the Level II software *every* transaction that occurred in the last 3 seconds is now noted and reported (volume, price and parties involved), instead of only the last transaction price and total trading in the last 6 seconds. This last change, together with the individual pre-trade volume reporting described above (i.e. the combination of changes listed first and last in Table 1), constitutes a considerable altercation, since this makes it in principle possible to integrate out information on both order placement and trading behavior of individual traders. Extracting such information could help to identify order placement and trading strategies of different market players, for example whether anyone may be building up positions in specific stocks.[6] Whether the potential for extracting such information has had a realized impact on market liquidity is the empirical question hand (section 3.2). Also, the overall result of the introduction of Level II – that order and trading behavior is generally more difficult to conceal – is likely of most relevance for major traders. Thus, we also specifically study how these changes are likely to alter the behavior of major traders and the corresponding effect it has on market liquidity (section 3.3).

Overall, the Level II data package therefore introduces pre- and post-trade transparency changes that considerably expand the information space. Additionally, two other aspects of the setting are worth mentioning. First, the analysis greatly benefits from the fact that all transparency

software retailer: http://product.gw.com.cn/level2.html (in Chinese). Partial information is also available on Level II in English: http://www.sse.com.cn/sseportal/en/c05/c03/c01/c01/p1074/c1505030101_p1074.shtml. For the 2nd-10th best bid-ask quotes only the total volume is reported (which was also true at the best bid/ask quote before the introduction of Level II).

[5] For example, in a recent study, Hendershott and Moulton (2011) show that reducing execution time by 10 seconds increases adverse selection and thereby results in wider bid-ask spreads, which is consistent with the results presented in section 3.2.

[6] We thank Joel Hasbrouck for sharpening our notion of these implications. Additionally, it can be argued that the Level II data allows for identifying the most profitable traders, but any such learning would inevitably take considerable time (say, at least 1-2 years).

changes go in the same direction, i.e. they are designed to increase transparency and are therefore very unlikely to counteract each other in any way. The Level II data package also does not replace any reported information in the existing transparency regime, but simply provides additional information beyond what was previously available. Thus, the introduction of Level II provides a ‘clean’ event setting naturally circumventing the challenges faced by existing literature where counteracting events have been difficult to disentangle (see e.g. Kim, Ok and Park, 2007). Second, as described above, the introduction of Level II includes both pre- and post-transparency changes. Although this has a clear advantage – since it implies that the study analyzes broad and overall transparency changes – it also comes with the shortcoming that it is not possible to separate the Level II effect into pre- vs. post-transparency implications.

Lastly, the data dissemination of the Level II data occurs through private software suppliers. More specifically, private software companies buy the Level II trading data from the Shanghai Stock Exchange, repackage it and supply it to investors through their own software program.[7] Only those who buy such software can get access to the Level II data details. The Shanghai Stock Exchange charges each private software supplier a royalty for every additional user of their software – and thus the Shanghai Stock Exchange compiles the number of subscribers of all Level II software packages available (this number is provided to us directly for the purpose of this study). All in all this supply side of the Level II data package resembles a market of perfect competition. The fundamental product is the same across all suppliers (same data) and in principle it can only differ in terms of packaging (in practice, however, the software interface across different suppliers looks very similar). These suppliers actively compete with each other to attract customers, which makes it possible to gain access to the Level II data at a moderate price. The software price is about $200 per annum and thus it is affordable to both institutional and individual investors.

2.3 Stock market structure

There are two major trading venues in China, namely the Shanghai and Shenzhen exchanges. The Shanghai Stock Exchange is China‘s largest exchange and at the end of the 2004-09 sample period it listed 870 firms with a market capitalization of $2.7 trillion, compared to 830 firms listed in Shenzhen with a market capitalization of $0.9 trillion. Both exchanges play an important role in China’s modern and advanced financial system, e.g. the financial services in Shanghai provide

[7] This supply side fragmentation partially explains the gradual allocation of the software, since not all investors may be able to buy the software simultaneously. Similarly, on the demand side, there might be incomplete information with regards to the availability of Level II and its usefulness.

200,000 people with jobs (2.2% of city total) and contributes 8% towards the country's GDP (*The Economist*, 2007).[8] The Shanghai and Shenzhen stock exchanges are fully government operated with streamlined market and trading characteristics. This alignment applies to e.g. trading hours, market design and regulations. Table 2 illustrates this by outlining the key features of the market microstructure in both exchanges (Panel A). Moreover, Table 2 also shows that investors on the two venues face very similar trading costs (Panel B), which are broken down across the various fee categories. First, stamp duty imposed by the tax authorities has been at equal levels in both exchanges at any given time throughout the sample period (i.e. changes have occurred simultaneously across venues). Second, this equality also applies to broker commissions during the sample period, which are capped at the same fixed level of transaction value on both stock exchanges. Lastly, the commissions include other levies (supervision, transfer and transaction fees) collected by brokers on behalf of the financial authorities and the stock exchanges. These levies are either equal across exchanges (the supervision fee) or remained unchanged throughout the sample period (e.g. transfer fee and transaction fee). Thus, to summarize, trading costs are nearly fully harmonized across the two exchanges – and the few documented *simultaneous* changes (cf. stamp duty) and minor differences in *levels* (cf. transfer and transaction fees) are fully captured and controlled for (differenced out) in the empirical methodology (difference-in-difference estimation), which is described in detail in the next section.

3 Empirical analysis

3.1 Data and sample specification

The Level II data service became available in August 2006 and covered all stocks listed on the Shanghai Stock Exchange. As no transparency change occurred for Shenzhen listed stocks at this time, those stocks constitute a natural control group. Thus, in order to measure the effect of Level II we obtain weekly data for all firms listed on both the Shanghai Stock Exchange and Shenzhen Stock Exchange between January 2004 and August 2009.[9] The study focuses on securities listed on the A-market, which is open to trade by domestic and qualified foreign investors, making it both relatively liquid and representative of other global stock markets. Hence, the dataset includes

[8] Statistics on employment and GDP contribution is on par with the financial sector in Tokyo, the leading financial hub in Asia in terms traded equity value (with Hong Kong and Shanghai as runners up). The ratio of financial employees to city population is also comparable to the greater metropolitan area of New York, Newark and Bridgeport (Nielsson and Wojcik, 2012).

[9] The Level II subscriber data is available to the authors up until August 2009. A weekly data frequency is chosen rather than daily, or intra-day, as any transparency effects may otherwise be confounded by short-term noise and volatility.

all firms ever listed in both exchanges during the sample period, which amounts to 844 firms in Shanghai and 750 firms in Shenzhen with readily available data. The key variables for these firms are summarized in Table 3.

Subscriber data

As noted in the introduction, the setting of the paper offers the possibility of not only measuring average effects of a transparency reform, but also to lay out the dynamics of such a change. To clarify this further, the paper studies two margins of transparency: (a) the extensive margin, i.e. new type of information being released (corresponding to the introduction of Level II) and (b) the intensive margin, i.e. given a specific type of information, how many investors are actually using it (corresponding to the number of Level II subscribers). Specifically, not only do we observe a discrete, one-time increase in the amount of released information but also a continuous change in the number of subscribers of that information.[10]

Although the subscriber data is a novel way to capture the intensive margin of transparency, it should be acknowledged that it is inevitably not a perfect measure of market-wide transparency, but rather serves as a reasonable proxy. Specifically, the stake size of each individual subscriber cannot be accounted for, which implicitly results in equal weighting of each investor. Although this is admittedly simplistic and likely to add some noise to our measure of transparency, it may not be unreasonable for Chinese data, which predominantly consists of investors with comparable wealth levels (China Securities Registration, 2009) and has an active presence of domestic, individual investors (*The Economist*, 2009). But more importantly, this issue merely effects the interpretation of the results, not their merit. More precisely, although one additional subscriber cannot be interpreted as an economically meaningful increase in market-wide transparency, an addition of 100,000 subscribers is more likely to constitute a real and representative change. Thus, the subsequent analysis will avoid interpretation of marginal effects and instead focus on larger and more intuitive 'step increases' in the number of subscribers. Also, an argument can be made that more influential traders (e.g. institutional traders) are among the first group of subscribers, which may lead to relatively large liquidity reactions in the first months following the Level II introduction. Thus, with this caveat in mind, the subsequent empirical analysis separately studies the immediate impact of the transparency increase (section 3.3).

[10] It should be noted that the exact distribution of Level II subscribers is unfortunately a confidential variable with important business implications for the Shanghai Stock Exchange. Due to the competitive importance that this variable has to the exchange, its full details cannot be openly disclosed. However, the authors can assert that this variable offers rich variability, with the number of subscribers going from zero to well beyond 300,000 at the end of the sample period. Further statistics on this variable can be confidentially provided to referees of an academic journal.

Lastly, it is worth noting is that the number of software subscribers represents a significant fraction of the investor base – and thereby a meaningful part of the transparency domain. Specifically, using aggregated annual data on stock market participation, we estimate that approximately 30% of active investors are subscribing to the software at the end of our sample, who moreover (assuming that larger investors subscribe first) can be estimated to hold approximately 64% of the stock market value.[11] Also, since it is impossible to continuously measure the fraction of investors subscribing (as the number of active investors is only reported annually), it is reassuring that the absolute weekly number of software subscribers will constitute a meaningful, large and economically significant area on the transparency domain.[12]

Outcome variables

The liquidity effects of more pre- and post-trade transparency are examined by quantifying changes in both turnover and spreads. These two outcome variables of interest capture different liquidity dimensions, namely the impact on i) the amount of trading activity and ii) the cost of trading. Both variables are calculated in a standard way, where turnover is defined as the ratio of the number of shares traded in a specific stock to the total number of shares outstanding in that stock. Likewise, quoted bid and ask prices are used to calculate spreads as the difference in ask and bid, divided by the midquote.[13]

Control group and identification

In order for Shenzhen firms to be a reliable control group it needs to be assumed that Shenzhen listed firms are inherently no different than Shanghai listed firms.[14] This ensures that

[11] These figures are based on information from the China Securities Registration (2009), where the number of active investors corresponds to the number of open trade accounts with at least one trade taking place during the year and having positive stock holdings of at least $20,000 at year end (note that this cutoff implies that the $200 annual fee represents at most 1% of wealth, which seems a reasonable upper bound on the number of potential subscribers to the software). Also, these estimates are likely to be quite conservative since further restrictions on the number of active investors can easily be justified, such as on the frequency of trading (e.g. strictly more than one trade per year) or by taking into account that one investor may control several trade accounts (or make trading decision for several other investors).

[12] Furthermore, the total number of investors has remained quite stable in the sample period (China Securities Registration, 2009), which further justifies using the absolute number of subscribers as our measure (as calculating the fraction roughly corresponds to dividing by a constant).

[13] Another common and straightforward measure of trading activity is value of volume, which was also examined throughout the entire analysis. The results were in all cases the same as for turnover. Thus, since turnover and value of volume both capture trading activity and the all results hold for either measure, only turnover (which is not currency denominated) is included for brevity. Also, although many other (liquidity) measures may be of interest, we limit the analysis to these two major measures (trading activity and costs), in an effort to limit the multidimensionality – and thereby enhance the tractability – of the analysis.

[14] Note that this assumption only needs to hold true for (unobservable) time-variant characteristics, since time-constant characteristics is controlled for in the fixed effects regression methodology that is introduced in section **Erreur ! Source du renvoi introuvable.**.

potential differences in liquidity do not merely reflect different characteristics of the listed stocks. To safeguard against such issues we define a working sample that is subject to two restrictions.

First, in September 2000 the Chinese government announced a policy change where henceforth all new technology firms would be listed on the Shenzhen Stock Exchange. The aim was to create a NASDAQ-style exchange to complement the Shanghai (NYSE-style) exchange. However, before September 2000 no such policy existed and no systematic mechanism was in place that determined the listing location of firms. Thus, in order to ensure that stocks across the two exchanges are as compatible as possible, we restrict our sample to include only firms listed in China before September 2000. Thereby we alleviate the potential concern that (time variant) firm characteristics may be contaminating the estimation results. This further improves on numerous existing studies that use e.g. NYSE and NASDAQ firms as treatment and control groups, despite possible inherent differences in (time-variant) firm characteristics.[15]

Second, before September 2000, firms that were located in either the city of Shanghai or Shenzhen may naturally be more likely to be listed at their local exchange (this is verified by statistical tests, which are omitted for brevity). Since the two cities may differ in terms of which kind of businesses they attract, this can potentially create a systematic difference in (unobservable, time-variant) firm characteristics across the two exchanges. To further ensure that such differences do not influence the estimation results, the working sample – consisting of firms listed on either exchange before September 2000 – is further restricted to firms that originate from outside the two cities. Summary statistics for this working sample are reported in Table 3 – along with the original, unrestricted sample. It can be observed that once the sample is restricted on listing date and location, the difference in mean values across the two exchanges becomes smaller for all variables. For example, once restricting on location and listing date, the average firm size – measured as either asset value or number of employees – converges across the two exchanges, which is consistent with more analogous firm characteristics in the treatment and the control group. Also worth noting, the existing literature typically finds that price movements are very similar across the two markets for various data frequencies (see e.g. Girardin and Liu, 2005).

Finally, in order to safeguard completely that Shenzhen firms are a reliable control group, it would be advantageous to establish statistically that prior to the transparency change Shenzhen firms followed a similar trend in the outcome variables to Shanghai listed firms. If this is the case, any observed post-event change in trend can be attributed to the transparency policy change (given an adequate regression methodology and controls, to be detailed in section **Erreur !**

[15] See e.g. Chung and Chuwonganant (2007), who attempt to address this issue by creating comparable stock samples across the two exchanges based on e.g. share price, trading volume, return volatility, etc.

Source du renvoi introuvable.). In order to verify this, each outcome variable is regressed on an exchange-specific, cubic time trend for the pre-event period (January 2004 – July 2006) and the statistical difference of these two non-linear trends is tested. Specifically, we estimate the following regression equation

$$y_{it} = \alpha + \gamma_1 t \cdot SHG_i + \gamma_2 t^2 \cdot SHG_i + \gamma_3 t^3 \cdot SHG_i + f_i + w_t + \varepsilon_{it} \qquad (1)$$

for both liquidity measures, *y*, where *SHG* indicates a dummy variable that takes the value of one for Shanghai listed firms and zero for Shenzhen firms. The term f_i indicates the fixed effects regression methodology and the implicit capture of all time-constant firm characteristics. In addition to this, weekly dummies (week fixed effects, w_t) are included to pick up the average weekly change in the outcome variables across all firms on both exchanges. Since all variation in outcomes variables that is common across exchanges is thereby filtered out, only exchange specific variation will remain. Hence, the joint significance of coefficients γ_1, γ_2 and γ_3 will test the equality of the two non-linear, exchange-specific trends.

Table 4 reports the estimation results in two different panels. Panel A reports the results when all Shanghai and Shenzhen firms are included in the sample. As already noted, stock characteristics are likely to be inherently different across the two exchanges and therefore the joint significance of the three interaction terms is non-surprisingly rejected for both liquidity measures (see χ^2-statistics and corresponding p-value in last row of Table 4). In other words, in Panel A the flexible time trend is significantly different across the two exchanges for both outcomes variables. Moreover, individual coefficients are even significantly different across exchanges in the case of spreads. In contrast, once restricting on firms that listed on either exchange before September 2000 and are located outside the two cities (Panel B), the pre-event time trends of the two firm groups are no longer statistically different. Also, the joint significance of the three time trend coefficients is rejected, as indicated by the χ^2-statistics. The fact that time trends are statistically the same across the two exchanges for both outcome variables in the pre-event period, verifies that Shenzhen listed firms are an appropriate control group for Shanghai listed firms, once restricting on firm location and listing date.

3.2 Overall effect (extensive margin)

Before applying a more technical regression methodology, it is useful to briefly present the raw data and gauge at long-term patterns. Figure 1 plots the two liquidity measures for the working sample over the full sample period. More precisely, the difference in liquidity measures across the two exchanges is plotted over time, thereby shedding light on whether the transparency change was effective. Since the effective amount of transparency is likely to depend on the number of subscribers to the transparency enhancing software, the gradual long-run liquidity dynamics are likely vary with the different subscription intensity over time (as we study further in section 3.4). Figure 1 seems to confirm this variability, showing a gradually increasing level of trading activity (turnover) for Shanghai firms relative to Shenzhen firms in the post-Level II period. In contrast, bid-ask spreads seem to become relatively wider for Shanghai stocks in the post-level II period (although this trend is reversed at the end of the sample period). However, it is important to emphasize that no causation is yet being established. Furthermore, the long-term pattern can naturally differ from the short-term impact that follows immediately after the software is becomes accessible (cf. section 3.3). Now, however, we first turn to examining the examining overall and long-term average impact of the transparency increase.

To estimate more accurately the overall relationship between increased trade transparency and liquidity, we regress the two liquidity measures on an event dummy that takes the value of one in the post-Level II period and zero otherwise. As this event dummy only takes the value of one for Shanghai firms in the post-Level II period, the dummy coefficient will quantify the average effect of releasing new type of information (namely the information embedded in the Level II software) on liquidity in 'treated' Shanghai listed firms, relative to the liquidity levels of the 'untreated' Shenzhen firms. Stated differently, the 'difference-in-difference' estimate resulting from the pre- vs. post-period comparison (first difference) across the Shanghai vs. Shenzhen exchanges (second difference) captures the liquidity impact of events occurring in post-period Shanghai only (the Level II impact), while all other non-varying or common market features are differenced out. For example, the methodology differences out non-varying trading costs (cf. commissions and levies) and common changes in costs (cf. stamp duty) as noted in section 2.3. The panel analysis is also restricted on the sample of firms that listed before September 2000 and are located outside Shanghai and Shenzhen (cf. section 3.1). Moreover, to further take into account any (unobserved) firm characteristics we employ a firm fixed effects regression methodology that captures all time-constant firm characteristics that might otherwise contaminate the regression results. Thus, the regression model is

$$y_{it} = \alpha + \beta \cdot D_{Subscr_{it}>0} + f_i + w_t + \gamma Z_{it} + \varepsilon_{it} \qquad (2)$$

where the dummy variable, $D_{Subscr>0}$, is equal to one for Shanghai firms in the post-event period (which corresponds to the period where there is a positive number of software subscribers) and zero otherwise. The term f_i indicates firm fixed effects and w_t denotes weekly dummies (week fixed effects) that pick up the average weekly change in the outcome variables across all firms on both exchanges. Since all variation in outcome variables that is common across exchanges is thereby filtered out, the coefficient of interest, β, will only measure variation *beyond* the average variation in outcome variables in each week. For example, if a countrywide liquidity shock occurs in, say, week 1 of 2008, then the average impact thereof is caught by the corresponding weekly dummy and therefore β only reports liquidity variation beyond this average (i.e. the impact unassociated with the common shock). Hence the week fixed effect controls for any overall, unrelated events to the fullest extent possible. Furthermore, any change in liquidity (beyond the average variation in each week) is measured relatively to the Shenzhen control group that does not offer subscription to the transparency enhancing software. Thus the only assumption needed – in order to attribute changes in liquidity to the transparency change – is that prior to the new transparency policy Shenzhen firms followed a similar trend in the outcome variables as Shanghai listed firms, which is already established in section 3.1 for the working sample.

The last term, Z_{it}, represents any other time-variant control variables that in general capture exchange (or stock) specific events or trends. More specifically, these may include endogenous market factors (e.g. bid-ask spreads may help to determine turnover, and vice versa) or other variables that may contribute to the liquidity variation (say, volatility). We return to such issues in section 3.5, where a careful sensitivity analysis is carried out to verify the robustness of all reported results. In addition, this last term represents an extra safeguard included in all subsequent analysis, which involves carefully controlling for another policy change that introduced a transparency enhancing software in 2007. The effect of this change is filtered out by a binary dummy variable since there is no subscriber data available for this software. This data limitation implies that this software introduction provides a far less attractive setting than the Level II transparency change and therefore the subsequent presentation does not focus on this event.[16] Instead, this discussion is left to the robustness section 3.5, which confirms all key results.

The estimation results from the model specification in equation (2) are reported in Table 5. The table shows the overall average change in liquidity associated with the one-time increase in

[16] To clarify briefly why this transparency change is not of interest, the lack of subscriber data for this software (named TopView) means that it is implausible to fully measure and interpret the effect of this change in a similar manner to the Level II analysis – thus it is excluded. Moreover, the software was relatively expensive ($3,000 a year) and only provided static end-of-day snapshots (not dynamic real-time data) that were easily obtainable at on-line piracy websites at the end of each trading day. The illegal snapshots distributed daily among non-subscribers further makes it implausible to measure the effective, gradual increase in transparency due to this event. In other words, even if any subscriber data were available, it would not be reliable since illegal copies were distributed daily among non-subscribers. All this implies that it is unfortunately impossible to capture the effective, gradual increase in transparency from this event in a credible way – in contrast to the favorable setting that the Level II software provides. Due to these extensive drawbacks we choose to filter out any potential effect this policy change may have had and instead focus our analysis entirely on the transparency change we can more reliably measure and interpret in our dataset.

transparency (pre- vs. post Level II introduction). First, turnover is positively and significantly affected by the transparency change. Specifically, column (1) indicates that the one-time increase in transparency (going from no software users to some positive number of users) causes an average increase in daily turnover of 0.121 percentage points per stock. This is a considerable increase compared to the average daily turnover level of 1.42 percentage points for Shanghai listed stocks (cf. summary statistics in Table 3), i.e. it corresponds to an approximately 8.5% increase in turnover. In monetary terms, this translates into a sizeable increase in daily volume of 5 million Yuan per firm – or approximately 800 thousand U.S. dollars. This average firm increase is therefore quite large, in particular when keeping in mind that this increase is directly associated with a market-wide (not firm specific event) increase in transparency. Second, the transparency change is associated with a statistically significant increase in bid-ask spreads (column 2), implying that trading costs may have increased with more trade transparency. More specifically, spreads have widened by 0.017 percentage points, which represents a 6.5% increase compared to the average spread for Shanghai stocks (cf. summary statistics in Table 3). In other words, even though trading activity rises, there are higher costs associated with trading in the Shanghai stock market.

The widening of bid-ask spreads deserves clarification. Although generally it may not be unreasonable to expect more trading volume to be associated with narrower bid-ask spreads, this result is not predicted by papers specifically studying the effects of withdrawing broker anonymity on bid-ask spreads. For example, Desgranges and Foucault (2005) present a theoretical model where allowing dealers to know the identity of traders can widen spreads. They argue that the existence of dealer-client relationships allows dealers to cream-skim for uninformed order-flow, i.e. primarily trade with those (uninformed) clients who tend to consistently provide the dealer with positive trading profits. This, on the other hand, increases the risk of informed trading for dealers without such relationships, which respond by raising their profit margin (widen bid-ask spreads) to counteract the higher probability of more informed (and thus less profitable) trades. These theoretical predictions are verified by empirical studies that find that average bid-ask spreads are wider in a less anonymous market structure (Simaan, Weaver and Whitcomb, 2003; Comerton-Forde, Frino and Mollica, 2005; Foucault, Moinas and Theissen, 2007). As noted in section 2.2, one of the major pre-trade transparency changes brought about by the Level II software was to lower the degree of anonymity by enabling users to concentrate their trades with counterparties of certain characteristics (such as small/uninformed order flow). Thus, as this allows some dealers to cream-skim for uninformed order-flow, it simultaneously leaves other dealers (who lack this capacity) at a higher average risk of entering informed and less profitable trades – making them seek protection in wider profit margins (wider spreads). Thus, the positive relationship between transparency and spread reported in Table 5 supports these findings of the literature.[17]

To summarize, Table 5 concludes that the market has benefitted from the increase in trade transparency in terms of more trading activity, while the downside is wider bid-ask spreads. This is informative in itself and typically a transparency event study will end here, i.e. by revealing the *average* treatment effect. Here, however, we additionally observe the continuous changes in the number of subscribers after the date at which the transparency enhancing software is introduced, further allowing us to study the immediate effect resulting from early subscribers (section 3.3) and the overall liquidity dynamics as more market players gradually subscribe (section 3.4).

3.3 Immediate impact (early subscribers)

Section 3.2 established the overall market effect on liquidity (increased turnover and widening spreads) over the full sample period. In addition to this, it is of specific interest to examine the impact the transparency change has had on different categories of traders, in particular on major institutional traders that are arguably the ones most affected by such a change. Major traders do not only have the most at stake, but they are presumably also the most responsive to any alteration in market conditions and trading operations, which makes them more likely to immediately exploit the increased transparency benefits of the Level II software. We do not directly observe the identity of traders, but since major traders are relatively more invested and active in the marketplace, it is reasonable to presume that institutional traders are among the first group of subscribers. Intuitively, this may lead to large liquidity reactions in the first few months of the Level II operation. Thus, we next empirically evaluate the immediate liquidity impact around the date of the software introduction.

To first examine this in a simple univariate setting, Panel A of Table 6 reports the results of an event-study that compares liquidity before and after the Level II introduction for both exchanges using standard *t*-tests. The analysis is restricted to the immediate six months before and after the Level II introduction. The results reveal that the liquidity measures have changed significantly on

[17] Similarly, Madhavan, Porter and Weaver (2005) theoretically describe how increased transparency allows informed traders to tap the liquidity offered by the limit order book more efficiently, which increases informed traders' expected profits. This may make uninformed traders less willing to provide liquidity, represented by wider bid-ask spreads. Interestingly, Madhavan, Porter and Weaver (2005) also add an empirical analysis that establishes widening bid-ask spreads from a policy change increasing pre-trade transparency, which is consistent with their argument – as well as our results. Finally, on top of this, the widening of bid-ask spreads is also consistent with faster transactions data (cf. change no. 4 in Table 1). This is e.g. supported by Hendershott and Moulton (2011) who show that reducing execution time by 10 seconds increases adverse selection and thereby results in wider bid-ask spreads

both exchanges, which reemphasizes one of the contributions of this paper, i.e. having a reliable control group and thereby avoiding to mistakenly associating countrywide changes in outcome variables to a market-specific transparency change. Namely, the raw double differencing shows significant disparities across the two markets, suggesting that the Shanghai liquidity change following Level II cannot be attributed entirely to countrywide changes. More specifically, comparing the pre- vs. post period, turnover has increased by 0.12 percentage points more for Shanghai vs. Shenzhen firms. This is a large liquidity impact as the overall difference in turnover between all Shanghai vs. Shenzhen firms is only 0.06 percentage points across the whole sample (and 0.01 percentage points for the working sample – see summary statistics in Table 3). Moreover, this change is fully on par with the overall increase in turnover reported in Table 5 and discussed in section 3.2 above. Hence, this indicates that the bulk of the Level II effect is attributable to the impact it has on early subscribers. In other words, the magnitude aligns with major traders being relatively more affected and responding more significantly to the transparency change compared to other market players. Additionally, Table 6 further reports that bid-ask spreads have narrowed less for Shanghai vs. Shenzhen firms over the year surrounding the Level II introduction. The relative change in spreads is sizeable (0.02 percentage points) since it reaches the same order of magnitude as the overall difference in spreads across markets over the whole sample period (see Table 3) – and again it corresponds fully with the overall change reported in Table 5. Thus, this relative widening of bid-ask spreads on Shanghai implies a considerable negative impact on trading costs immediately following the introduction of the transparency enhancing software.

These raw univariate results are confirmed in Panel B, which shows the results of a more elaborate multivariate analysis following the previously described model in section 3.2 and corresponding regression equation (2). Again focusing on the immediate impact surrounding the six months before and after the Level II transparency change shows a strong and statistical significant relationship between liquidity and increased transparency. This more careful analysis leads to slightly lower magnitudes compared to Panel A, but the results still indicate that the immediate impact of the first subscribers (0.105 and 0.014) accounts for the vast majority of the overall effect reported in Table 5 (0.121 and 0.017). The impact on turnover translates into an increase in daily volume of 4.3 million Yuan ($690,000) per firm listed on the Shanghai stock exchange. This average firm increase is therefore of an economic magnitude that is significant for even the largest of traders. Similarly, the widening of bid-ask spreads represents a 5.4% increase compared to the average spread for Shanghai stocks (cf. summary statistics in Table 3). This represents a considerable increase in trading costs, in particular for those traders who are the most active market participants.

Overall, the magnitude of the immediate liquidity impact follows the established predictions. For example, the widening of bid-ask spreads conforms to earlier results and existing theories of the impact of less broker anonymity (cf. discussion in section 3.2). But furthermore, when focusing solely on major (informed) traders, there may be additional mechanisms at work that widen spreads, resulting in the quantitatively large magnitudes observed in Table 6. Specifically, Kryzanowski and Lazrak (2009) note that if the intensified trading (higher turnover) is due to increased informed trading then liquidity may be adversely affected (wider spreads). To elaborate, Chowdhry and Nanda (1991) model fragmented markets where there is a preference of informed traders to trade in the thickest market to better hide their trades. Thus, more trading activity – such as increased turnover in our setting – may simply hide more informed trading (Barclay and Warner, 1993; Chakravarty, 2001) and this can lead market makers to react by increasing their profit margin – i.e. widening spreads – to counteract higher probability of more informed (and thus less profitable) trades. This scenario is explicitly observed within the setting of this paper. More specifically, by the very nature of the event being studied – i.e. the introduction of an information enhancing software – the market participants become more informed overall about market statistics. Thus, as the pool of knowledgeable traders is larger, dealers become more likely to trade with such investors. The increased risk of trading with such counterparties can lead dealers to widen their bid-ask spreads.[18]

Arguably, this described effect is likely to be the strongest in the initial stages following the introduction of Level II. Namely, since big institutional traders – who are relatively more active in the market – are likely to be among the first subscribers to the transparency enhancing software, the probability of trading with a more informed partner (a Level II subscriber) increases the most initially. Thus the immediate widening of bid-ask spreads aligns with market makers adjusting their behavior (widening bid-ask spreads) in reaction to a higher risk of trading with more informed counterparties. This immediate impact contrasts later stages when less active market participants (such as households) represent a larger share of additional subscribers. Then the probability of market makers trading with an informed counterparty does not rise to the same

[18] It is worth noting the in the outlined literature traders are generally thought of as being informed about fundamentals, whereas in our setting traders obtain information on trade statistics. However, if trading behavior reflects (at least partly) information on fundamentals, then becoming more knowledgeable on trade statistics can result in a similar response by dealers. We thank Yakov Amihud for raising our awareness of this issue.

extent and thereby this effect gradually recedes (which is consistent with the dynamics reported in section 3.4 below, which shows more moderate changes in bid-ask spreads at later stages).[19]

Other measures of trading behavior

The immediate increase in turnover and widening of spreads is likely to emerge from the impact the transparency change has on major institutional traders. To verify this, we deepen the analysis to consider other market variables that are likely to change from altered trading behavior of major traders. Most notably, major traders that carry relatively large volumes on a day-to-day basis are likely to attempt to lower their price impact by hiding their trading strategy (e.g. Comerton-Forde et al., 2011). A common strategy for informed traders to conceal their actions is to break up their large trades into several smaller pieces (Barclay and Warner, 1993; Chakravarty, 2001). However, this is likely to be less advantageous in markets so transparent that they offer limited space to hide, i.e. where such trading strategies can be identified and documented by other market participants. More specifically, as multiple trades are costly (in particular with wider spreads and costly small trades, cf. Chakravarty, 2001), major traders realize less value from breaking up their trades if such tactics are observable anyhow by other market players. This is exactly the predicted effect in the Shanghai setting where the high level of transparency comes from the two key changes that directly work to illuminate investors' trading strategies. Specifically, as previously described in section 2.2, by revealing trader characteristics (trader size) and all individual transactions, any subscriber of the Level II software should in principle be able to identify the trading patterns of any major trader – for example, whether anyone is building up (or down) positions in specific stocks. In such a highly transparent market where costly attempts to hide one's trades are not likely to be successful, traders are incentivized to enter relatively fewer transactions with higher average volumes per trade.

Hence, to examine whether the trading behavior of major traders is truly affected by the Level II transparency change, we compile data on the number of trades and average trade size for every stock in our working sample covering the six months before and after the introduction of Level II.[20] Panel C in Table 6 reports the results from the benchmark regression equation (2) that

[19] On top of this, the effect could further amplify when relatively few people have access to the detailed transparency data, as this in principle gives rise to an adverse selection scenario that leads uninformed market participants to exit the market (cf. Chowdhry and Nanda, 1991). Thus, if small traders subtract from the market following Level II and thus it predominantly consists of major traders, then that will raise the probability of trading with an informed counter-party – which again may widen bid-ask spreads further.

[20] This data is obtained from a private data vendor named SINA (http://finance.sina.com.cn/money/), which is the only source known to us to provide this data for the Chinese market. The service offers daily documents for each listed stock, so obtaining this data involves downloading, processing and merging over 200,000 separate data files before merging it to an aggregate weekly level.

estimates the Level II impact on Shanghai listed firms relative to the Shenzhen control group. The estimates support the above predictions. There are on average 59 fewer trades per day for each Shanghai stock in the working sample, which translates into a 10.5% decrease (the pre-Level II daily average is 558 trades per stock). Consistently, the average size of each individual trade increases by 9,633 Yuan ($1,570) for every stock, which corresponds to a rise of 16.7% (the pre-Level II trade size is 57,800 Yuan per stock). Thus, the immediate impact on trading behavior is both statistically and economically significant.

Lastly, to verify the magnitudes of these percentage estimates – and to mitigate the effect of potential large numerical values/outliers – the last two columns in Panel C report estimates of the same analysis carried out in logs. The results are quite robust, showing a 5.8% decline in the average daily number of trades per stock and a 15% increase in the average volume per trade.

Thus, to conclude, these auxiliary results support that the Level II transparency change has a considerable impact on major traders, leading them to alter their trading behavior. Moreover, these changes may not only be limited to trade size and frequency, but may further spill over to other market outcomes. For example, it can be argued that a higher price impact of larger trades can potentially work to raise market volatility (we return to volatility analysis in section 3.5, verifying increased volatility). But keeping the focus on the liquidity impact of more trade transparency, we conclude that there is a sharp immediate reaction in both liquidity and trading behavior as traders start subscribing to the transparency enhancing software. This conforms with the idea that the most active and invested market participants (i.e. major institutional investors) are among the first subscribers, and that they are both strongly affected and significantly responsive to the transparency change.

3.4 Gradual increase in transparency access (intensive margin)

Although the results in section 3.3 show that the bulk of the overall liquidity impact of increased transparency is immediate, it still leaves room for evaluating the subsequent liquidity dynamics resulting from additional subscribers. Notably, even though later subscribers are associated with a relatively incremental cumulative effect, the associated liquidity dynamics of their participation can nonetheless shed light on the overall functional form between liquidity and the intensive margin of transparency. In other words, studying the evolution of liquidity outcomes over the entire sample period can reveal how the overall impact (studied in section 3.2) gradually comes into effect, i.e. how the incremental benefits of more transparency differ depending on how many people have access to the transparency enhancing information at any point in time. For example, although the results above may suggest that liquidity outcomes of increased transparency follow the law of diminishing returns on the intensive margin – implying a concave function between pre-existing levels of transparency and the marginal liquidity benefits thereof (cf. Eom, Ok and Park, 2007) – such a relationship is not the only possible pattern. Instead, one could e.g. imagine that increased trade transparency may initially lead to worse market outcomes (e.g. wider spreads) when relatively few people have access to the detailed transparency data, but that this trend is later reversed (i.e. temporary non-monotonicity in liquidity outcomes). To elaborate, this could occur in the presence of adverse selection where relatively few, early subscribers might use the detailed trading information for their own interests at the expense of the market as a whole. For example, Chowdhry and Nanda (1991) note that when information is asymmetrically allocated less informed traders may choose not to participate in the market. In our setting, any such adverse selection drawbacks could gradually recede as more traders would subscribe to the transparency-enhancing data package, implying a non-monotonic relationship between liquidity and the intensive margin of transparency.[21]

To investigate such dynamics we estimate changes in liquidity as the number of Level II subscribers gradually increases. Specifically, the two liquidity measures are regressed on a function of the number of Level II subscribers, in addition to the same set of controls as used previously (cf. equation 2). Specifically, we estimate

$$y_{it} = \alpha + g(Subscr._{it}) + f_i + w_t + \gamma Z_{it} + \varepsilon_{it} \qquad (3)$$

where $g(\cdot)$ can in principle be any function of the number of Level II subscribers and other variables are defined as before. In order to put minimal constraints on the function $g(\cdot)$, it is assumed to follow a flexible 5th order polynomial of the form

$$g(Subscr._{it}) = \beta_1(Subscr._{it}) + \beta_2(Subscr._{it})^2 + \ldots + \beta_5(Subscr._{it})^5 \qquad (4).$$

This semi-parametric framework allows us to estimate the coefficients β_1-β_5 and then use those estimates to plot the non-linear relationship between the liquidity measures, y_{it}, and the number of subscribers. Figure 2 displays the results. Due to the week fixed effects structure in equation (3), the figure displays the variation in liquidity for Shanghai firms *beyond* the average variation in liquidity across all firms (listed on either Shanghai or Shenzhen exchange). Values are initially bound at zero as the estimated value of liquidity is zero when no one subscribes to the

[21] Moreover, as another example, it is frequently argued that even though more transparency is likely to be beneficial on average (e.g. increased turnover), it can nonetheless be detrimental to liquidity if it becomes too excessive. For example, Cespa and Foucault (2009) argue that although a higher level of transparency promotes informational efficiency, full transparency is not socially optimal. Relating this to our setting it might be possible that liquidity deteriorates as the transparency level surmounts above a specific threshold.

transparency enhancing software (cf. equations 3 and 4). Turnover then depicts an upward trend as more and more traders subscribe to the software. Thus, Figure 2 displays how the previously established result – of increased trading activity with more transparency – gradually comes into effect. The cumulative change adds up to around 0.18 percentage points, which can be compared to the average 0.12 percentage point increase established in Table 5 (this average could intuitively be graphically represented as a horizontal line extending through the entire range of software subscribers in Figure 2). Also consistent with previous results, the overall effect of more transparency is to widen spreads. However, the dynamics are non-monotonic as the pattern of widening bid-ask spreads only holds initially. As more traders subscribe the effect gradually wears out and ultimately bid-ask spreads start to narrow, although they do not reach their pre-event levels (leaving the overall effect positive). Also notably, the figures resemble the overall post-Level II pattern observed when plotting the raw data in Figure 1 (this similarity reflects the near-randomization of the treatment vs. control group, since otherwise a systematically different control group would imply significantly different firm fixed effects across the two firm groups, resulting in another pattern in Figure 2).

Even though the model described in equations (3) and (4) is informative, it is unfortunately not very tractable for numerical analysis. Thus, in order to quantify numerically the general trends observed in Figure 2, the pattern is summarized by breaking the polynomial into a three-step function. More specifically, although the flexible specification in equation (4) allows for an informative graphical representation, it has the disadvantage that it is difficult to numerically filter out the general trend in the relationship between transparency and liquidity. Furthermore, a parsimonious step function also better allows for numerically testing the significance of the liquidity changes at different levels of transparency (rather than doing this numerically for every point of the polynomial). Thus, in order to better quantify the relationship, the average levels of liquidity for different *intervals* of transparency (rather than at every single point) are established by simplifying equations (3) and (4) into a three step function of the following form

$$\begin{aligned} y_{it} &= \alpha + \beta_1 D_{1\ (0<Subscr._{it}\leq 100{,}000)} \\ &\quad + \beta_2 D_{2\ (100{,}000<Subscr._{it}\leq 200{,}000)} \\ &\quad + \beta_3 D_{3\ (200{,}000>Subscr._{it})} \\ &\quad + f_i + w_t + \gamma Z_{it} + \varepsilon_{it} \end{aligned} \tag{5}$$

where the three dummy variables equal one if the number of subscribers is in the corresponding interval, and zero otherwise. The intervals are chosen such that the entire range of subscribers is divided into three equal parts.[22] This three-step model intuitively summarizes the non-linear relationship established in Figure 2 by filtering out the average level of transparency for three different intervals of software subscribers. The graphical representation of this model is added to Figure 2, which highlights the general trend in the relationship between liquidity and transparency. The corresponding coefficient estimates and statistical tests are reported in Table 7.

Table 7 numerically reveals that the transparency impact on liquidity varies with the level of information usage. For turnover, the incremental liquidity effect is initially relatively modest (0.021) but as the number of subscribers increases the cumulative turnover effect becomes statistically positive and gradually reaches an increase of 0.18 percentage points (the resulting average increase in turnover over the whole subscriber range is 0.12 percentage points, as previously reported in Table 5). This shows that the positive effect from more transparency (cf. Table 5) comes gradually into effect and accumulates as more traders enjoy access to the additional pre- and post-trade information.

The difference between the liquidity effects at various ranges of transparency is statistically verified at the bottom of Table 7. More precisely, the results show that the turnover effect of increased transparency is statistically greater (by 0.159 percentage points) with relatively many software subscribers, compared to the initial stage of relatively few users. In other words, this statistically verifies that the impact on liquidity statistically differs across the range of subscribers. Hence, this highlights the relevance of being able to identify gradual transparency impacts, relative to one-time changes in transparency that other studies have naturally been confined to. More specifically, the possibility to capture liquidity effects across a larger spectrum is valuable since the effect may very well differ across the various stages of the software usage – as is shown to be the case in Table 7.

Compared to turnover, bid-ask spreads are more responsive to the increase in transparency, i.e. the three-step function in Figure 2 – and corresponding estimates in Table 7 – reveal an initial and relatively large increase in spreads that becomes relatively stable thereafter. In other words, the average impact on bid-ask spreads (reported to be 0.017 in Table 5) is reached at the initial stage of relatively few subscribers (increase of 0.019 in Table 7). With more subscribers to the transparency enhancing software the bid-ask spreads remain stable around this level (up to 0.022

[22] The highest number of subscribers in the dataset is just above 300,000 so natural cutoff points seem to be at 100,000 and 200,000 subscribers. The cutoffs remain virtually unchanged if they are determined such that the number of observations is equal in each of three intervals. Further, in principle it is of course possible to split the sample into a higher number of intervals, but here the analysis is restricted to three separate steps of transparency levels (number of subscribers) to better *summarize* the overall trend in the relationship between liquidity and transparency. More specifically, to do this in a quantitatively meaningful manner, it is necessary to work with a parsimonious model where the numeric interpretation of estimated coefficients is both manageable and tractable.

and then down to 0.016), where the difference is not statistically different across the three subscriber levels. Overall, this implies that initially more transparency can be harmful to bid-ask spreads, but the detrimental effect wears out once a critical mass has access to the transparency enhancing software (but does not fully reverse). Also, as with turnover, the average effect (0.017 from Table 5) differs considerably from the impact the transparency enhancing software has at different stages of transparency (initial change is 0.019, then 0.004 increase at second step, followed by a decrease of 0.007 – see Table 7). This again highlights how the 'treatment effect' differs across the intensive margin of transparency.

To summarize this section, it is apparent that the dynamic relationship between trade transparency and liquidity is non-monotonic and therefore it cannot be bluntly stated that increasing transparency on the intensive margin will outright increase (or decrease) the level of liquidity. More specifically, although a transparency change on average raises turnover and widens spreads (as established in section 3.2), this section has established that the dynamic incremental effect is likely to depend on the degree of transparency already in the system. This non-monotonic relationship – which is further tested and verified in the subsequent robustness section – is a noteworthy result for several reasons. Specifically, this result implies that on the intensive margin it cannot be assumed that the average treatment effect will necessarily apply across a wide spectrum of transparency levels. To create an intuitive analogy, it cannot be assumed that a transparency-increasing regime introduced across all EU countries will necessarily improve market outcomes for each member state – such a transparency change should rather be separately evaluated depending on the pre-existing level of transparency within each country. Furthermore, the variation in results across pre-existing transparency levels can help to explain the counter-acting conclusions of the existing, empirical literature. More precisely, each empirical study is bound to evaluate the effect of a transparency change relative to the pre-existing market conditions in each setting. Thus, results may differ since the transparency level already in place differs across each market being studied.

3.5 Robustness and further results

This section introduces several changes in methodology that underline the robustness of the results established in previous sections. In doing so, the motivation for employing previously presented models is better established and further justified. In addition to such a sensitivity analysis, this section adds a brief analysis of marginal (not level) effects of increased transparency and concludes by evaluating the Level II transparency change in Shanghai relative to another (smaller) control sample, namely Shanghai stocks cross-listed in Hong Kong.

Different functional form: Linear relationship

An argument can be made that perhaps the most natural place to start the analysis is to model the relationship between transparency and liquidity as a linear one. More specifically, the simplest modeling choice is likely to be

$$y_{it} = \alpha + \beta(Subscr._{it}) + f_i + w_t + \gamma Z_{it} + \varepsilon_{it} \tag{6}$$

where all variables are defined as before. Despite being statistically tractable and straightforward, this model has the immediate disadvantage that it provides much less flexibility and offers less economic content than e.g. the 5th order relationship expressed in equation (4). However, for completeness, this (1st order) specification is examined in Table 8, where the sample remains Shanghai and Shenzhen listed firms listed on either exchange before September 2000 and originating from outside the two cities. The results are in line with previously established conclusions – specifically, an increase in Level-II software subscribers is associated with higher turnover and wider bid-ask spreads. Also, although the change in functional form implies that the magnitudes of estimated coefficients are not directly comparable to former specifications, the results are remarkably similar. To illustrate this, the number of subscribers is rescaled into hundreds of thousands, which implies that for 100,000 additional subscribers, turnover increases by 0.073 percentage points. Thus, using the midpoint of subscribers (150,000) provides an average increase in turnover of $0.073 \cdot 1.5$ = 0.11 percentage points, which is on par with the average effect reported in Table 5 (0.121). Similarly, the average effect on bid-ask spreads can be calculated to be 0.008 percentage points, which is not far off from the estimated value of 0.017 in Table 5.

Different functional form: Log-log specification

Since there is no apparent reason to presume that the relationship between transparency and liquidity is linear, a relatively simple log-log specification can be applied in order to allow for non-linear effects and mitigate the influence of potential outliers. Moreover, the argument that major traders subscribe earlier than other market participants implies that the marginal effect of each additional subscriber may decreases as the size of the marginal subscriber gradually becomes smaller. Statistically, this possible scenario is captured with a logarithm form that assumes decreasing marginal effects. Thus, the model now becomes

$$\ln(y_{it}) = \alpha + \beta \ln(Subscr._{it}) + f_i + w_t + \gamma Z_{it} + \varepsilon_{it} \tag{7}$$

quantifying the average liquidity effect (measured by β) that can be associated with the introduction of the Level II software. The log-log specification implies that the estimated regression coefficients have a direct economic interpretation in terms of elasticity – namely, a 1% increase in the number of software subscribers is associated with a 0.012% (0.001%) increase in turnover (bid-ask spreads). Thus, the qualitative results reassuringly remain unchanged from previous specifications, with increasing turnover and widening bid-ask spreads.[23]

Marginal effects within each subscriber interval

The main results on the intensive margin of transparency also deserve further scrutiny. Namely, the three-step equation (5) – with corresponding estimates reported in Table 7 – can easily be generalized to allow for more flexibility within each interval. As an example of that, the three-step model can be generalized to a three-slope model, where the marginal transparency effect on liquidity is allowed to differ within each of the three subscriber intervals (no longer assumed to be constant). Graphically, this implies that the three horizontal lines in Figure 2 are allowed to have non-zero slopes within each interval. Thus, the resulting function will be closer to the overall pattern of the 5th order polynomial, but a parsimonious three-slope function will still maintain the ability to numerically quantify general trends and test their differences (which is practically infeasible for the polynomial, as discussed in section 3.4). In other words, it is possible to test whether the three slopes are different across intervals, implying different marginal effects of increased transparency within each stage of Level II subscription (i.e. non-monotonicity). More precisely, the following three-slope model is estimated

$$\begin{aligned} y_{it} = \alpha &+ \delta_1 D_{1\,(0<Subscr._{it}\leq 100{,}000)} + \beta_1 Subscr._{it}\, D_{1\,(0<Subscr._{it}\leq 100{,}000)} \\ &+ \delta_2 D_{2\,(100{,}000<Subscr._{it}\leq 200{,}000)} + \beta_2 Subscr._{it}\, D_{2\,(100{,}000<Subscr._{it}\leq 200{,}000)} \\ &+ \delta_3 D_{3\,(200{,}000>Subscr._{it})} + \beta_3 Subscr._{it}\, D_{3\,(200{,}000>Subscr._{it})} \\ &+ f_i + w_t + \gamma Z_{it} + \varepsilon_{it} \end{aligned} \tag{8}$$

where the relationship between transparency and liquidity is allowed to vary linearly within each subscriber interval (the first three rows represent three linear equations). This model can also be

[23] Also, although the economic magnitude may at first seem humble, it is important to keep in mind the underlying range of the explanatory variable (0 - 300,000 number of users). This implies that a 1% increase is initially a very moderate magnitude, which then steadily increases over time as the number of users rises. Therefore, as the log-log specification is silent on how many additional software subscribers a 1% increase represents, the estimated magnitudes naturally cannot be directly related to previous results. The log-log specification can at most relate to log-measures, i.e. the overall liquidity increase can be calculated to be [ln(300,000)-ln(1)]$\cdot$0.012 = 15% in log-turnover and, similarly, 1.3% for log-spreads.

thought of as a direct three-step extension of the linear model presented in equation (6). The estimates are reported in columns 5-6 in Table 8, where the coefficients of interest are naturally not comparable to earlier results as they are reporting marginal effects (slopes) at each interval, rather than levels (steps). As expected, the slope coefficients convey a similar pattern as depicted by the 5^{th} order polynomial in Figure 2 (thus graphics are excluded for brevity). For example, the marginal effect of increased transparency leads bid-ask spreads to initially widen (0.015), then spreads remain around the same level (non-significant -0.002), before again narrowing (-0.017). A test of whether all three slopes are equal is strongly rejected (not reported), which reinforces the previously established result that the liquidity impact depends on the degree of transparency already in place – i.e. there is a non-monotonic relationship between transparency and liquidity. Furthermore, this non-monotonicity now becomes marginally present for turnover as well, where turnover initially decreases (-0.156) before increasing again (0.210). The equality of all three slopes is accordingly rejected for turnover as well (not reported).

Exclusion of the 2007-08 period

The Chinese stock market was very turbulent in the last decade. After a stock market slump in 2001-2005, the market rebounded in 2006. This contributed to an existing frenzy of stock market speculation (Ma, 1996; Girarding and Liu, 2003), which fueled immense turnover and volatility in 2007. The stock price rally in China went far beyond the experiences of other world markets, as demonstrated in Figure 3 where historically high fluctuations in the S&P500 index seem miniscule in comparison to the Chinese market. As in other world markets, stock prices in China reached historic highs in 2007 before plummeting in 2008.

The unusual boom-bust era of 2007-08 may potentially affect the estimated liquidity impact of Level II, although notably Figure 3 reveals very similar patterns for the Shanghai and Shenzhen stock markets. Hence, because previously established results measure the liquidity impact on Shanghai listed firms relative to their Shenzhen counterparts, this period is not likely to drive the differential results across the two markets. But to fully verify this we also explicitly exclude the 2007-08 calendar years from the analysis. The results are reported in columns 7-8 of Table 8, which reruns the three-step regression model of equation (5). As the 2007-08 period roughly coincides with the period in which Level II had 100,000–200,000 subscribers, the coefficient estimate at this interval is naturally dropped. The results show that excluding the boom-bust period has no effect at all on the remaining estimates. More precisely, the initial impact of Level II (going from 0 to 100,000 subscribers) is unchanged for both liquidity measures and the cumulative change (over 200,000 subscribers) is also the same (cf. Table 7). Also, repeating the analysis of the overall impact of Level II (i.e. the extensive margin reported in Table 5) similarly produces unchanged results (not reported). Thus, in conclusion, a strict exclusion of this period reconfirms that previous results can be fully contributed to the transparency changes of the Level II software.

Finally, it is worth noting that the robustness of excluding the 2007-08 period further rules out the impact of other market changes in that period. For example, as noted in section **Erreur ! Source du renvoi introuvable.** – and detailed in footnote 1616 – the analysis takes extra care to control for the introduction of another transparency enhancing software (named TopView) in January 2007. Specifically, distributed piracy versions of the software content and the non-availability of subscriber data prevents a meticulous analysis (as opposed to the Level II transparency change). Thus, any potential effect of this change is filtered out by a binary dummy throughout the paper. But moreover, as the controversy around the TopView software led it to be cancelled in January of 2009, the period in which the software was in place coincides exactly with the 2007-08 crisis period. Thus, the results in Table 8 (columns 7-8) also reconfirm the non-significance of this change on the estimated Level II impact.

Market factors: Liquidity and volatility

So far the analysis has set aside potential issues of endogeneity. More precisely, the variation in liquidity measures may be partly explained by various market variables (such as volatility), which in return are determined by liquidity. Madhavan, Porter and Weaver (2005) give a concrete example of this by pointing out that observed changes in spreads may not be solely due to changes in transparency, but may also be a function of e.g. turnover and return volatility. This implies that if these factors are not controlled for the results could be biased. Despite this fact, Eom, Ok and Park (2007) note that many studies have not bothered to control for such factors or done so using inapplicable procedures. Hence, here we follow the methodology of Madhavan, Porter and Weaver (2005) and Eom, Ok and Park (2007) by controlling for both liquidity and volatility in our regression equations. The key results are reported in columns 9-10 in Table 8, in which the three-step equation (5) is estimated with the added endogenous controls. As shown, spreads are a significant determinant of turnover, and vice versa. As expected, return volatility also affects both liquidity measures. However, all coefficient estimates of the Level II effect are virtually unchanged, implying that our previous inferences do not result from endogenous changes in liquidity or volatility. In other words, even after controlling for other factors that may affect liquidity in this period, the results remain unchanged and thereby confirm our uncontrolled finding that liquidity is affected by the transparency change.

Lastly, although the primary focus of this study is to measure the liquidity impact of Level II, it is of additional interest to examine the accompanied volatility impact thereof. Thus, instead of only employing volatility as a control variable, Table 8 also reports key regressions equations with volatility as the outcome variable. In short, the results show overall increased volatility in the post-Level II period (column 11), where the immediate impact is particularly large (column 12). More specifically, there is an immediate 0.217 increase in average daily standard deviation of returns, which is a sizeable 6% increase compared to the average daily volatility level (3.56 as reported in Table 3). The results thereby align with the previously reported liquidity estimates, where the change in the information set has the strongest effect on the first subscribers to the transparency enhancing software. This is further verified when studying the intensive margin of the gradual transparency increase (column 13) that shows an immediate effect, followed by smaller and non-monotonic volatility changes.

Further results: Hong Kong cross-lists

Lastly, it is of interest to push the analysis a step further by evaluating whether the Level II transparency-enhancing event had any influence on Chinese stocks that are cross-listed elsewhere. More specifically, a small sub sample of 42 Shanghai firms (and 8 Shenzhen firms) that are cross-listed in Hong Kong, may or may not be affected by the Shanghai specific transparency change. This will depend on the fundamental nature of the transparency change and on how different liquidity measures (turnover and bid-ask spreads) are determined in the market. To clarify this point it is useful to discuss each liquidity measure separately.

It has been established in this paper that the increase in turnover on Shanghai is directly associated with the transparency enhancing event of Level II – an event which in contrast provides no additional trading information on the Hong Kong order book. This observation, however, does not necessarily imply that the volume of Hong Kong cross-listed stocks will be unaffected. Specifically, volume patterns are generally not exchange specific, so this increased turnover effect on Shanghai is likely to spread to other markets – even if those markets are not directly affected by the transparency change. For example, Chowdhry and Nanda (1991) present a model in which fragmented markets exist in equilibrium and informed traders benefit by splitting orders across markets.[24] Menkveld (2008) investigates this empirically for a sample of U.S. and U.K. cross-listed stocks and finds that traders indeed engage in order splitting across markets. Thus, if there is a market specific change that increases local trading activity, this increase should

[24] See also related work on fragmented markets in Pagano (1989), Biais (1993), Bernhardt and Hughson (1997), Biais et al. (2000), de Frutos and Manzano (2002) and Yin (2005).

be transmitted to other markets as investors tend to trade in the same stock across multiple markets. This is likely to apply in the sample of cross-listed Chinese stocks, where the correlation of turnover across markets is found to be 0.91 over the sample period. In other words, the observed volume increase in Shanghai associated with greater transparency is likely to spill over to Hong Kong as well.

In contrast, there is no reason to presume this aligned pattern also holds true for bid-ask spreads, since those are determined quite differently across markets. As argued above, the widening of bid-ask spreads is consistent with the fact that Level II software allows subscribers to better identify traders. However, the Level II software only provides this information for the Shanghai order book, whereas it is not possible to infer the identity of traders on the Hong Kong exchange. Thus, there is no reason for market makers to change bid-ask quotes in Hong Kong since the Level II software is silent on possible trader identities in the Hong Kong order book. This presumption is consistent with very low correlation of bid-ask spreads across markets, which is calculated to be only -0.02 (and not significantly different from zero) for cross-listed stocks over the sample period.

In order to empirically investigate these relationships we revisit the regression framework of equation (5), but now employ a triple difference methodology. Namely, the effect of Level II (before-after difference) is compared across Shanghai and Shenzhen listed stocks (second difference), relative to their Hong Kong issues (third difference). More specifically, in the cross-listing sample each firm has two observations; one from either Shanghai or Shenzhen, the other one from Hong Kong. The difference between these two observations is taken for each pair of stocks and the effect of Level II is measured for the Shanghai group relative to the Shenzhen group. Compared to only examining Shanghai and Hong Kong stocks before and after the introduction to Level II (i.e. double differencing), the advantage of employing a triple difference methodology (i.e. Shanghai vs. Hong Kong differences compared to Shenzhen vs. Hong Kong differences) is that this allows us to control for general trends in liquidity. More specifically, this methodology controls for the general trend in the liquidity difference between Shanghai and Hong Kong stocks (by assuming this trend is the same for Shenzhen vs. Hong Kong stocks).[25]

[25] Intuitively, the triple difference methodology can be thought of as measuring the

(diff. betw. Shanghai and HK after Level II) - (diff. betw. Shenzhen and HK after Level II)

minus

(diff. betw. Shanghai and HK before Level II) - (diff. betw. Shenzhen and HK before Level II).

In technical terms, this can more precisely be written as the general regression equation

$$y_{it}^{e} = \alpha + D_{e=SH} \cdot g(Subscr._{it}) + f_i^{e} + w_{it} + w_t^{e} + \gamma Z_{it}^{e} + \varepsilon_{it}^{e}$$

for each stock exchange $e \in \{\mathrm{SH,SZ,HK}\}$ where the dummy variable takes the value of one for Shanghai listed stocks. We can write the difference between Shanghai and Hong Kong observations as

The estimates are reported in columns 14-15 of Table 8. In short, the results are as expected. First, there is no statistical difference in variation in turnover between the pair of stocks that are issued both in Shanghai and Hong Kong. The absence of statistical difference suggests that turnover has also increased for Hong Kong cross-listed stocks as a result of the transparency change. In other words, the increase in turnover for Shanghai listed firms (established in e.g. section 3.2) has also spilled over to the Hong Kong market among cross-listed firms, consistent with the predictions of existing literature. Also as expected, spreads react differently in the two markets. The previously established result of wider bid-ask spreads is only observed in the Shanghai market for cross-listed firms, as indicated by the significantly positive difference in column 15. This conforms to the idea that bid-ask spreads widen in Shanghai as trader identification becomes feasible, in contrast to Hong Kong where no such transparency change takes place and thus there is no apparent reason for changed bid-ask quotes in Hong Kong.

4 Concluding remarks

It is established that an increase in trade transparency on the Shanghai Stock Exchange has led to increased trading activity among Shanghai (and Hong Kong cross-listed) stocks. Although increased trading activity is generally associated with narrower bid-ask spreads, the contrary holds true within the setting of this study. More precisely, broker anonymity and more informed trading results in wider bid-ask spreads, which contradicts the frequent policy claim that 'more is better' when setting the level of trade transparency. In other words, the conclusion that more transparency can be detrimental to market quality has in fact been actively ignored by policy makers who have generally pushed for more transparency whenever markets have turned, in the honest belief that only in "exceptional circumstances … transparency sometimes hurts the customer" (Wall Street Journal, 2010).

$$dy_{it}^{SH} = y_{it}^{SH} - y_{it}^{HK} = g(Subscr._{it}) + (f_i^{SH} - f_i^{HK}) + (w_t^{SH} - w_t^{HK}) + \gamma(Z_{it}^{SH} - Z_{it}^{HK}) + (\varepsilon_{it}^{SH} - \varepsilon_{it}^{HK})$$

$$= g(Subscr._{it}) + FE_i + W_t + \gamma(Z_{it}^{SH} - Z_{it}^{HK}) + \mu$$

and similarly for Shenzhen,

$$dy_{it}^{SZ} = FE_i + W_t + \gamma(Z_{it}^{SZ} - Z_{it}^{HK}) + \mu_{it}$$

where no subscription software is available. Writing these two equations in one, we get the regression equation

$$dy_{it}^{e} = D_{e=SH} \cdot g(Subscr._{it}) + FE_i + W_t + \gamma(Z_{it}^{e} - Z_{it}^{HK}) + \mu^{e}{}_{it}$$

for exchanges $e \in \{SH,SZ\}$. Thus, we regress the difference in liquidity measures on the number of subscribers (replacing $g(\cdot)$ with a three-step function), firm fixed effects, week fixed effects and other potential controls. As such, the model is intuitively the same as before, except the liquidity for each stock is measured as the difference between its Shanghai (or Shenzhen) value and its Hong Kong value.

These overall effects are the strongest immediately following the transparency change, suggesting a significant impact on institutional traders subscribing relatively early. Additionally, there is evidence of changed trading behavior (fewer trades carrying more volume) and alterations in other market outcomes besides liquidity, such as increased volatility. Thus, the transparency impact is wide reaching and with counter-acting welfare implications. In other words, even if high transparency may generate a more just market and less opaqueness surrounding trading intentions, it cannot be concluded that it is necessarily welfare improving.

To further complicate policy intervention, it is established that liquidity does not react monotonically to increasing levels of transparency (cf. Figure 2), implying that there may be no ‘one-size-fits-all’ policy available. More specifically, the incremental effect of increased transparency depends heavily on the degree of transparency already in the system. This indicates that a policy recommendation beneficial in one country may be detrimental to another.

To summarize, the results provide noteworthy policy considerations by revealing that the effect of increased transparency i) may be detrimental to the market and ii) highly sensitive to the existing level of transparency. From a policy standpoint, these two results are of value given the seemingly unshaken and contrasting policy expectation of better market outcomes with more trade transparency. Instead, the findings suggest that the merits of transparency altering policies must be evaluated in relation to pre-existing transparency levels within the each setting. Finally, the result that different outcomes are likely with different starting points of transparency has not been previously documented in the empirical literature – and can further reconcile its opposing results since every empirical analysis is bound to evaluate transparency effects relative to a regime already in place in the corresponding market.

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Figure 1. Difference in liquidity across exchanges

The figure displays the difference in liquidity measures across the two exchanges over time. More precisely, the trend reflects the liquidity differences of Shanghai listed firms versus Shenzhen listed, where the sample is restricted on firms listed on either exchange before September 2000 and originating from outside the two cities. Turnover and spread are measured as defined in the summary statistics (Table 3). The vertical line represents the date the transparency enhancing software was introduced.

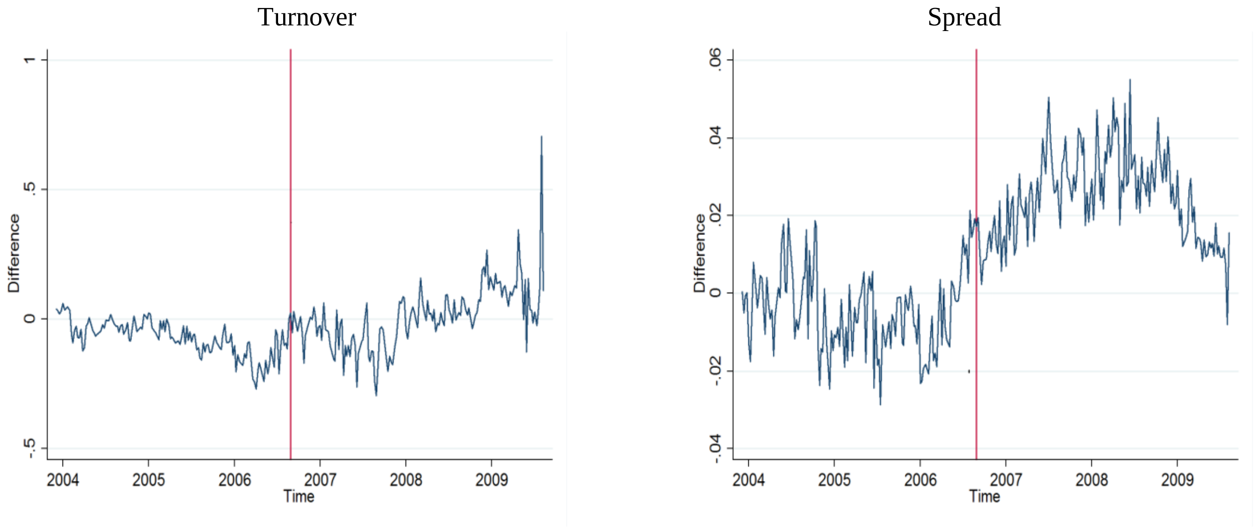

Figure 2. Relationship between transparency and liquidity

The figures show the liquidity benefit of increasing the degree of market-wide transparency (number of Level 2 subscribers). The figures are produced by estimating the non-linear relationships between each outcome variable and the number of Level 2 subscribers, which is fully described in equations 3 and 4 in section 3.4. The relationships are shown for Shanghai firms that are listed before September 2000 and located outside the two cities. More specifically, the figure shows the variation in liquidity on Shanghai *beyond* the average variation in liquidity across all firms on either Shanghai or Shenzhen exchange – which is achieved by applying firm and week fixed effects. Also plotted is the average level of liquidity for different ranges of transparency (ranges of software subscribers) in order to highlight the overall pattern of the flexible functional form (these averages are established from regression equation 5). More precisely, the average level of liquidity is shown for 0 and 100,000 subscribers, then for 100,000-200,000 subscribers and lastly for more than 200,000 subscribers. The figures include 90% and 95% confidence intervals for these average levels of liquidity at different ranges of subscribers (different stages of transparency).

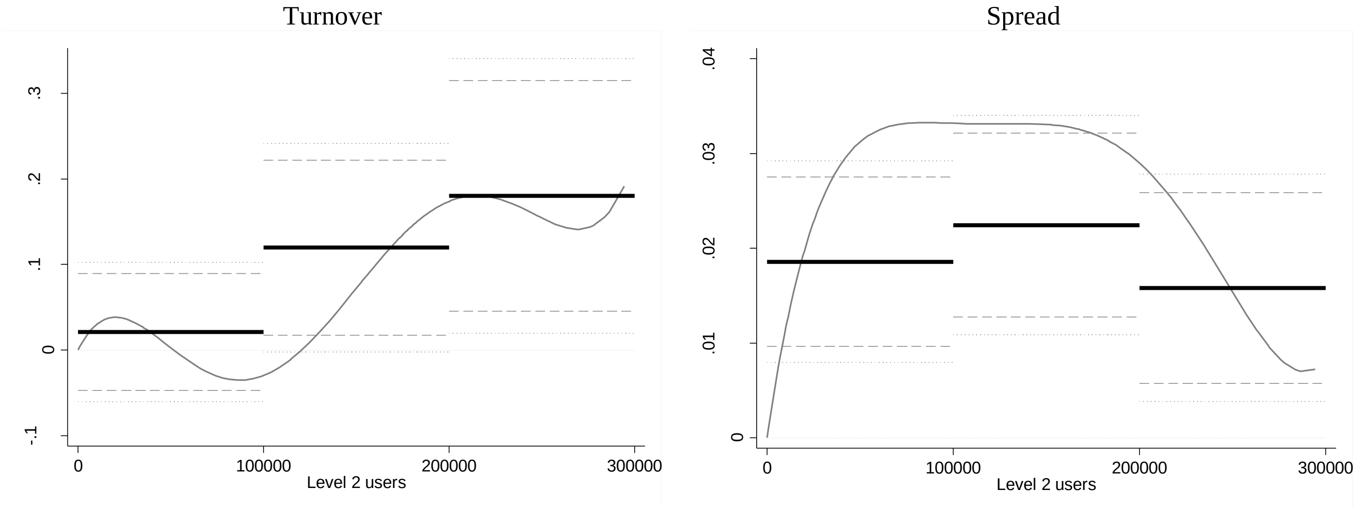

Figure 3. Chinese stock prices vs. S&P500

The figure displays the evolution of stock price indexes in China and the U.S. in 2000-2010. The Chinese indexes are the Shanghai and Shenzhen all composite indexes, whereas the S&P500 represents the U.S. market. For comparison purposes, each index has been set to a value of 100 in January 2000. Source: Datastream.

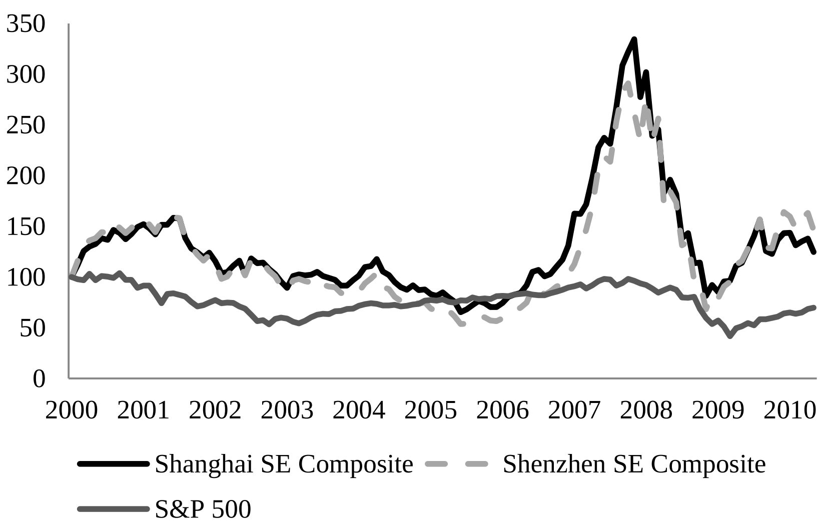

Table 1. Transparency changes

The table summarizes the pre- and post-trade transparency changes that took place with the introduction of the Level II data package on the Shanghai Stock Exchange. The Level II data and the accompanying software were introduced in August 2006 and could be obtained by any trader at a cost of approximately $200 p.a.

Pre-trade transparency increases	1. Volume of individual requests/offers is detailed, which helps infer trader characteristics.
	2. Best 10 bid-ask quotes openly reported, rather than merely the top 5.
	3. Bid/ask withdrawals shown for the 10 companies with most withdrawals (no withdrawals previously reported).
Post-trade transparency increases	4. Screen reporting transactions updated every 3 seconds instead of every 6 sec.
	5. Every transaction in the past 3 seconds reported, not only total trading in the last 6 seconds.

Table 2. Market and trading characteristics

The table summarizes the key market and trading characteristics of Shanghai and Shenzhen stock exchanges. A few additions should be noted to Panel A. First (*), there is after hours trading. Block trades are permitted at 15:00-15:30, where trades are negotiated between brokers off market at prices which must be between the day's high and low prices. Price, volume and trader identification are released to the market after the close of this trading session. Second (**), neither of the exchanges have designated market makers and they offer only limit orders for the continuous auction, which thereby are the only source of liquidity (no market-, stop market-, stop limit-, fill or kill-, IOC nor incomplete orders). The order validity period is at maximum 1 day. The same applies to the call auction (i.e. no market orders, market-on-open orders nor market-on-close orders). Third (***), the call auction design is such that there is 10 minute pre-open period reserved for the call auction. There is neither order non-cancellation period nor any volatility/imbalance extension. Panel B shows the trading costs associated with trading in Shanghai and Shenzhen stock exchanges. All trading costs are a percentage of transaction value. Through the commissions the brokers collect all listed levies (supervision fee, transfer fee and transaction fee). The transfer fee is imposed by the depository and clearinghouse, which is 50/50 owned by the two exchanges. Source: Chan, Menkveld and Yang (2007, 2008), Comerton-Forde and Rydge (2006), The Handbook of World Stock, Derivative and Commodity Exchanges (2004-2010), China Securities and Futures Statistical Yearbook (2002-2012), websites of the two stock exchanges, Ministry of Commerce and other Chinese government websites listed in Panel B. The direct website links to relevant subpages are readily available upon request (due to their length the short version is reported).

Panel A: Trading structure

Trading hours	9:30-11:30 & 13:00-15:00*
Trading mechanism	Electronic, consolidated open limit order book (COLOB) ** Continuous auction Market opening: Call auction*** Market closing: No call auction
Priority rules	Continuous trading: Price-time Call auction trading: Price-time
Tick size	A shares: RMB 1c B shares: USD 0.001 or HKD 0.01
Price variation controls	Stock prices may fluctuate within a range of ±10% of the previous closing price and in opening call auction orders can only be submitted within this range.

Panel B: Trading costs

Fee	Description	Level and changes	Online source:
Stamp duty	Imposed by tax authorities.	Stamp duty has ranged from 0.1-0.3% of transaction value in the sample period, but the level has been the same across venues at any given point in time. More specifically, stamp duty changed three times (in Jan. 2005, May 2007 and April 2008), where the change was always simultaneous and of equal size across the two stock exchanges.	gov.cn csrc.gov.cn
Commissions	Imposed and collected by broker.	Maximum level of 0.3% of transaction value on both exchanges since May 2002. This level includes levies listed below and is collected via commissions.	people.com.cn csrc.gov.cn
Other levies (coll. via commissions):			
- supervision fee	Imposed by China Securities Regulatory Commission.	0.004% of transaction value for both exchanges during 2003-2012.	gov.gn mofcom.gov.cn csrc.gov.cn
- transfer fee	Imposed by China Securities Depository and Clearing Corp.	Shanghai: Unchanged level of 0.1% in 1998-2012. Shenzhen: Collected as part of the transaction fee (0.00255%) and unchanged up until 2012.	chinaclear.cn sse.com.cn
- transaction fee	Imposed by stock exchanges.	Shanghai: Unchanged level of 0.011% in sample period. Shenzhen: Unchanged level of 0.01475% in sample period (0.0122% net of the transfer fee).	crsc.gov.cn szse.cn china.org.cn

Table 3. Summary statistics

This table reports total number of firms and means of firm variables (with standard deviations in parentheses) over the Jan. 2004 – Aug. 2009 period. The table shows summary statistics separately for the original (total) sample and the subsample which is restricted on firms listed before September 2000 and originating from outside the two cities of Shanghai and Shenzhen. The reported returns are the average daily returns (all daily averages are reported on a weekly frequency in the dataset). Volatility is measured as the average daily standard deviation in price over the past 20 business days with non-missing observations. Spread is the difference between closing bid and ask prices divided by the midquote (and scaled by 100 to be interpreted in percentages). Turnover is the weekly average of the number of shares traded per day as a ratio of the total number of shares outstanding for each particular firm. Assets are the average value of total assets at the time of listing (time invariant). Similarly, employees are the average number of employees at time of listing.

	Original sample			Working sample (pre-2000 and non-local)		
	All firms	Shanghai	Shenzhen	All firms	Shanghai	Shenzhen
No. of firms	1594	844	750	767	370	397
Returns (%)	0.08	0.09	0.08	0.09	0.09	0.09
	(1.99)	(1.97)	(2.02)	(2.02)	(2.01)	(2.02)
Volatility (%)	3.56	3.51	3.63	3.57	3.56	3.59
	(1.73)	(1.74)	(1.72)	(1.79)	(1.78)	(1.80)
Spread (%)	0.24	0.25	0.23	0.26	0.26	0.25
	(0.15)	(0.15)	(0.16)	(0.16)	(0.16)	(0.16)
Turnover (%)	1.40	1.38	1.44	1.43	1.42	1.43
	(1.46)	(1.46)	(1.45)	(1.51)	(1.52)	(1.50)
Assets	256	305	180	201	214	188
(¥millions)	(543)	(665)	(240)	(316)	(377)	(242)
Employees	3,263	3,807	2,415	2,778	2,865	2,694
	(17,279)	(21,953)	(3,431)	(4,219)	(4,895)	(3,441)

Table 4. Comparison of treatment and control group

The regressions in this table fit an exchange specific flexible time trend (a 3rd order polynomial) to the dependent variable over the pre-event period (January 2004 - July 2006). This allows the evaluation of whether the time trends are different for the two exchanges before the transparency changes are introduced. Panel A compares Shanghai listed firms to those listed in Shenzhen. Panel B repeats Panel A, but restricting on firms listed on either exchange before September 2000 and also on firms originating from outside the two cities. The regressions include firm and week fixed effects, where the latter controls for joint trends across the two markets. Robust standard errors are reported in parentheses and are clustered by firm and week, i.e. taking into account that i) the errors for the same firm may not be independent across time and ii) that in any given week the errors may not be independent across firms. Significance is reported at the 10% (*), 5% (**) and 1% (***) level. The exact coefficient (st.error) values on the 2nd and 3rd order terms in column (2) are -6.8E-5 (2.5E-5) and 8.2E-8 (3.1E-8). Also reported in the last row of the table is the χ^2-statistics (and the corresponding p-value) testing the joint significance of the three interaction terms, where the 5% critical value is 5.99 with two degrees of freedom. This χ^2 is approximately equivalent to the corresponding F distribution in large samples.

	Panel A: Shanghai vs. Shenzhen – all firms		*Panel B:* Shanghai vs. Shenzhen - firms listed before Sept.2000 & located outside the two cities	
	(1) Turnover	(2) Spread	(3) Turnover	(4) Spread
t*Shanghai	-0.017	0.018***	0.052	0.012
	(0.034)	(0.007)	(0.038)	(0.009)
t^2*Shanghai	0.000	-0.000***	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
t^3*Shanghai	-0.000	0.000***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Firm FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
Observations	162,868	162,868	93,679	93,679
No. of firms	1,346	1,346	767	767
R-squared	0.328	0.163	0.360	0.178
χ^2-statistics &	8.09	7.19	2.06	3.54
(p-value)	(0.02)	(0.03)	(0.36)	(0.17)

Table 5. Overall liquidity effect of increased transparency (extensive margin)

The table shows the average level of change in liquidity for associated with the introduction of the Level II software. Specifically, the table reports estimates of equation (2) where the effect is averaged out for the entire range of Level II subscribers. The results reflect the differences of Shanghai listed firms versus Shenzhen listed, where the sample is restricted on firms listed on either exchange before September 2000 and originating from outside the two cities. Robust standard errors are reported in parentheses and are clustered by firm and week, i.e. taking into account that i) the errors for the same firm may not be independent across time and ii) that in any given week the errors may not be independent across firms. Significance is reported at the 10% (*), 5% (**) and 1% (***) level.

	Turnover	Spread
	(1)	(2)
$D_{Level\ II}$ (Subscribers>0)	0.121**	0.017***
	(0.058)	(0.005)
Observations	198,297	198,297
Firm fixed effect	Yes	Yes
Week fixed effect	Yes	Yes
R-squared	0.519	0.386
Number of firms	767	767

Table 6. Immediate liquidity impact (early subscribers)

The table shows the average level of change in liquidity (Panel A-B) and trading behavior (Panel C) associated with the introduction of the Level II software. In all panels the sample period is six months before and after the introduction of Level II. All reported results show the differences of Shanghai listed firms versus Shenzhen listed, where the sample is restricted on firms listed on either exchange before September 2000 and originating from outside the two cities. Panel A shows the results from a standard event-study, without controlling for other relevant variables, using conventional *t*-tests. Each *t*-test is based on approximately 8-9 thousand observations. It should be noted that figures in Panel A do not always perfectly add up, which is due to rounding (not rounding errors). Significance at the 10%, 5% and 1% level is established for a *t*-statistics of value 1.645, 1.960 and 2.576, respectively. Panels B and C report multivariate regression estimates of equation (2). In Panel C the number of trades is defined within a trading day for each stock. Trade size is the average value traded in Chinese Yuan (normalized to 2006 value) within a trading day for each stock. Both of these variables are averaged weekly to maintain consistency in the data frequency throughout paper. All other variables are defined as in the summary statistics in Table 3. Robust standard errors are reported in parentheses and are clustered by firm and week, i.e. taking into account that i) the errors for the same firm may not be independent across time and ii) that in any given week the errors may not be independent across firms. Significance is reported at the 10% (*), 5% (**) and 1% (***) level in Panels B and C.

Panel A: Univariate liquidity analysis

	Pre-Level II	Post-Level II	Diff.	*t*-value
Turnover				
Shanghai	1.32	1.69	0.37	19.13
Shenzhen	1.46	1.71	0.25	12.94
			0.12	4.25
Spread				
Shanghai	0.31	0.27	-0.04	-20.11
Shenzhen	0.31	0.25	-0.06	-29.16
			0.02	4.71

Panel B: Multivariate liquidity analysis

	Turnover (1)	Spread (2)
$D_{\text{Level II}}$ (Subscribers>0)	0.105**	0.014***
	(0.041)	(0.004)
Observations	32,774	32,774
Firm fixed effects	Yes	Yes
Week fixed effects	Yes	Yes
R-squared	0.502	0.632
Number of firms	764	764

Panel C: Multivariate analysis on trading behavior

	No. of trades (1)	Trade size (2)	Ln(No. of trades) (3)	Ln(Trade size) (4)
$D_{\text{Level II}}$ (Subscribers>0)	-59.4***	9,633***	-0.058**	0.150***
	(19.4)	(3,161)	(0.026)	(0.031)
Observations	26,093	26,093	26,093	26,093
Firm fixed effects	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes
R-squared	0.759	0.231	0.780	0.820
Number of firms	763	763	763	763

Table 7. Effect of gradually increasing transparency access (intensive margin)

The table shows the average level of liquidity for different ranges of transparency (ranges of software subscribers), as further illustrated in Figure 2. More precisely, the average level of liquidity is shown for 0-100,000 subscribers, then for 100,000-200,000 subscribers and lastly for more than 200,000 subscribers. The difference in the average level of liquidity between different intervals of subscribers (levels of transparency) is also reported. Specifically, the table reports dummy coefficient estimates of equation (5), along with the statistical difference of those estimates. The results reflect the differences of Shanghai listed firms versus Shenzhen listed, where the sample is restricted on firms listed on either exchange before September 2000 and originating from outside the two cities. Robust standard errors are reported in parenthesis and are clustered by firm and week, i.e. taking into account that i) the errors for the same firm may not be independent across time and ii) that in any given week the errors may not be independent across firms. Significance is reported at the 10% (*), 5% (**) and 1% (***) level.

	Turnover	Spread
	(1)	(2)
D_1(0<Subscribers<100,000)	0.021	0.019***
	(0.042)	(0.005)
D_2 (100,000<Subscribers<200,000)	0.120*	0.022***
	(0.062)	(0.006)
D_3 (200,000<Subscribers)	0.180**	0.016***
	(0.082)	(0.006)
Observations	198,297	198,297
Firm fixed effect	Yes	Yes
Week fixed effect	Yes	Yes
R-squared	0.520	0.386
Number of firms	767	767
$D_2 - D_1$	0.098	0.004
	(0.073)	(0.004)
$D_3 - D_2$	0.060	-0.007
	(0.089)	(0.005)
$D_3 - D_1$	0.159**	-0.003
	(0.081)	(0.005)

Table 8. Robustness and further results

The table shows further tests and extensions of previously establish results. First (columns 1-2), the linear relationship between liquidity and transparency is estimated by running the regression $y_{it} = \alpha + \beta(Subscribers_{it}) + f_{it} + w_t + \gamma Z_{it} + \varepsilon_{it}$, using the standard notation, where the number of subscribers is measured in hundreds of thousands. Second (columns 3-4), a log-log regression model of the form $\ln(y_{it}) = \alpha + \beta\ln(Subscribers_{it}) + f_{it} + w_t + \gamma Z_{it}$ is evaluated. Third, (columns 5-6), the marginal effect of increased transparency is estimated separately for the three intervals of software subscribers (using three slope function, rather than a three step function – see details in equation (8)). Fourth (columns 7-8), the Jan.2007–Dec.2008 boom-bust period (also coinciding with the operation of another transparency enhancing software named TopView) is excluded from the analysis. Fifth (columns 9-10), potentially endogenous market variables are controlled for by adding them to the benchmark model of equation (5). Sixth (columns 11-13), the key analysis of the paper is repeated using volatility as the outcome variable, as defined in the summary statistics in Table 3. Finally (columns 14-15), the liquidity effect on stocks of firms listed both in Shanghai and Hong Kong is examined (relative to effect on stocks of firms listed both in Shenzhen and Hong Kong – i.e. triple differencing). In columns (1)-(13) the results reflect the differences of Shanghai listed firms versus Shenzhen listed, where the sample is restricted on firms listed on either exchange before September 2000 and originating from outside the two cities. In all columns, robust standard errors are reported in parenthesis and are clustered by firm and week, i.e. taking into account that i) the errors for the same firm may not be independent across time and ii) that in any given week the errors may not be independent across firms. Significance is reported at the 10% (*), 5% (**) and 1% (***) level.

Panel A: Functional form and data restrictions

	Linear		Log-log		3 slopes		Excl. 2007-08	
	Turnover	Spread	Ln(Turn.)	Ln(Spr.)	Turnover	Spread	Turnover	Spread
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Subscribers	0.073**	0.005**						
	(0.031)	(0.002)						
Ln(Subscribers+1)			0.012**	0.001***				
			(0.006)	(0.000)				
D_1 (0<Subscr.<100’)					0.046	0.017***	0.031	0.019***
					(0.046)	(0.006)	(0.040)	(0.006)
D_2 (100’<Subscr.<200’)					-0.283*	0.032**		
					(0.155)	(0.013)		
D_3 (200’<Subscr.)					0.143	0.058***	0.173**	0.016**
					(0.313)	(0.018)	(0.084)	(0.006)
Subsc. $\cdot D_1$(0<Subsc.<100’)					-0.156*	0.015*		
					(0.088)	(0.008)		
Subsc. $\cdot D_2$(100’<Subsc.<200’)					0.210**	-0.002		
					(0.107)	(0.008)		
Subsc. $\cdot D_3$ (200’<Subsc.)					0.013	-0.017**		
					(0.130)	(0.007)		
Observations	198,297	198,297	198,297	198,297	198,297	198,297	164,221	164,221
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.520	0.386	0.520	0.386	0.520	0.386	0.526	0.378
Number of firms	767	767	767	767	767	767	767	767

…Table 8 continued.

Panel B: Market factors and further results

	Market factors		Volatility impact			Hong Kong	
	Turnover	Spread	Extensive	Immediate	Intensive	Turnover	Spread
	(9)	(10)	(11)	(12)	(13)	(14)	(15)
$D_{Level\ II}$ (Subscribers>0)			0.095**	0.217***			
			(0.042)	(0.068)			
D_1 (0<Subscr.<100')	0.017	0.019***			0.093*	-0.003	0.181*
	(0.038)	(0.005)			(0.054)	(0.225)	(0.098)
D_2 (100'<Subscr.<200')	0.125**	0.024***			0.063	-0.251	0.546***
	(0.051)	(0.006)			(0.081)	(0.370)	(0.204)
D_3 (200'<Subscr.)	0.172**	0.018***			0.097*	-0.370	0.256**
	(0.079)	(0.006)			(0.050)	(0.654)	(0.126)
Turnover		-0.013***					
		(0.001)					
Spread	-0.911***						
	(0.068)						
Volatility	0.233***	-0.004***					
	(0.011)	(0.001)					
Observations	197,881	197,881	197,881	32,774	197,881	9,395	9,393
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.568	0.397	0.517	0.401	0.517	0.249	0.189
Number of firms	767	767	767	764	767	50	50