Does Financial Market Structure Impact the Cost of Raising Capital?

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Abstract

We provide evidence on market structure and the cost of raising capital by examining market structure changes in US equity markets. Only the Nasdaq's Order Handling Rules (OHR), the one reform that reduced institutional trading costs, lowered the cost of raising capital. Using a difference-in-differences framework relative to the NYSE and that exploits the OHR's staggered implementation, we find that the OHR reduced the underpricing of seasoned equity offerings by one to two percentage points compared to a pre-OHR average of 3.6 percent. The effect is largest in stocks with the largest reduction in institutional trading costs after the OHR.

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1 Introduction

Financial markets facilitate raising capital, trading, and price discovery by connecting investors with firms and investors with each other. Frictions, such as illiquidity, that prevent buyers from matching with sellers quickly and at low cost affect the ability of firms to raise capital and, consequently, their investment decisions.[1] It is well known that market structure affects liquidity and the cost of trading (Madhavan, 2000). However, there is limited evidence on how the structure of the secondary markets impacts the cost of raising capital in the primary market through financing frictions.

Our paper examines whether changes in secondary market structure causally impact the issuing costs of seasoned equity offerings (SEOs).[2] We examine how the cost of raising capital via a SEO changes following significant US equity market structure changes over the recent decades: the reduction in the tick-size from eighths to sixteenths, and the subsequent reduction to pennies, the start of Autoquoting on the NYSE, and the Order Handling Rules (OHR) on Nasdaq.[3] Figure 1a graphs SEO underpricing from 1996 to 2004, where underpricing measures the price difference between newly issued stock and the price in the secondary market prior to the SEO. The trend line is estimated using local polynomial (LOWESS) regressions of SEO underpricing on a date index. Each market structure event is marked by a line if it occurs on a single date or, by a gray area, if the event date is staggered over time across stocks.

Figure 1 about here

The most noticeable movements in underpricing occur prior to 2000. There is a marked

[1]Wurgler (2000) provides evidence on how countries with more developed financial markets are associated with better capital allocation. Levine (1997) discusses the importance of financial frictions, e.g., secondary market liquidity, on investment and economic growth.

[2]SEOs are important sources of financing for firms, accounting for between 65% and 89% of annual US equity underwriting activity between 2000 and 2018 (SIFMA, 2019).

[3]These events are described in more detail in the following section where we also discuss why more recent changes that occur more gradually over time, such as Reg NMS and high-frequency trading, are more difficult to use for causal identification.

decline in underpricing around the introduction of sixteenths and the OHR, which overlap in time. There is an increase in underpricing from mid-1998 to 2000, when there are no market structure changes. This coincides with volatility associated with the dot-com boom and bust, likely making it more expensive to raise capital for reasons unrelated to secondary market structure. There are no substantial changes in underpricing around the other market structure changes, although there is a general decline in underpricing from 2001 through to the end of the sample. While the sixteenths and OHR events overlap in time, the OHR only affects Nasdaq stocks and sixteenths affects both Nasdaq and NYSE stocks. Figure 1b reports underpricing split by exchange. Figure 1b shows that the decline in underpricing occurs only in Nasdaq stocks, consistent with the OHR rather than sixteenths causing underpricing to decline. The other trends in underpricing by exchange appear unrelated to the market structure changes.

The time series in Figures 1a and 1b are the simple unconditional average underpricing. While the decline in underpricing occurs around the OHR and only in Nasdaq stocks, it is possible that for reasons unrelated to the OHR, market conditions changed only for Nasdaq stocks, e.g., Nasdaq stocks became relatively more volatile or the composition of issuing companies changed. A first approach to examining this is to estimate difference-in-differences regressions for SEOs on the Nasdaq vs. the NYSE around the OHR introduction. These regressions, which include standard controls such as company size, trading volume and volatility, show that the OHR reduces underpricing on Nasdaq relative to the NYSE by a statistically significant amount of almost one percentage point.[4]

The OHR were implemented in a staggered fashion, across 22 distinct dates covering a 10-month period in 1997. This allows us to further examine whether the decline in underpricing around the OHR can be explained by changes in market conditions for Nasdaq stocks, and not NYSE stocks, that are not due to the OHR. We do this by treating the OHR as a quasi-random experiment and estimating its direct effect on SEO costs in a pooled difference-in-

[4]For Autoquoting, the equivalent estimate for the relative reduction in underpricing on the NYSE is around 0.6 percentage points but this estimate is not significant at the 10% level.

differences framework using only Nasdaq stocks.[5] We find that the OHR had a statistically and economically significant effect of reducing SEO issuing costs by reducing underpricing. In our most general specification, SEOs of companies with stock trading under the OHR were less underpriced by 1.96 percentage points, as compared to a 3.6% pre-OHR average SEO underpricing. Total issuing costs (underpricing plus explicit fees in the issuing process) were 2.07 percentage points lower than the 9.21% pre-OHR average.

If market structure and liquidity affect the cost of raising capital, it is not immediately evident why only the OHR should affect underpricing. All of these events increased liquidity as measured by a decline in the bid-ask spread. However, there is heterogeneity in the events' impact on other dimensions of liquidity, particularly the trading costs for larger trades by institutions. Sixteenths and decimalization reduced market depth, particularly at the best price, making it difficult to determine whether the trading costs for institutions increases or decreases. Jones and Lipson (2001) show that institutional trading costs for NYSE increased after sixteenths while Werner (2003), Bollen and Busse (2006) and Chakravarty, Van Ness, and Van Ness (2005) provide mixed evidence on the impact of decimalization on institutional trading costs. There is no research directly examining the impact of Autoquoting on institutional trading costs, but Anand, Irvine, Puckett, and Venkataraman (2013) depict institutional trading costs from Ancerno covering 1999 to the end of our sample period which shows there is little change in these costs around Autoquoting.

In contrast to the other events, the OHR reduced both the bid-ask spread and institutional trading costs (Barclay, Christie, Harris, Kandel, and Schultz, 1999; Conrad, Johnson, and Wahal, 2003). Taken together, these results suggest that it is the change in institutional execution costs, rather than costs for small, retail-sized trades that matter for underpricing.

We use proprietary data from Plexus to more directly link institutional trading costs to the cost of raising capital. Using trade records that identify the cost of execution at the

[5] While the cohort of OHR stocks included in the first 13 waves was determined by relative trading volume, there was a large degree of randomization within broad categories of stocks. In addition, our findings hold when examining only the later phases of the OHR where trading volume was not used when assigning stocks to the OHR.

parent-order level, we investigate how the OHR affected institutional trading costs in the cross-section of stocks. Two categories of stocks experienced the relatively larger improvements in institutional trading costs from before to after the OHR: stocks with low market capitalizations and stocks with high average dollar trading volume. Consistent with lower institutional trading costs leading to lower SEO issuing costs, the effect of the OHR on underpricing is largest in these two categories of stocks.

Why would institutional execution costs matter more than bid-ask spreads for SEO underpricing? Similar to a seller-initiated block-trade, a SEO involves locating a buyer or group of buyers willing to absorb a large supply of stock.[6] Reducing trading frictions in the secondary market for SEO participants reduces the expected costs of buyers absorbing the SEO proceeds, as they anticipate being able to quickly and more cheaply liquidate their positions in the secondary market if needed.

Institutions are key players in the market for SEOs. Gao and Ritter (2010) discuss their crucial role in both fully marketed SEOs, as participants in the book-building process, and accelerated offerings, where they deal directly with the winning bank or syndicate in the reselling process. Not only do institutions own around 50% of all US equities at the beginning of our sample (Gompers and Metrick, 2001), a fraction that has become more significant over time, they are also over-represented in primary market transactions relative to retail traders. Gibson, Safieddine, and Sonti (2004) and Demiralp, D'Mello, Schlingemann, and Subramaniam (2011) document that total institutional ownership increases by between six and nine percentage points on average from the quarter before to the quarter after a SEO takes place.[7] Gibson et al. (2004) and Chemmanur, He, and Hu (2009) further find that institutions are able to identify and trade successfully on information produced in the SEO issuing process, both before, during, and after the issue. Lower execution costs make these

[6]Figure 2 in Corwin (2003) shows that average cumulative market-adjusted returns undergo a significant price drop in the days prior to the offer, followed by a significant reversal over subsequent days. A similar pattern is shown in Figure 1 in Kraus and Stoll (1972) for block sales.

[7]Kim and Park (2005) suggest that, similar to the levels for IPOs found in Aggarwal, Prabhala, and Puri (2002), around 70% of SEOs are allocated to institutions.

strategies more profitable and encourage more institutional participation. Execution costs for institutions, rather than bid-ask spreads, can therefore directly impact the discount that institutions require to participate in a SEO.

Our paper contributes to the literature studying the association between secondary market liquidity and the cost of raising equity capital.[8] After controlling for underwriter pricing practices, Corwin (2003) estimates a positive but statistically weak association between bid-ask spreads and the underpricing of SEOs. We extend this literature by isolating a source of exogenous variation in liquidity, that is plausibly exogenous from information asymmetry, that allows us to identify a direct causal effect between trading costs and capital costs, rather than reduced-form associations. In contrast to this prior literature, for the OHR, we find robust support for improved liquidity for institutional investors causing lower underpricing. In addition to underpricing, we also use the OHR to identify the effect of liquidity on the explicit fees charged in the issuing process. Butler, Grullon, and Weston (2005) show that various measures of stock liquidity are associated with lower fees charged by investment banks for SEOs. Using plausibly exogenous variation in trading costs, we only find weak evidence that liquidity impacts investment bank SEO fees. Importantly, we find no evidence that these fees increase in a way that would offset the benefits of reduced underpricing — issuing firms are better off after the reform. Our results also have direct relevance for policy makers who are actively experimenting with market structure to promote issuance in public equity markets (e.g., the 2016 SEC tick-size pilot).

The remainder of this paper proceeds as follows. Section 2 describes the major market structure changes in detail, discusses previous work examining how they impacted liquidity and develops testable hypotheses regarding these changes. Section 3 describes our data sources and provides summary statistics. Section 4 analyzes the effect of market structure and liquidity on SEO underpricing across all the events. Section 5 estimates the effect of

[8]Bessembinder, Hao, and Zheng (2015) study how secondary market liquidity affects the IPO decision. Ellul and Pagano (2006) find that the expected level of liquidity and liquidity risk are associated with IPO underpricing.

market structure on SEO issuing costs using the staggered introduction of the OHR on Nasdaq. Section 6 explores the association between institutional trading costs and SEO issuing costs. Section 7 compares our results to the prior literature and Section 8 concludes.

2 Market Structure Changes and Testable Hypotheses

US equity market structure has changed dramatically over the last three decades. We examine four market structure changes whose immediate impact is well identified. Two events are significant market-wide changes: the tick-size reductions from eighths to sixteenths, and the subsequent reduction to pennies. The other two events are market-specific changes: the introduction of the OHR on the Nasdaq and the introduction of Autoquoting on the NYSE. Another important regulatory change is Regulation NMS (National Market System), that set out a vision of a market composed of multiple trading venues all linked together via rules dictating access and trade priority. However, in contrast to the events we study, the impact of Reg NMS is not easily identifiable at a single point in time because many of the changes needed to incorporate and take advantage of it occurred across the industry over a period of time leading up to the effective date. For this reason we exclude Reg NMS from our analysis.[9] A detailed description of the four well-identified events is provided in this section.

2.1 Tick Size Reductions

On May 27, 1997, the SEC approved a reduction in tick-size from eighths to sixteenths. This change was implemented by the Nasdaq on June 2, 1997, and by the NYSE on June 24, 1997. On January 28, 2000, the SEC ordered the exchanges and NASD to begin implementing decimalization. This process was completed on the NYSE on January 29, 2001 and by the Nasdaq on April 9, 2001. Numerous academic studies report that these tick-size reductions had a large impact on bid-ask spreads (Chordia, Roll, and Subrahmanyam, 2011). However, the evidence on whether these tick-size reductions changed institutional trading costs is

[9] We find no evidence that Reg NMS impacted SEO underpricing (see Table A.1 in the Appendix).

mixed, with the balance tilted towards costs either increasing or being unchanged (Jones and Lipson (2001); Werner (2003); Bollen and Busse (2006); Chakravarty et al. (2005); Anand et al. (2013), Eaton, Irvine, and Liu (2018)).

2.2 Order Handling Rules on Nasdaq

The OHR changed Nasdaq from a dealer-oriented over-the-counter (OTC) market to a more centralized order-driven market structure. Stoll (2006) describes the OHR as transforming Nasdaq and causing the rise of electronic trading. The OHR reforms were prompted by anti-competitive dealer behavior (Christie and Schultz, 1994). The OHR increases competition in liquidity supply in two main ways. First, the Limit Order Display Rule requires market makers to display investor limit orders if they are priced better than the market maker's quote. This rule enables investors to compete against dealers for order flow, and enables investors to access limit orders that were not previously displayed to the market. Second, the Quote Rule requires market makers to publicly display their best quotes. market makers had been previously able to post different quotes on Nasdaq and on Electronic Communications Networks (ECNs), which were not universally accessible.[10]

Consistent with the OHR being one of the most important changes to secondary market trading, Barclay et al. (1999), McInish, Van Ness, and Van Ness (1998), Weston (2000), and Chung and Van Ness (2001) demonstrate that following the OHR, transaction costs for an average-sized trade declined by about one third. Barclay et al. (1999) show that spreads decline for all stocks, but decline by a larger magnitude in less active stocks, and for stocks with large pre-OHR spreads. Most large institutional buy and sell orders are broken up into smaller orders that are executed in many small transactions. Using order-level data from institutions, Conrad et al. (2003) show that the OHR also significantly decreased execution costs for large institutional orders, especially for broker-executed orders (compared with ECNs).

[10]Other changes in the OHR include a reduction in the Minimum Quote Size from 1,000 shares to 100 shares and the relaxation of the Excess Spread Rule.

2.3 Autoquoting on NYSE

In response to the decline in depth at the best bid and ask prices that occurred following decimalization, the NYSE introduced "Autoquote", which automatically disseminated a new inside quote whenever there was a relevant change to the limit order book. Autoquoting reduced the capacity constraints on specialists and clerks, enabling them to more effectively manage their quotes, and allowed algorithmic liquidity demanders and suppliers to respond more quickly. The Autoquote software was gradually rolled-out by the NYSE between January 29, 2003 and May 27, 2003. Using Autoquote as an instrument for algorithmic trading, Hendershott, Jones, and Menkveld (2011) show that quoted and effective spreads narrow under Autoquote. While no papers have explicitly examined Autoquote's impact on institutional trading costs, the time series graph of institutional trading costs Figure 1 of Anand et al. (2013) shows no clear change during the Autoquote event in 2003.

2.4 Testable Hypotheses

A summary of the main findings in the literature on market structure changes and liquidity is provided in Table 1.

Table 1 about here

All four market structure changes led to improved bid-ask spreads and therefore increased liquidity for small-sized trades. Our first hypothesis tests whether observed changes in capital costs around the events are related to changes in bid-ask spreads:

Hypothesis 1: *If better liquidity for small trades impacts SEO issuing costs, then all four events will lower SEO issuing costs.*

Institutions owned around 50% of all US equities around the time of the first market structure change we study (Gompers and Metrick, 2001) and play an even more important role in absorbing the supply of stock from SEOs and IPOs relative to retail traders (see e.g., Gibson, Singh, and Yerramilli (2003); Kim and Park (2005); Demiralp et al. (2011)). Trading frictions that affect the expected costs of liquidating a large position resulting from an SEO can increase the discount that institutions require to participate in these transactions. The bid-ask spread is a poor proxy for these trading costs due to factors such as price impact, opportunity costs and speed of order book replenishment (Bertsimas and Lo, 1998; Obizhaeva and Wang, 2013). The cost of executing institutional-sized trades should therefore matter for SEO issuing costs more than the bid-ask spread. The OHR is the only event for which there is clear evidence of an improvement in the cost of executing institutional-sized trades. The OHR only affected Nasdaq stocks and was implemented for Nasdaq in a staggered fashion over a 10 month period. These observations motivate our second testable hypothesis:

Hypothesis 2: *If liquidity for institutional-sized trades matters for SEO issuing costs, then the OHR will lower SEO issuing costs. The OHR will lower costs on Nasdaq relative to the NYSE and for Nasdaq stocks trading under the OHR relative to Nasdaq stocks not yet trading under the OHR.*

Improvements in trading costs may not be uniform across stocks. We formalize an additional hypothesis that tests whether any cross-sectional variation in the effect of market structure change on liquidity is consistent with trading costs driving SEO issuing costs:

Hypothesis 3: *Stocks with relatively larger liquidity improvements should have larger improvements in issuing costs.*

3 Data and Summary Statistics

SEO and issue characteristics for issues that took place on the Nasdaq and NYSE during the period January 1996 to May 2004 are obtained from the Securities Data Company (SDC) New Issues database. This covers one year before the roll-out of the earliest event (the OHR) and one year after the end of the last event (Autoquote). Similar to Lee and Masulis (2009) and Karpoff, Lee, and Masulis (2013), we include SEOs of common shares by public US companies with an offer price of at least \$5, sold on a firm commitment basis and exclude rights issues and depository receipts. Sales by real estate investment trusts are excluded as are issues with a filing date of more than 12 months before the beginning of our sample. For each SEO that meets the requirements, we observe the 9-digit CUSIP, the stock ticker symbol, the issue date as determined by SDC, the offer size (in \$ millions) and the offer price.

For each stock in our sample, we obtain CRSP daily data containing the closing price, best bid and ask, volume traded and shares outstanding. From these data we construct control variables including the log of market capitalization (Ln(MARKET_CAP)), the log of stock price (Ln(PRICE)), the standard deviation of one month daily returns (VOLATILITY) and monthly volume traded in \$ millions (VOLUME). These controls are similar to those used by Corwin (2003).

We also construct the percentage difference between the closing price and bid price on the day prior to the issue, referred to as CLOSE_TO_BID. Corwin (2003) uses this variable to control for the practice of "pricing at the bid", where issue prices were determined relative to the closing bid quote, rather than the closing trade price, as discussed in Lee, Lochhead, Ritter, and Zhao (1996). Corwin (2003) argues that this was mainly practiced for Nasdaq issues during our sample period because closing bid quotes for these stocks is less noisy than the closing price, which was simply the last reported trade from a single market maker which could be at the bid or the ask. On the NYSE, the closing price was determined by an auction that consolidated order flow, so closing prices were less noisy as they better reflected aggregate supply and demand for NYSE stocks. Underwriters may have preferred pricing to the Nasdaq bid because it was the market selling price and a SEO is a large sale. Corwin (2003) found CLOSE_TO_BID to be important, so we control for it to ensure this does not confound our analysis.

We use the method of Safieddine and Wilhelm (1996) to adjust the issue date for SEOs that occur after the close of trading.[11] We also obtain the value of the VIX index on the issue date from CBOE (2017) and the monthly value of the Baker and Wurgler (2006) sentiment index orthogonalized to macroeconomic indicators from Jeffrey Wurgler's webpage (referred to as VIX and SENTIMENT, respectively).[12] Our sample includes a total of 2,278 SEOs that meet our selection criteria and have corresponding CRSP data as matched by 9-digit CUSIP.

We construct three related dependent variables that capture SEO issuing costs. The first variable, UNDERPRICING, is the negative of the log return from the previous closing transaction price to the offer price in percentage terms, as per Corwin (2003). The issue price is taken from SDC while the closing price is recorded in CRSP on the day prior to the issue date. The second variable, GROSS_SPREAD, is defined as the percentage difference between the gross issuing proceeds and the net issuing proceeds, relative to the gross proceeds. Gross spreads capture the explicit fees that issuing firms pay to the underwriters, managers and syndicate members in the issuing process. The final variable, TOTAL_ISSUING_COST, is the sum of underpricing and gross spreads. For each SEO, we also calculate the value of the issue divided by the market capitalization. All variables capturing stock and issue characteristics are winsorized at the 1% level, except for the Ln(PRICE).

Table 2 contains summary statistics of our data. The first seven columns of Table 2 refer to the pooled sample of SEOs across the Nasdaq and NYSE. The final two columns contain exchange specific means. The mean underpricing of SEOs pooled across both exchanges is 2.84%, with a standard deviation of 3.52. The median underpricing is 1.81%. SEO gross spreads are a much larger cost component than underpricing on average, with a mean of of 5.00%. This variable is however significantly less variable than SEO underpricing. The standard deviation of gross spreads is only 1.18, less than two-fifths of the standard deviation

[11] Safieddine and Wilhelm (1996) use spikes in trading volume to identify the actual SEO issue date. If the day following the stated issue date has at least twice the trading volume of the stated issue date, then the issue date is adjusted to be the next trading day. Corwin (2003) and Karpoff et al. (2013) both use this method to identify the "correct" issue date.

[12] Link: http://people.stern.nyu.edu/jwurgler/.

of underpricing. These summary statistics indicate that cross-sectional variability in total issuing costs is likely to be driven primarily by SEO underpricing, rather than explicit fees paid to service providers in the issuing process. The average SEO represents 24% of the current market capitalization of the firm, the average bid-ask spread is 1.46% and average one month standard deviation of returns is 3.52%.[13]

Table 2 about here

The final two columns of Table 2 contain exchange-specific means for our sample. Consistent with prior literature, Nasdaq SEOs are on average more heavily discounted than NYSE SEOs, with average underpricing of 3.38% for Nasdaq issues vs. 1.70% for NYSE issues. Nasdaq SEOs tend also to be for a smaller dollar amount of stock than for NYSE SEOs ($134m vs. $339m) but the relative size of issues is more similar across the two exchanges (24% for Nasdaq vs. 23% for NYSE). Nasdaq stocks that undertake SEOs tend to be smaller (which follows from the comparisons of dollar amount and relative size), have more volatile returns, and higher bid-ask spreads than NYSE stocks undertaking SEOs during our sample period.

4 Underpricing and Market Structure Reforms

Figure 1a depicts non-parametric time trends in underpricing of SEOs pooled across the Nasdaq and NYSE, with important market structure changes in vertical shading. Average underpricing varies from a minimum of approximately 2.5% to a maximum of around 3% throughout the sample period although there is little overall trend up or down in the smoothed average of underpricing pooled across exchanges during this period.

Of the four major events that we study, only the OHR and overlapping tick-size change from eighths to sixteenths are associated with a discernible reduction in average SEO un-

[13] The equivalent averages from Corwin (2003) are 2.21% for close to offer underpricing, 23.75% for relative size, 2.48% for bid-ask spread and 3.19% for one month standard deviation of returns. The data used in Corwin (2003) covers 1980 to 1998 for the issuing characteristics and 1993 to 1998 for liquidity.

derpricing. The smoothed trend in pooled underpricing reduced from approximately 3% prior to the roll-out of the OHR to approximately 2.5% after the completion of the roll-out. For decimalization and Autoquote, there are no pronounced reductions in underpricing from before to after, although the period from the beginning of decimalization to the end of the sample period coincides with a small reduction in average underpricing, in the order of approximately 0.1 to 0.2 percentage points.

The OHR and Autoquote only affected a single exchange: Nasdaq for the OHR and NYSE for Autoquote. Any improvement in the underpricing from these events should be observed only on the exchange where the change in market structure occurred. Reductions in underpricing on the relevant exchange may also be obscured in the pooled underpricing trend due to noise from the exchange with no change in market structure.

Figure 1b depicts local polynomial trends of underpricing for SEOs split by exchange. There is a clear reduction in underpricing on Nasdaq SEOs around the implementation of the OHR/sixteenths, with no associated change in underpricing for NYSE SEOs. This is consistent with the OHR having a meaningful impact on underpricing of Nasdaq SEOs. Prior to the OHR, average SEO underpricing for Nasdaq stocks was approximately 4%. Following the completion of the roll-out, this number falls to around 3%. If the change in tick-size from eighths to sixteenths reduced SEO underpricing, then Figure 1b suggests that this effect must be isolated to Nasdaq stocks, not NYSE stocks. We do not believe that there are convincing reasons for such an argument. Indeed, since NYSE stocks have lower inside spreads on average relative to Nasdaq stocks, narrowing the tick-size would likely affect a greater fraction of NYSE stocks compared with Nasdaq stocks, suggesting ex-ante that the change to sixteenths would be more meaningful for NYSE stocks.[14] The implementation of Autoquote coincides with a small reduction in average underpricing for NYSE stocks.

The graphical evidence in Figures 1a and 1b does not control for possible changes in

[14] Smith (1998) examines the complete implementation of the OHR and the reduction in tick-size from eighths to sixteenths. He shows that the inside spread is more likely to be set by orders placed in ECNs in active, high-priced stocks. Depth results for the full sample are also mixed, with high-priced stocks exhibiting greater declines/smaller increase in depth compared to lower-price stocks.

SEO characteristics or test for statistical significance. We estimate simple regressions of underpricing on issuer controls, issue controls, macroeconomic indicators and pre-/post-event dummies to determine whether the changes in market structure are associated with statistically significant reductions in underpricing. These regressions also control for potential changes in average SEO characteristics over time (issue size, firm size, volatility, etc.) that may affect or be correlated with underpricing. For each market structure event, we create sub-samples containing all SEOs in the year before the implementation of the change and the year following the final implementation. For each sub-sample, we estimate a regression of the form:

$$Y_{it} = \alpha + \rho_1' X_{it} + \rho_2' Z_t + \beta POST_t + \varepsilon_{it} \tag{1}$$

where Y_{it} is the log close to offer return (UNDERPRICING) for SEO i at time t, X_{it} is a vector of issue-specific control variables including log of market capitalization of issuing stock (Ln(MARKET_CAP)), relative issue size (RELATIVE_SIZE), standard deviation of returns during the month of issue (VOLATILITY), the log of issue price (Ln(PRICE)), log of volume traded during the month of issue (VOLUME) and a dummy variable for issues on the NYSE (NYSE) and Z_t is a vector of time-varying control variables to capture changes in market-wide conditions at a daily or monthly frequency including the value of the Baker and Wurgler (2006) sentiment index (SENTIMENT) and the value of the VIX index on the issuing date (VIX). The variable POST is a dummy variable taking the value one if the issue occurs in the post-implementation period.[15]

In these regressions β captures the change in average SEO underpricing from the pre-event period to the post-event period conditional on characteristics of the issue or issuing company, market-wide sentiment and volatility. The estimates from these regressions cannot distinguish between an effect due to the change in market structure and time effects that affect all SEOs, such as changes in other macroeconomic conditions that are not directly

[15] Sentiment is shown to affect equity issuance behavior and costs in Lowry (2003), Baker and Stein (2004) and McLean and Zhao (2014).

controlled for. Instead, these regressions examine the statistical significance of any changes in average underpricing around the events while controlling for changes in SEO and issuer characteristics over time. Parameter estimates and heteroskedasticity-robust t-statistics from these regressions are contained in the first four columns of Table 3, under the sub-heading "Pooled Pre-/Post-Event OLS".

Table 3 about here

The POST coefficient is negative for all events except decimalization. However, the associated t-statistics are only significant at the 10% level for the OHR. For this event, the coefficient is -0.59 indicating that after controlling for issue and stock characteristics, average underpricing of SEOs pooled across the NYSE and Nasdaq was approximately 59bps lower in the year after the roll-out compared with the year prior. For decimalization, the point estimate is positive and of similar magnitude to the negative coefficient for the OHR, but the associated t-statistic is 1.21.[16]

For the two events that directly affected a single exchange in isolation, the OHR and Autoquote, the effect of the change in market structures across the two exchanges is estimated using the following regression:

$$Y_{it} = \rho_1' X_{it} + \rho_2' Z_t + \delta_0 PRE_t + \delta_1 POST_t + \delta_2 EXCH_{it} + \beta POST_t \times EXCH_{it} + \varepsilon_{it} \quad (2)$$

where Y_{it}, X_{it}, Z_t and POST are defined as in Equation (1), PRE is a dummy for SEOs prior to the reform and EXCH takes the value one if the SEO takes place on the exchange undergoing the change in market structure and zero if the SEO is on the other exchange.[17] All other details, including sample construction, are equivalent to the pooled OLS regressions

[16] If VIX and SENTIMENT are excluded, the decimalization coefficient is above one and significant at the 5% level. This demonstrates the importance of controlling for market-wide conditions during this event, especially when the post-event period coincides with the aftermath of the bursting of the dot-com bubble and includes the terrorist attacks of September, 2001.

[17] For the OHR, EXCH is one for Nasdaq SEOs and zero for NYSE SEOs. For Autoquote, EXCH is one for NYSE SEOs and zero for Nasdaq SEOs.

in the first four columns of Table 3. Equation (2) is a standard difference-in-differences model for a single treatment date (i.e., with time dummies, treatment status dummies and their interactions) with additional control variables. In Equation (2), β is a treatment effect that compares the change in conditional mean underpricing for SEOs on the treated exchange (where the market structure change takes place) with the change in the conditional mean underpricing on the control exchange (where no market structure change occurs) from before to after the change in market structure.

These regressions have the advantage of directly controlling for any average time fixed effects that drive variation in market-wide underpricing in the pre- and post-event periods. The difference-in-differences specification can also distinguish between the changes in underpricing across exchanges for these two events. Both features are crucial for understanding any potentially causal relationship between market structure changes and capital costs. The coefficient estimates for Equation (2) are contained in the final two columns of Table 3 under the sub-heading "Cross-Exchange Diff-in-Diff".

For the OHR/sixteenths period, we obtain a negative and significant treatment effect, indicating that these events led to a reduction in underpricing that is 0.95% larger than any reduction in underpricing that took place on the NYSE over the same period. This represents nearly thirty percent of the mean underpricing for Nasdaq SEOs over the entire sample period. This reduction is statistically significant and is not driven by market-wide time effects or changing characteristics of issuers and issues from before to after the OHR/sixteenths implementation. The smaller coefficient for the OHR in the Pooled Pre/Post analysis in Table 3 appears to reflect that NYSE underpricing did not change around the event, and that the OHR is the driver of the cost improvement, rather than the tick-size change that affects all stocks.[18] For Autoquote, the event that impacts NYSE but not Nasdaq, the equivalent coefficient estimate is -0.58 and the associated t-statistic is -1.08.

The evidence in this section shows that the implementation of the OHR is the only

[18]As mentioned above, this interpretation would not be accurate if, for some reason, the tick-size change affected Nasdaq stocks more than NYSE stocks, which seems implausible.

event associated with a reduction in SEO issuing costs. Other market structure changes are not associated with clear or significant reductions in SEO issuing costs. Our explanation for why the OHR led to a significant reduction in issuing costs but other events did not relates to the effect of each change in market structure on institutional trading costs. Only the OHR is associated with a clear and significant reduction in these costs.[19] At the time of the OHR, institutions held around 50% of all equities outstanding (a share that has grown over time) and are typically allocated a relatively larger fraction of shares in primary market transactions. Costs of trading in large quantities required by institutions can differ markedly from the bid-ask spread due to factors such as price impact and opportunity costs (Bertsimas and Lo, 1998) or the speed at which the order book replenishes (Obizhaeva and Wang, 2013). Together, our evidence shows that changes to the bid-ask spread alone, as driven by tick-size changes and Autoquoting, are not sufficient to drive improvements in capital costs (contradicting Hypothesis 1). Meaningful reductions in institutional trading costs are also required (supporting Hypothesis 2).

The difference-in-differences specification in Table 3 does have some limitations. First, it relies on an assumption of parallel trends in average underpricing across exchanges. If average underpricing is subject to differing time effects across the two exchanges, then our treatment effect estimate is biased. Potential spillovers of the effect of market structure changes across exchanges would further complicate our interpretation of these regressions, e.g., if Autoquote had a beneficial impact on Nasdaq stocks as well as NYSE stocks, perhaps by encouraging investment in high-frequency trading technology that is then used to trade securities on all exchanges. We also cannot conclusively rule out that it is, in fact, the sixteenths change that drove the improvement in Nasdaq underpricing but for some reason did not affect NYSE SEOs.

These concerns can be addressed by directly focusing on SEOs within the Nasdaq during the roll-out of the OHR (Hypothesis 2). The OHR were implemented in a staggered fashion

[19] Although there is no direct evidence in the literature for Autoquote's impact on institutional trading costs, Figure 1 in Anand et al. (2013) shows no obvious change in costs following Autoquote's introduction.

throughout the universe of Nasdaq stocks. Therefore, we can use the OHR implementation directly as a quasi-natural experiment and examine the effect of the reforms on issuing costs.

5 The Order Handling Rules and SEO Issuing Costs

During the period around the OHR (1996-1998), Nasdaq firms primarily raised capital through equity. Nasdaq firms had fewer bond issuances for a smaller aggregate amount: there were 739 SEOs for $57 billion and 192 bond issuances for $30 billion. Beyond the importance of equity issuance in this period, the OHR's staggered implementation enables within Nasdaq analysis. Individual Nasdaq stocks begin trading under the OHR over 22 successive waves. The first wave of stocks began trading under the OHR on January 20, 1997 and the last wave began October 13, 1997. The first 13 waves included the "Top 1000" Nasdaq stocks by median dollar volume, with each wave including the 10 largest volume stocks and a random draw of eight stocks from the top five deciles. Wave 14, which began on 4 August, was the first wave from which stocks were drawn from the entire universe of Nasdaq stocks. The initial waves comprised only 50 stocks, but the majority of stocks are phased-in in large groups of approximately 850 stocks during September and the first half of October.[20]

The OHR is attractive for identifying a potential causal association for several reasons: assignment to waves on observables (trading volume), randomization within each wave and the exchange-wide implementation of the new market structure. Furthermore, as the one event for which we have clear evidence of a meaningful reduction in institutional trading costs, causal evidence that the OHR affects SEO issuing costs helps further pin down the

[20] A summary of the number of stocks phased-in in each wave is provided in Figure A.1 in the Appendix. Further details about the roll-out are provided in Smith (1998). The implementation schedule for the OHR was obtained from two sources: Nasdaq equity trader alerts during 1997, published via Nasdaq (2017) and proprietary information provided by Nasdaq. Trader alerts detail each stock in each phase from Wave 2 (February 10, 1997) onwards. These were usually issued to market participants one to two weeks before each phase. The Nasdaq list also covers the first 50 stocks in the pilot program on January 20, 1997. The two datasets are highly consistent and we use the trader alerts where possible as these are the most official record according to Nasdaq economists.

importance of institutional trading in the capital raising process, relative to liquidity for small trades. We therefore use the OHR as a treatment variable and create a difference-in-differences specification for SEOs on the Nasdaq, regressions that are designed to test Hypothesis 2. From the sample of all SEOs described in Section 3, we construct a Nasdaq sub-sample covering the entire OHR roll-out from January 1997 to October 1997.[21] We then estimate a series of regressions that can be expressed in a general form as follows:

$$Y_{it} = \gamma_c + \mu_t + \beta OHR_{it} + \rho' X_{it} + \varepsilon_{it}, \tag{3}$$

where Y_{it} is an issuing cost variable observed for the i^{th} SEO during time period t, OHR is the OHR status of the issue (value of one if trading under the OHR at time of issue and zero otherwise). The vector X_{it} contains stock and issue specific controls including log of market capitalization (Ln(MARKET_CAP)), issue size as a fraction of shares outstanding (RELATIVE_SIZE), standard deviation of mid-quote returns (VOLATILITY), log of stock price (Ln(PRICE)), log of dollar volume traded (Ln(VOLUME)) and percentage difference between the closing price and bid price on the day prior to the issue (CLOSE_BID_DIFF). Market capitalization, volatility, price and dollar volume are defined as at the end of 1996. We define these variables prior to the initiation of the OHR to limit possible indirect effects that the OHR may have on these variables, for example via volume traded or price. The parameters γ_c are fixed effects defined by membership of each of the phase-in waves, i.e., γ_c takes the value of one if stock i was included in the c^{th} wave of stocks; μ_t are time fixed effects, where time is defined either as calendar month or by the series of dates at which new stocks were introduced to the OHR, i.e., μ_t takes the value of one if the issue occurs in the t^{th} month or between the OHR inclusion dates of the $t-1^{th}$ and t^{th} waves, depending on how the time fixed effects are being defined.

[21] There are 213 Nasdaq SEOs during this period in the SDC Platinum data. Of this sub-sample, 12 do not have CRSP data available as at January 1, 1997. These companies issue an SEO at some point in our sample, but are yet to IPO by the date at which we define our control variables. Another five cannot be matched to the OHR implementation schedule, leaving a total of 196 SEOs for this analysis.

With wave-cohort fixed effects and time fixed effects defined by the dates of each wave's introduction to the OHR, Equation (3) is analogous to a treatment effect around a single treatment date, but where assignment to treatment or control occurs across multiple groups and periods. A similar approach is used in both Bertrand and Mullainathan (2003) and Gormley and Matsa (2011), and is also applied in the context of corporate bond issuing costs and transparency by Brugler, Comerton-Forde, and Martin (2020). The coefficient β is our pooled analogue of the coefficient on the interacted term between the treatment dummy and the post-treatment period dummy in a difference-in-differences model using a single treatment period. It captures the average treatment effect across the multiple events on underpricing in percentage point terms. Pooling the 22 treatment dates into a single regression allows us to control for cohort-specific effects and consequently we are not as reliant on the parallel trends assumption as we would be when analyzing the difference-in-differences around a single event.

We estimate Equation (3) under five specifications: excluding controls and fixed effects (i.e., regressing underpricing only on OHR status), including all controls other than CLOSE_BID_DIFF, including these controls with monthly fixed effects, including these controls, wave-cohort fixed effects and time fixed effects based on wave dates, and finally, adding CLOSE_BID_DIFF to the control variables with wave-cohort and time-fixed effects based on wave dates. Implementation of the OHR is not truly random. If it were, arguably the most rigorous way to estimate Equation (3) would be to exclude all control variables as inclusion of the wave-cohort fixed effects can theoretically remove any time-invariant stock characteristics that may affect SEO underpricing and differ systematically across cohorts. The fact that OHR status is driven in part by relative trading volume motivates us to incorporate the controls. For all models and specifications, we calculate White's heteroskedasticity-robust standard errors and report tests based on these standard errors.[22]

[22]Cameron and Miller (2015) note that cluster-robust parameter covariance matrices can be downward biased when there are few clusters and that this problem can be particularly problematic when the number of observations by clusters varies. Given the highly unbalanced nature of the clusters in our sample and the relatively few clusters (either 10 or 23 depending on how the time fixed effects are defined), we rely on our

Figure 2 plots the number of SEOs per month by phase-in status. Until the end of July 1997 most SEOs are done by companies with stocks not trading under the OHR. After this time, we observe the number of SEOs done by OHR companies rise and non-OHR companies fall, until October 1997, at which time all stocks were included in the program.

Figure 2 about here

Table 4 contains summary statistics of the Nasdaq SEOs during the OHR implementation period subsample. The mean SEO underpricing in this sample is 2.98%, with a standard deviation of 3.21. The median underpricing is 2.03%. The average gross spread in the subsample is 5.43%. The average issue size represents 27% of the market capitalization of the firm. These values are roughly comparable with those for the longer sample of Nasdaq stocks presented in Table 2. The equivalent Nasdaq averages from Corwin (2003) are 2.72% for close to offer underpricing, 26.84% for relative size, 2.95% for bid-ask spread and 3.41% for one month standard deviation of returns. The data used in Corwin (2003) covers 1980 to 1998 for the issuing characteristics and 1993 to 1998 for liquidity.

Table 4 about here

Table 5 contains the same summary statistics split by OHR-status of the stock. Table 5 demonstrates that issuing costs are unconditionally lower for Nasdaq SEOs after they are phased into the OHR, though this can reflect that the order of the stocks in the implementation of the OHR is not truly randomized (e.g., stocks with higher relative trading volume are more likely to enter the program earlier).

Table 5 about here

Figure 3 further demonstrates this point. Underpricing is lower for stocks completing SEOs after they are phased into the OHR throughout the sample. However, this may not

simple White standard errors.

reflect only a causal effect of the OHR on underpricing, but also systematic differences in characteristics across OHR vs. non-OHR stocks. As such, our empirical approach tries to distinguish between changes that are due to the OHR and those that are simply due to different characteristics across stocks in different phases.

Figure 3 about here

5.1 Difference-in-differences Regressions

Coefficient estimates and associated t-statistics for the regression of Equation (3) for SEO underpricing, gross spreads and their sum (total issuing costs) are contained in Table 6. The first column for each issuing costs variable reports results from a regression of the cost variables onto the OHR dummy and a constant term, without controls or fixed effects. The second column for each cost variable report results from regressions that include all controls described in Section 3, 23 time fixed effects based on the roll-out dates of the OHR program and also cohort fixed effects for stocks in each wave of the OHR implementation schedule.[23]

Table 6 about here

For underpricing, the unconditional difference for OHR vs. non-OHR stocks is -1.57 with a t-statistic of -3.69 (Column 1). Inclusion of control variables, time fixed effects and cohort fixed effects (Column 2) increases the magnitude of the treatment effect coefficient to -1.96, which remains significant at the 1% level. The size of the coefficients represent between 49% and 61% of the sample standard deviation in underpricing. The underpricing of secondary equity issues is lower for stocks trading under the OHR and that therefore have significantly lower institutional trading costs at the issue date, in support of Hypothesis 2.

Similar to Corwin (2003), CLOSE_BID_DIFF is a positive and significant determinant of

[23]Results for all five specifications by issuing cost variable are contained in Tables IA.1, IA.2 and IA.3 in the Internet Appendix available at `https://www.dropbox.com/s/sr7t7kxyeucjp19/BCFH_SEO_2020_IA.pdf?dl=0`.

SEO underpricing, which supports the role of pricing at the bid behavior in SEO underpricing of Nasdaq stocks. An important difference between our difference-in-differences results and the reduced form regressions of Corwin (2003) is that OHR status has both an economically and statistically significant effect on underpricing, even after controlling for this variable. In Corwin (2003), transaction costs, as measured by the bid-ask spread, become insignificant when CLOSE_BID_DIFF is incorporated as a control. Our results show that the trading environment at the stock level has an economically and statistically significant effect on capital costs in excess of what can be explained by the pricing at the bid practices of Nasdaq underwriters.

The first two columns of Table 6 show that, using a model with granular cohort effects, time fixed effects and control variables, the OHR leads to a statistically and economically significant improvement in the underpricing component of SEO issuing costs. The next step we undertake is to understand whether the changes in the implicit (underpricing) component of issuing costs are accompanied by a similar change in the explicit costs of raising equity capital via SEOs. These explicit costs are measured by the gross spreads variable, defined as the percentage difference between net and gross issuing proceeds. This variable captures the explicit fees that issuing firms pay to the underwriters, managers and syndicate members in the issuing process.

Examining the role of the OHR on gross spreads helps determine whether or not the OHR had an effect on total issuing costs. While there is no obvious ex-ante reason to believe that the OHR would lead to higher explicit issuing costs, if it were the case that these costs rose for companies with stock trading under the OHR, then there could be no net reduction in issuing costs from the reform. Columns 3 and 4 of Table 6 contain the relevant estimates using gross spreads as the dependent variable.

Without conditioning on control variables or fixed effects, explicit fees for stocks trading under the OHR are approximately 46bps lower than for stocks not trading under the OHR (Column 3). Although this only constitutes around one-fifth to one-third of the effect on underpricing, the parameter does represent approximately 60% of the total standard deviation of gross spreads. Inclusion of control variables, unobserved cohort effects in the OHR roll-out, and time effects based on the roll-out dates (Column 4), the OHR parameter estimate becomes economically insignificant, falling to -0.11 respectively, as well as statistically insignificant (t-statistic -0.76).

Our use of the OHR roll-out crucially relies on controlling for any cohort-specific effects as well as changes in average characteristics across roll-out dates. For gross spreads, the model in Column 4 achieves this in the least restrictive way and, for this reason, is our most reliable specification.[24] We thus interpret the results for gross spreads in Table 6 as indicative of the OHR's limited, or not robust, effect on the explicit fees charged in the issuing process. What matters for our purposes is that there is no evidence in Table 6 that the OHR was accompanied by an increase in explicit SEO costs. The reduction in the underpricing component of issuing costs is therefore very likely to translate into real reductions in total issuing costs.

As a final test of the hypothesis that the OHR actually reduces total issuing costs (Hypothesis 2), we estimate Equation (3) using the sum of underpricing and gross spreads, referred to as total issuing costs. Columns 5 and 6 of Table 6 contains these regressions. By construction, there exists a linear relationship between the point estimates in Columns 1–4 in Table 6 and Columns 5 and 6, whereby the point estimates for total issuing costs in any specification are the sum of the respective estimates for gross spreads and underpricing. We therefore know that point estimates for the effect of the OHR on total issuing costs are negative. The additional columns of Table 6 are necessary to ensure that the effect of the OHR on total issuing costs is statistically significant.

For each of the total costs regressions in Table 6, the OHR parameter is negative and significant at the 5% level or better. Companies with stock trading under the OHR, and that

[24]Table IA.2 of the Internet Appendix demonstrates the importance of controlling for possible unobserved cohort effects, as our regressions that do not control for these effects (i.e., that exclude the term γ_c from the specification) also suggest that the OHR had a negative effect on explicit costs.

have lower institutional trading costs, also have lower total cost of equity capital compared with companies with stock yet to be phased into the program, providing further support to Hypothesis 2. In terms of economic significance, total issuing costs are predicted to be around two percentage points lower for stocks trading under the OHR, which represents around 55% of the sample standard deviation of total issuing costs.

5.2 Robustness

In addition to the tick-size change, the OHR implementation period coincided with another regulatory change, namely the adoption of Regulation M ("Reg M"). Hatheway and So (2006) describe how on March 4, 1997, the SEC eased restrictions on passive market making for underwriters during the five days leading up to the offering. Because underwriting investment banks were often market makers in the stock, pre-Reg M limits on their market making could impact prices and liquidity prior to the SEO. This could impact SEO underpricing. Our evidence from comparisons in issuing cost changes across exchanges and across issues with stock trading under different OHR statuses within the Nasdaq strongly suggests that the OHR is directly responsible for the improvement in issuing costs. Both Reg M and the tick-size change were introduced for all Nasdaq and NYSE issues on single dates. It is hard to justify why Reg M and sixteenths are responsible for any improvement in issuing costs when the improvement is concentrated in Nasdaq issues, and also remains robust to cohort and time fixed effects with the Nasdaq.

Nevertheless, as a robustness check, we estimate Equation (3) using the sub-sample of SEOs that take place after June 2, 1997, as this sub-sample does not include any change in tick-size or Regulation M. These regressions address potential concerns that the implementation of these two additional trading rules is a confounding factor. Another benefit of using this sub-sample is that it concentrates on a period when stocks were being selected into the OHR randomly from the entire universe of Nasdaq stocks that were yet to be phased-in. If non-random selection into treatment and control groups was a confounding factor, we would also expect to see much weaker results using this sub-sample. Identifying the OHR treatment effect in the short sample requires variation in OHR status for Nasdaq SEOs. Figure 2 indicates that substantial variation in OHR status of Nasdaq SEOs takes place in this shorter period. Table A.2 in the Appendix contains the parameter estimates and standard errors for this shorter sample period. The OHR treatment effect on underpricing remains negative and both economically and statistically significant. The possible confounding effects earlier in 1997 are not responsible for the OHR treatment effect.

We also estimate Equation (3) while excluding all SEOs from technology companies, defined as members of industries 32 - Telecommunications, 35 - Computers and 36 - Chips & Electronic Equipment under the Fama-French 48 Industry Portfolio designations. These estimates are in Table A.3 in the Appendix. The effect of the OHR remains significant and negative in this non-technology sample, indicating that our results are not driven by industry-specific trends in the technology sector.

6 Institutional Trading Costs and SEO Issuing Costs

Section 4 shows that SEO underpricing does not decline for the market structure changes that reduce bid-ask spreads but not institutional trading costs. In contrast, underpricing declines with the OHR. Conrad et al. (2003) show that the OHR reduced institutional trading costs overall. We use the same data used by Conrad et al. (2003) from the Plexus Group to more directly link the decline in institutional trading costs to the decline in SEO underpricing. The Plexus data contain parent orders and associated trades from 59 institutions over the period January 1996 to June 1998 inclusive. These data have been widely used to study institutional trading costs, for example Keim and Madhavan (1997), Jones and Lipson (2001), Conrad, Johnson, and Wahal (2001), Conrad et al. (2003) and Huberman and Stanzl (2005) amongst others.

We build on the Conrad et al. (2003) results by identifying how the OHR affected institutional trading costs for Nasdaq stocks in the cross-section. We identify stock characteristics that are correlated with larger or smaller OHR-induced drops in trading costs. We then split our SEO samples along these characteristics and test whether the largest impact on issuing costs occurs in the sub-samples with the largest reductions in execution costs, as per Hypothesis 3.

To measure trading costs, we construct implicit costs (IC) at the order-level as per Equation (1) of Conrad et al. (2003):

$$IC_{ijt} = \frac{P_{ijt}}{P_{ijt}^{prev}} - 1 \tag{4}$$

where P_{ijt} is the trade-volume weighted average price for the i^{th} order in stock j at time t and P_{ijt}^{prev} is the closing price on the day prior to the date of the decision to trade for the same stock. Like Conrad et al. (2003) we compute the execution costs for any unfilled component of an order using the closing price ten days after the decision to trade.[25]

We use a sub-sample of the Plexus data corresponding to orders in Nasdaq stocks placed between July 1, 1996 and June 30, 1998. We match this sub-sample to CRSP to obtain market capitalization, volatility, and dollar trading volume by month. We also match our OHR phase-in schedule to the Plexus data to obtain the OHR status of each Nasdaq stock as at the time of the order. Time series of average monthly implicit costs by OHR status and average implicit costs during the 60 days before and after each stock's OHR implementation are presented in Figure 4. Average implicit costs for Nasdaq stocks in our sample period are 87bps. The average for Nasdaq stocks prior to OHR inclusion is 107bps and after the OHR is 80bps.

Figure 4 about here

We use the Plexus data matched with CRSP and the OHR phase-in schedule in the

[25]There are approximately one million orders in the raw dataset. We clean these using the method outlined in Conrad et al. (2003) leaving us with around 816,000 orders in total. Our final sample has very similar summary statistics to Conrad et al. (2003). Their sample contains 2.15 million trades resulting from 797,000 parent orders with an average implicit costs across the four order types they study of 39bps (as per Table 2 and information on page 114). Our sample consists of 2.14 million trades from 816,000 orders with an average implicit execution cost of 42.9bps.

following regressions:

$$IC_{ijt} = \mu_j + \rho_t + \beta_0 OHR_{jt} + \varepsilon_{ijt} \tag{5}$$

$$IC_{ijt} = \mu_j + \rho_t + \gamma' X_{ijt} + \beta_0 OHR_{jt} + \varepsilon_{ijt} \tag{6}$$

$$IC_{ijt} = \mu_j + \rho_t + \gamma' X_{ijt} + \beta_0 OHR_{jt} + \sum_{j=1}^{P} \beta_j OHR_{jt} \times X_{ijt} + \varepsilon_{ijt} \tag{7}$$

where IC is defined as per Equation 4, μ_j and ρ_t are stock and time (monthly) fixed effects, X_{ijt} is a vector of stock and order controls (log market capitalization (Ln(MARKET_CAP)), one month volatility (VOLATILITY), log price (Ln(PRICE), log of one month dollar trading volume (Ln(VOLUME)), order size relative to average trading volume (RELATIVE_VOLUME)) and OHR_{jt} is the OHR status of stock j at time t. Control variables are defined either on the day or month prior to the order date.

Equation (5) gives an estimate of the average effect of the OHR on the costs of institutional orders for Nasdaq stocks. Equation (6) adds controls to this specification. Equation (7) allows the effect of the OHR to vary across stock characteristics by interacting the OHR status with the control variables. This final specification is most relevant for our purposes as it identifies the stock characteristics that are correlated with larger or smaller OHR-induced changes in institutional execution costs. Standard errors are clustered by stock and estimates from these regressions are contained in Table 7.

Table 7 about here

The effect of the OHR on order-level institutional costs is about 36-40bps (Columns 1 and 2). A reduction of 36-40bps represents about two-fifths of the Nasdaq sample average and about one-third of the pre-OHR Nasdaq sample average. A relative reduction in trading costs of this magnitude is similar to the findings of Barclay et al. (1999), McInish et al. (1998), Weston (2000), and Chung and Van Ness (2001).[26] Table 6 shows that the OHR reduced

[26]Conrad et al. (2003) also find that the OHR significantly reduced order-level costs for single-mechanism

SEO underpricing by between 150–200bps, which is around four to five times larger than the effect of the OHR on a typical institutional order (Table 7). However, relative to shares outstanding, a typical SEO is orders of magnitude larger than a typical institutional order in the Plexus data.[27] The large disparity between the size of a typical institutional order in the secondary market and a typical SEO likely explains much of the difference in magnitudes. This disparity in relative terms is also substantially less than in basis point terms, as a 40bps decline in institutional execution costs represents about 37% of the pre-OHR average while a 200bps decline in SEO underpricing represents about 54% of the pre-OHR average.

Only two interaction terms in Column 3 are statistically significant at the 5% level or better: LN(MARKET_CAP) and Ln(VOLUME). Institutional trading costs fell more for stocks with smaller market capitalization relative to larger stocks, conditional on other characteristics. Costs also fell more for stocks with larger average trading volume relative to stocks that trade less. These results may reflect less competition among dealers in smaller stocks. Similarly, the benefits of allowing investor limit orders to execute against each other may also be higher for more active stocks, all else being equal.[28]

We split our sample of SEOs during the OHR roll-out into categories based on these two characteristics. Our goal is to test whether the categories of stocks for which the OHR led to the greatest reduction in institutional trading costs also had the greatest improvements in SEO issuing costs (Hypothesis 3). We perform two splits of the sample from Table 6. In the first split, we group SEOs by whether the issuing firm has a market capitalization above or below the median value at the beginning of our sample. In the second split, we group SEOs

trades in Nasdaq stocks, and that improvement is concentrated in broker-executed trades compared with ECN trades. Comparing the effect size in Table 7 with the results of Conrad et al. (2003) is complicated by interaction terms between OHR status and the order mechanism being used (ECN vs. broker-executed) in Conrad et al. (2003).

[27]For the sample of Nasdaq orders used in Table 7, the average order corresponds to approximately 0.16% of the stock's total market capitalization. The mean size of an SEO by Nasdaq companies over a comparable window represents 27% of the stocks' total market capitalization.

[28]Examining changes in institutional costs on a stock-by-stock basis would be a more direct way to examine the impact of cross-sectional differences in changes to institutional costs. However there are an insufficient number of institutional orders in the Plexus data to reliably estimate effects on a stock-by-stock basis as the average number of orders per issuing company is around 20 over the entire OHR roll-out period.

by whether average daily dollar trading volume of the issuing firm in 1996 is above or below the median value. We then re-run our treatment effect regressions for each sub-sample. If our conjecture regarding the importance of institutional trading costs in determining SEO underpricing is correct, we expect to see that stocks in the low market capitalization and high dollar volume categories to exhibit the greatest improvement in issuing costs due to the OHR.

Table 8 about here

Panel A of Table 8 reports regressions for sub-samples split by market capitalization. Panel B reports equivalent regressions for sub-samples split by dollar volume. Columns 1 and 2 of each panel contain estimates for the below-median sub-samples. Columns 3 and 4 of each panel contain the estimates for the above-median sub-samples. For small stocks (Columns 1 and 2 of Panel A), the OHR led to a reduction in underpricing of between -1.6 and -3.4 percentage points. These reductions are significant at the 5% level or better under both specifications. For larger stocks (Columns 3 and 4 of Panel A), the estimated effect of the OHR is statistically significant, but only between -0.8 and -1.1 percentage points depending on the specification.[29] For low dollar volume stocks (Columns 1 and 2 of Panel B), the treatment effect excluding controls and fixed effects is -1.06 while the equivalent effect with controls and fixed effects is -0.66. Neither effect is statistically significant at the 10% level. For the high volume sub-sample (Columns 3 and 4 of Panel B), the equivalent estimates are -1.64 and -2.44. Both effects are statistically significant at the 5% level or better for high volume stocks.[30] Consistent with a reduction in SEO issuing costs being due to lower institutional trading costs (Hypothesis 3), the OHR's effect on underpricing is largest in the stock categories with the largest institutional trading cost improvement.

[29] Pre-OHR average underpricing for small stocks is 4.5% and for large stocks it is 2.3%. Pre-OHR average underpricing for low volume stocks is 4.3% and for high volume stocks it is 2.8%.

[30] Tables IA.4 and IA.5 in the Internet Appendix contain all five difference-in-differences specifications. Evidence from these are qualitatively similar to those in Table 8, though results that exclude cohort and wave fixed effects appear to understate the differences across the volume sample splits.

7 Discussion and Comparison with Previous Evidence

Two key papers that relate to our work are Corwin (2003) and Butler et al. (2005). Section 5.5.1 compares our results with Corwin (2003), who estimates a positive but statistically weak association between bid-ask spreads and the underpricing of SEOs. Butler et al. (2005) show that various measures of stock liquidity are associated with lower fees charged by investment banks for SEOs. The methodological approaches of both Corwin (2003) and Butler et al. (2005) are based on least squares regressions of issuing costs onto stock and issue controls. In this sense, this evidence is reduced form insofar as it is measuring the conditional association between issuing costs and the control variables.

For control variables that capture liquidity and transaction costs, least squares regressions can suffer from a number of sources of endogeneity. Arguably the most important of these is the existence of an unobserved variable that theoretically drives both stock liquidity and issuing costs: information asymmetry. An extensive literature links information asymmetry between different investors and the underpricing of new equity issues (see e.g., Rock, 1986, Beatty and Ritter, 1986, Carter and Manaster, 1990, etc.). Butler et al. (2005) mention that underwriters face adverse selection risk and can set fees accordingly. An equally well established literature, including Copeland and Galai (1983), Glosten and Milgrom (1985) and Kyle (1985), links stock liquidity and information asymmetry. Failure to control adequately for this generally unobserved variable will lead to omitted variable bias in a simple reduced form framework.

An additional contribution of our paper is that we isolate a plausibly exogenous source of variation in trading costs that is unaffected by these sources of endogeneity. By doing so, we can identify a direct causal effect, rather than reduced-form associations. In contrast to this prior literature, we find robust support for improved liquidity causing lower underpricing but only weak evidence that liquidity impacts investment bank SEO fees. Since our sample period does not correspond exactly to those studied in Corwin (2003) and Butler et al. (2005), it is possible that the differences in our conclusions are not due to our empirical strategy and are instead due to different samples. To check this, we replicate the regressions of Corwin (2003) and Butler et al. (2005) using our sample period covering January to October 1997. Tables A.4 to A.6 in the Appendix contain these results. Similar to Corwin (2003), we find weak evidence in our sub-sample that bid-ask spreads affect SEO underpricing when CLOSE_BID_DIFF is included as a control, while we find a strong statistical association between explicit costs and bid-ask spreads, using both the regression specification of Corwin (2003) and Butler et al. (2005).

While the market structure changes we study were intended to impact trading costs and not directly targeted at the information environment in which a firm issues equity, it is useful to discuss how likely are possible changes in information asymmetry and how these could impact our estimates. Whether these changes in market structure affect the information environment is particularly important given the strong theoretical emphasis on the role of information asymmetry in the issuing process.[31] Changes in trading regulation or technology affect the way buyers and sellers interact with each other, but do not obviously or directly affect the type or quantity of information available to investors that is useful for pricing seasoned equity issues. It is conceivable that there is an indirect effect where market structure changes influence the amount of private information revealed in secondary market prices. If, for example, more informed traders exert more influence on the market clearing price of shares in the secondary market following a particular reform, or are encouraged to reveal more private information via their trading, then this could reduce informational frictions in the issuing process.

While it is not possible to explicitly measure the indirect effect of the reforms on information relevant for pricing a SEO, empirically or theoretically the indirect effect seems unlikely

[31] Asymmetric information between different types of investors (or between some investors and the firm itself) can lead to equilibrium underpricing as compensation for the "winner's curse" (Rock, 1986). When an informed firm deals with an uninformed but strategic underwriter, underpricing can be the result of signaling by high-quality firms (Giammarino and Lewis, 1988). Baron (1982) provides an alternative explanation for asymmetric information in the reverse direction while Parsons and Raviv (1985) consider underpricing as a form of surplus sharing between an underwriter with market power and investors with private information. The theoretical link between information and trading costs is also well established (see e.g., Copeland and Galai, 1983; Glosten and Milgrom, 1985; Kyle, 1985.)

to be significant. First, existing empirical evidence finds little or no change in information asymmetry in the trading process. Weston (2000) finds that the OHR reform did not affect the informational component of the costs of trading (i.e., the adverse selection component of spreads). For the other changes in our sample (sixteenths, decimalization, Autoquote) the literature finds either no effect on information in secondary market trades (Bacidore, 2001), or a reduction in adverse selection costs (Gibson et al., 2003; Chakravarty et al., 2005; Hendershott et al., 2011), suggesting that transaction prices and bid-ask quotes arguably did incorporate more private information after these reforms. If market structure influencing information asymmetry is important we would expect to detect an improvement in issuing costs for these events, but we do not.

Second, changes in transaction costs should only affect information asymmetry at the margin. Information that was sufficiently valuable to trade on at higher transaction costs would continue to be obtained when trading costs decline. With lower costs, investors have incentive to acquire information that is less valuable: information that was previously unprofitable at higher trading costs, but is profitable at the lower trading costs. It is unclear that information that is only marginally valuable in expectation would meaningfully change market maker adverse selection risk. Third, changes in the composition of informed traders take time to evolve whereas we find the improvement in issuing costs occurs over a relatively narrow (nine-month) period over which the OHR is progressively phased-in.

While there is no empirical evidence that this market structure change impacted information asymmetry, our estimates could be viewed as measuring the sum of the direct effect of a reduction in trading costs and any indirect effect smaller trading costs have on the information environment. If the indirect effects are a significant component of our estimates then our findings highlight several ways secondary market trading impacts corporate financing costs.

8 Conclusion

We examine the association between major market structure changes and the cost of raising capital in the US equities markets over the last two decades. We find that only the OHR, which reduced institutional trading costs as well as bid-ask spreads, altered the cost of raising equity. Tick size reductions on both Nasdaq and NYSE, and Autoquoting on NYSE, which significantly reduced bid-ask spreads but not institutional trading costs, did not influence the cost of raising capital. The staggered introduction of the OHR allows us to provide direct causal evidence of the link between secondary market liquidity and the cost of raising capital. The OHR reforms significantly reduced the total SEO issuing costs by one to two percentage points from a pre-reform average of about nine percent. This decline is driven by a reduction in SEO underpricing. Consistent with lower institutional trading costs reducing the cost of raising capital, the OHR's effect on underpricing is largest in categories of stocks that also have the largest improvement in institutional trading costs from before to after the OHR.

Eaton et al. (2018) discuss the large literature examining stock market liquidity and real corporate decisions through the lens of tick-size changes (e.g., Fang, Noe, and Tice, 2009; Bharath, Jayaraman, and Nagar, 2013; Edmans, Fang, and Zur, 2013; Fang, Tian, and Tice, 2014; Norli, Ostergaard, and Schindele, 2014; Brogaard, Li, and Xia, 2017). Central to each of these papers is the behavior of large institutional investors such as block-holders. Evidence that tick-size changed institutional trading costs is, however, mixed, with the balance tilted towards costs either increasing or being unchanged. Thus, the OHR may be preferable to the tick-size events for researchers looking for exogenous variation in liquidity that is meaningful for institutional investors and block-holders to study corporate finance issues. The OHR are also advantageous from an identification standpoint because they only affect Nasdaq stocks and are introduced in a staggered manner within Nasdaq.[32]

[32] The OHR roll-out occurred in 1997. While this is generally considered to be before the Nasdaq technology stock 'bubble,' the post-OHR, pre-bubble period is not long. decimalization primarily occurred in early 2001 and market-wide volatility increased substantially later that year following September 11, 2001.

More generally, changes in market structure have complex and heterogeneous effects on the different agents that make up a market. In our context, only one event clearly affected the cost of trading for the most important participants in new stock offerings: institutions. In other contexts, such as the rise of high-frequency and algorithmic trading, regulatory changes like the Volcker rule, or entry and exit of trading platforms, a granular understanding of heterogeneous effects across participants and the links from this to the underlying economics of the research question can be similarly beneficial for identifying causal effects.

Studying the impact of market structure and liquidity on the cost of raising capital is important for policy and academic reasons. For academics, it provides a deeper understanding of the link between secondary market liquidity, investment, and capital structure. The decline in the number of IPOs and publicly listed firms in the US (Doidge, Karolyi, and Stulz, 2013) has prompted legislation requiring market structure experiments, like the 2016 SEC tick-size pilot. Our results suggest that market structure reforms reducing intermediation lower the costs of raising capital. To the extent that the stock market suffers from excess intermediation and illiquidity, carefully crafted market structure reforms could improve investment and risk sharing in the economy.[33] Policy makers should focus on ensuring that reforms enhance liquidity for institutional investors.

If our market structure results extend beyond firms raising equity there are potential implications for other asset classes. Corporate bonds traditionally trade over-the-counter. Market structure innovations increasing dealer competition, such as request-for-quote auctions (Hendershott and Madhavan, 2015), and enabling direct transactions between investors could lower the cost of debt issuance. Government bonds also trade over-the-counter and rules like the OHR that allow limit order providers to compete with dealers could possibly lower the cost of government debt issuance (see Huh and Kim, 2019 for evidence on how the structure of the secondary market for mortgage-backed securities impacts mortgage rates).

Our results also provide a possible detailed economic channel for the literature examining

[33] A possible source of excess intermediation and illiquidity is high-frequency traders, although there is not yet academic research to support this.

the interactions of financial market development, law and regulations, and economic growth. While a large body of research explores the empirical association between financial development and economic growth (e.g., Levine 1997; Levine and Zervos 1998; Rajan and Zingales 1998; Beck and Levine 2004), extensive reviews of this literature emphasize that accurately identifying the mechanisms connecting the operation of financial markets and the decisions of firms that drive economic growth remains a major challenge to researchers (Levine, 1997, 2005; Popov, 2018). We provide a well-identified, in-depth study of how law/regulation impacts financial markets and the cost of raising capital. Our results suggest that increased investment due to lower costs of capital arising from reduced institutional trading costs is possibly an important potential channel for how financial development can increase employment and economic growth. However, the period of staggered introduction of the OHR regulatory change is likely too short to identify its direct effect on economic growth.

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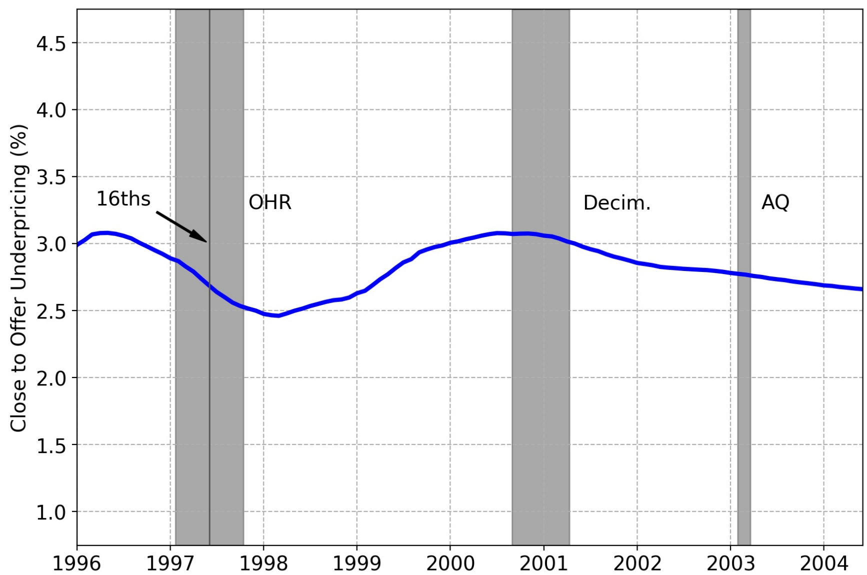
Figure 1: SEO Underpricing Time Series

This figure plots the mean SEO underpricing by month for all SEOs from January 1996 to May 2004. Underpricing is defined as the negative of the log return from the previous closing price to the offer price in percentage terms. The line is average underpricing smoothed over time using Locally Weighted Scatterplot Smoothing (LOWESS) with tuning parameter of one third. Each market structure event is marked by a line if it occurs on a single date or a gray area corresponding to the window over which the change was implemented. The four market structure events are: OHR, sixteenths, decimalization, and Autoquote. Panel A pools all NYSE and Nasdaq SEOs. Panel B graphs underpricing for NYSE and Nasdaq SEOs separately.

(a) Pooled Underpricing on NYSE and Nasdaq



(b) Underpricing Split by Exchange

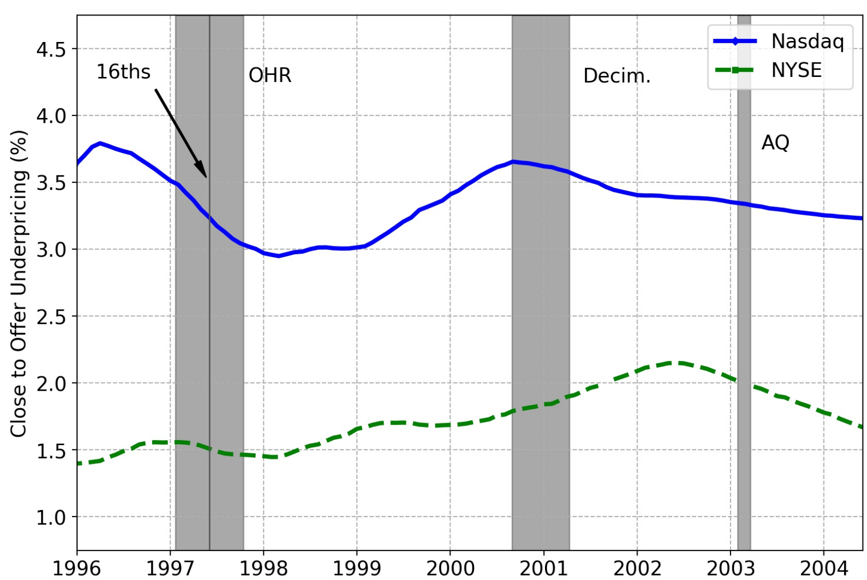


Figure 2: Number of SEOs by OHR Status

This figure plots the number of SEOs issued by Nasdaq-listed companies by OHR status. The sample includes all Nasdaq SEOs that meet our sample restrictions for which we can match OHR status in the Nasdaq equity trader alerts. The line with the legend "Non-OHR" refers to SEOs by companies with stock that is yet to be phased-in to the OHR and the line with the legend "OHR" refers to SEOs by companies with stock that trades under the OHR as at the issue date.

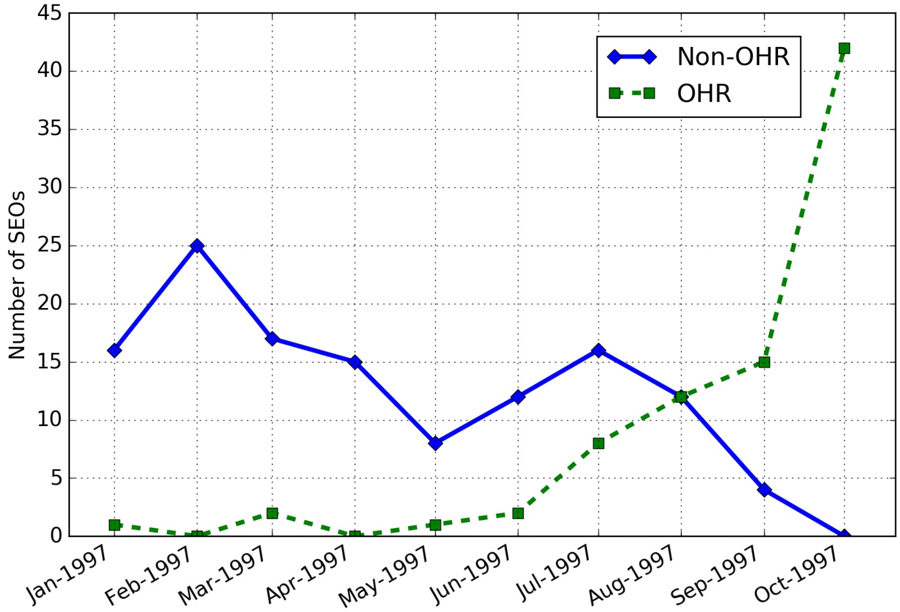


Figure 3: SEO Underpricing by OHR Status

This figure plots the mean SEO underpricing by month and OHR status for all Nasdaq SEOs between January and October 1997. Underpricing is defined as the negative of the log return from the previous closing price to the offer price in percentage terms. The line with the legend "Non-OHR" refers to SEOs by companies with stock that is yet to be phased-in to the OHR and the line with the legend "OHR" refers to SEOs by companies with stock that trades under the OHR as at the issue date.

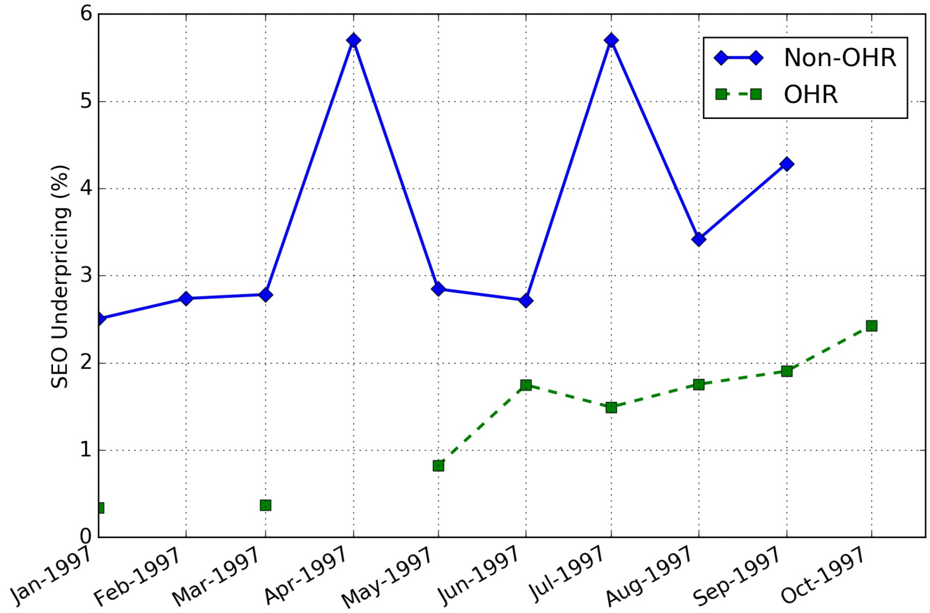
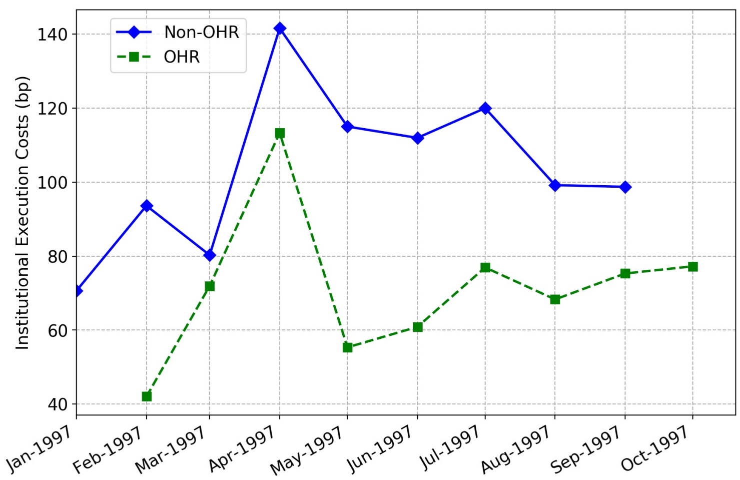


Figure 4: Plexus Institutional Execution Costs and OHR Implementation

This figure plots average institutional trading costs in Nasdaq stocks over the OHR implementation period. Figure 4a presents monthly average costs for stocks trading under the OHR and stocks yet to trade under the OHR. Figure 4b presents the average costs for Nasdaq stocks in the 60 days before and after OHR implementation.

(a) Execution Costs by OHR status



(b) Execution Costs around OHR Implementation Date

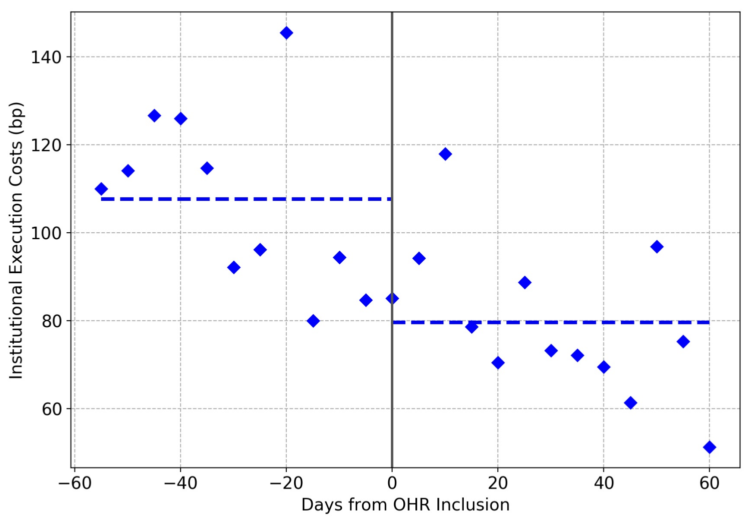


Table 1: Summary of Trading Cost and Market Reform Evidence

This table summarizes the existing literature on the effect of four major market structure changes on bid-ask spreads and the cost of trading for institutions. The market structure changes are the introduction of the Order Handling Rules on Nasdaq (OHR), tick-size changes from eighths to sixteenths and then decimals on both Nasdaq and the New York Stock Exchange (NYSE), and the introduction of Autoquote on the NYSE.

	Bid-ask Spreads	Institutional Trading Costs
OHR	Decline of about 1/3: Barclay et al. (1999); McInish et al. (1998) Weston (2000); Chung and Van Ness (2001).	Significant decline (especially for broker-executed orders): Conrad et al. (2003).
Tick Size Changes (Decimalization & Sixteenths)	Decline of 20% or more: Chordia et al. (2011) and others.	Mixed evidence regarding institutional costs: Jones and Lipson (2001); Werner (2003) Bollen and Busse (2006); Chakravarty et al. (2005).
Autoquote	Decline of 20% or more: Hendershott et al. (2011).	No evidence of lower institutional costs: Figure 1 of Anand et al. (2013).

Table 2: Summary Statistics - NYSE and Nasdaq SEOs

This table reports means, standard deviations, minimums, maximums and 25th, 50th and 75th quantiles for offering and trading characteristics for our sample. The sample includes SEOs on the Nasdaq and NYSE occurring between January 1, 1996 and May 31, 2004 that meet the selection criteria outlined in Section 3. UNDERPRICING is defined as the negative of the log return from the previous closing price to the offer price in percentage terms. GROSS_SPREAD is the percent difference between net and gross offer proceeds. TOTAL_ISSUING_COST is the sum of UNDERPRICING and GROSS_SPREAD. VALUE is the offer price times the number of shares issued, in $ millions. RELATIVE_SIZE is the ratio of the offer value to the market capitalization. MARKET_CAP is the number of shares outstanding times the closing price as at the day prior to issue date, in $ billions. Ln(PRICE) is the log of the closing price prior to the issue date. VOLUME is the dollar volume traded in the month of issuance, in $ millions. VOLATILITY is the standard deviation of daily mid-quote returns during the month of issuance. BIDASK is the difference between the closing ask and bid price, as a percentage of mid-quote price, in the 21 trading days before the issue date. All variables excluding Ln(PRICE) are winsorized at the 1% level. There are 2,278 SEOs meeting our selection criteria.

	Mean	Std. Dev	Min	25%	50%	75%	Max	Mean (Nasdaq)	Mean (NYSE)
UNDERPRICING	2.84	3.52	-3.54	0.37	1.81	3.98	20.2	3.38	1.70
GROSS_SPREAD	5.00	1.18	0.00	4.50	5.05	5.67	19.2	5.34	4.26
TOTAL_ISSUING_COST	7.84	4.03	-2.07	5.25	6.87	9.30	39.4	8.73	5.96
VALUE ($m)	199	379	7.65	47.0	89.2	184	3197	134	339
RELATIVE_SIZE	0.24	0.19	0.02	0.12	0.19	0.28	1.38	0.24	0.23
MARKET_CAP ($b)	1.71	7.76	0.01	0.22	0.50	1.19	318	0.96	3.32
Ln(MARKET_CAP)	6.31	1.34	1.64	5.39	6.21	7.08	12.6	5.99	6.99
Ln(PRICE)	3.24	0.63	1.61	2.84	3.23	3.62	5.52	3.19	3.34
VOLUME	328	823	0.48	21.8	71.8	249	12937	299	390
VOLATILITY	3.52	2.02	0.18	2.15	3.04	4.40	12.5	4.04	2.41
BIDASK	1.46	1.30	0.03	0.55	1.09	1.95	8.47	1.49	1.39

Table 3: OLS Underpricing Regressions around Major Market Structure Events

This table reports coefficients (t-statistics) from regressions of UNDERPRICING on firm, offer, and market characteristics around the four market structure events: OHR, sixteenths, decimalization, and Autoquote. The first four OLS regressions estimate the change in UNDERPRICING in the one year before and after each event using a sample of SEOs pooled across exchanges. All variables are defined as per Table 2 other than POST, which equals one for the year after the event and zero for the year before the event, and EXCH which equals one for SEOs on the NYSE and zero for SEOs on Nasdaq. The final two regressions estimate the difference-in-differences in UNDERPRICING across the two exchanges for the two events that only affected one exchange and not the other (OHR and Autoquote). EXCH equals one for SEOs on the exchange undergoing the market structure change and zero otherwise. The key regressor is POST $\times$ EXCH, which estimates the treatment effect of the reform. Standard errors and associated t-statistics are estimated using White's heteroskedasticity-robust estimator.

	Pooled Pre-/Post-Event OLS								Cross-Exchange Diff-in-Diff			
	OHR		Sixteenths		Decimalization		Autoquote		OHR		Autoquote	
INTERCEPT	9.60	(2.93)	14.6	(4.57)	10.0	(2.15)	8.57	(2.33)				
Ln(MARKET_CAP)	-0.36	(-1.35)	0.15	(0.57)	0.32	(0.96)	0.30	(0.77)	-0.39	(-1.47)	0.29	(0.74)
RELATIVE_SIZE	0.94	(1.19)	1.88	(2.63)	0.52	(0.64)	2.89	(1.75)	0.86	(1.10)	2.84	(1.74)
VOLATILITY	0.64	(4.52)	0.67	(4.56)	0.55	(4.58)	0.71	(4.15)	0.64	(4.51)	0.71	(4.12)
Ln(PRICE)	-1.36	(-4.35)	-1.56	(-4.57)	-1.27	(-2.91)	-0.16	(-0.47)	-1.34	(-4.31)	-0.14	(-0.41)
Ln(VOLUME)	-0.12	(-0.44)	-0.50	(-1.94)	-0.33	(-0.98)	-0.41	(-1.32)	-0.11	(-0.40)	-0.42	(-1.34)
SENTIMENT	-0.51	(-1.09)	-0.62	(-1.18)	0.22	(0.70)	-0.54	(-1.29)	-0.49	(-1.05)	-0.52	(-1.27)
VIX	0.02	(0.48)	-0.02	(-0.55)	-0.06	(-1.19)	-0.07	(-1.77)	0.02	(0.57)	-0.07	(-1.81)
EXCH	-0.41	(-1.77)	-0.60	(-2.65)	-0.60	(-1.21)	-0.29	(-0.84)	0.81	(2.82)	0.00	(0.01)
PRE									8.79	(2.77)	8.51	(2.32)
POST	-0.59	(-1.79)	-0.32	(-1.02)	0.73	(1.21)	-0.70	(-1.27)	8.84	(2.72)	8.08	(2.24)
POST $\times$ EXCH									-0.95	(-2.54)	-0.58	(-1.08)
N	785		786		493		292		785		292	
R^2	0.26		0.26		0.14		0.17		0.26		0.17	

Table 4: Summary Statistics — Nasdaq SEOs

This table reports means, standard deviations, minimums, maximums and 25th, 50th and 75th quantiles for offering and trading characteristics for our SEOs on the Nasdaq occurring between January 1, 1997 and October 31, 1997 that meet the selection criteria outlined in Section 3. All variables are defined as per Table 2 other than CLOSE_BID_DIFF which is the percentage difference between the closing price and the last bid price on the day prior to the issue, and OHR which is a dummy variable taking the value of one if the stock of the company making an SEO is trading under the OHR on the issue date and zero otherwise. MARKET_CAP and Ln(PRICE) are now calculated as at January 2, 1997, and VOLUME and VOLATILITY are now calculated over the month of December 1996. All variables excluding Ln(PRICE) and OHR are winsorized at the 1% level. There are 196 SEOs meeting our selection criteria.

	Mean	Std. Dev	Min	25%	50%	75%	Max
UNDERPRICING	2.98	3.21	-2.10	0.74	2.03	4.10	20.2
GROSS_SPREAD	5.43	0.77	3.22	5.00	5.43	5.87	8.57
TOTAL_ISSUING_COST	8.41	3.60	3.22	5.89	7.30	9.84	26.2
VALUE ($m)	79.4	79.0	7.57	33.0	54.7	96.0	687
RELATIVE_SIZE	0.27	0.17	0.02	0.15	0.24	0.33	1.03
MARKET_CAP ($m)	333	447	16.1	94.5	175	423	3316
Ln(MARKET_CAP)	5.25	1.05	2.78	4.55	5.17	6.05	8.11
Ln(PRICE)	2.88	0.57	1.25	2.56	2.88	3.26	4.35
VOLUME ($m)	55.2	92.9	0.15	6.87	21.6	60.3	662
VOLATILITY	3.00	1.45	0.32	2.09	2.75	3.98	8.43
CLOSE_BID_DIFF (%)	1.28	1.45	-0.80	0.00	0.81	1.99	7.69
BIDASK (%)	2.30	1.40	0.31	1.32	1.99	2.95	8.75
OHR	0.39	0.49	0.00	0.00	0.00	1.00	1.00

Table 5: Summary Statistics — Nasdaq SEOs Split by OHR Status

This table reports means, standard deviations, minimums, maximums and 25th, 50th and 75th quantiles for offering and trading characteristics for the sample of SEOs in Table 4, split by OHR status of the issuing company. All variables are defined as per Table 4.

		Mean	Std. Dev	Min	25%	50%	75%	Max
UNDERPRICING	OHR	2.03	2.50	-0.49	0.39	1.36	2.67	11.7
	Non-OHR	3.60	3.48	-2.10	1.08	2.67	5.81	20.2
GROSS_SPREAD	OHR	5.16	0.75	3.22	4.88	5.10	5.68	7.14
	Non-OHR	5.61	0.73	3.48	5.05	5.56	5.94	8.57
TOTAL_ISSUING_COSTS	OHR	7.18	2.81	3.22	5.43	6.53	7.78	18.2
	Non-OHR	9.21	3.83	3.33	6.53	8.26	11.6	26.2
VALUE ($m)	OHR	104	98.9	7.62	44.0	77.5	134	687
	Non-OHR	63.0	57.7	7.57	28.5	45.0	73.1	330
RELATIVE_SIZE	OHR	0.25	0.17	0.06	0.13	0.22	0.32	1.03
	Non-OHR	0.28	0.16	0.02	0.17	0.24	0.34	1.01
MARKET_CAP ($m)	OHR	402	574	16.1	86.3	200	530	3316
	Non-OHR	288	337	21.6	107	167	346	1810
VOLUME ($m)	OHR	62.5	81.9	0.15	6.38	22.5	87.5	421
	Non-OHR	50.5	99.4	0.22	7.59	21.3	52.8	662
VOLATILITY	OHR	2.95	1.36	0.48	2.13	2.64	3.98	6.94
	Non-OHR	3.04	1.51	0.32	2.04	2.81	4.01	8.43
BIDASK (%)	OHR	1.49	0.78	0.31	0.86	1.45	1.90	4.43
	Non-OHR	2.83	1.46	0.68	1.76	2.46	3.60	8.75

Table 6: Issuing Costs OHR Pooled Difference-in-Differences Regressions

This table reports coefficients (t-statistics) from difference-in-differences regressions of SEO issuing costs on firm and offer characteristics and the OHR status of the stock being issued. The three dependent variables, UNDERPRICING, GROSS_SPREAD and TOTAL_ISSUING_COST, are defined as per Table 2. The key regressor, OHR, and other control variables are defined as per Table 4. The first column for each dependent variable is for a regression using the OHR dummy variable and a constant term. The second column includes control variables, time fixed effects based on the 22 roll-out dates and cohort fixed effects based on the wave in which each company's stock was included in the OHR. Standard errors and associated t-statistics are estimated using White's heteroskedasticity-robust estimator.

	UNDERPRICING				GROSS_SPREAD				TOTAL_ISSUING_COST			
	(1)		(2)		(3)		(4)		(5)		(6)	
INTERCEPT	3.60	(11.3)			5.61	(83.6)			9.21	(26.3)		
Ln(MARKET_CAP)			-0.85	(-1.61)			-0.46	(-5.24)			-1.31	(-2.35)
RELATIVE_SIZE			0.88	(0.55)			-0.34	(-1.16)			0.54	(0.32)
VOLATILITY			0.25	(1.50)			0.01	(0.26)			0.26	(1.49)
Ln(PRICE)			-1.02	(-1.83)			-0.02	(-0.19)			-1.04	(-1.74)
Ln(VOLUME)			0.15	(0.55)			-0.02	(-0.43)			0.13	(0.45)
CLOSE_BID_DIFF			0.61	(2.88)			-0.02	(-0.65)			0.59	(2.67)
OHR	-1.57	(-3.69)	-1.96	(-2.75)	-0.46	(-4.20)	-0.11	(-0.76)	-2.03	(-4.28)	-2.07	(-2.75)
N	196		196		196		196		196		196	
R^2	0.06		0.41		0.08		0.71		0.08		0.49	
Fixed Effects	None		PI-Date & OHR		None		PI-Date & OHR		None		PI-Date & OHR	

Table 7: Plexus Execution Costs and OHR Implementation

This table reports coefficients (t-statistics) for panel regressions of institutional trading costs for Nasdaq stocks on OHR status, control variables and interactions of OHR status and control variables. The dependent variable, IC, is the percent difference between the trade-volume weighted average price for an institutional order and the closing price on the day prior to the date of the decision to trade, as per Section 6. Ln(MARKET_CAP) and Ln(PRICE) are calculated on the day prior to the order date. Ln(VOLUME) and VOLATILITY are calculated over the month prior to the order date. RELATIVE_VOLUME is order size divided by average trading volume over the month prior to the order date. Model A reports results from a regression of IC onto OHR status (OHR) with stock and monthly fixed-effects. Model B adds control variables alongside stock and monthly fixed-effects. Model C interacts the OHR status of each stock with the control variables. Standard errors are clustered at the stock level.

	(1)		(2)		(3)	
	Model A		Model B		Model C	
OHR	-39.5	(-7.01)	-36.0	(-6.61)	-43.9	(-1.71)
Ln(MARKET_CAP)			-33.6	(-3.00)	-35.7	(-3.05)
VOLATILITY			0.77	(0.88)	0.96	(0.84)
Ln(PRICE)			-15.5	(-1.26)	-24.8	(-1.95)
Ln(VOLUME)			-4.07	(-1.31)	8.33	(2.42)
RELATIVE_VOLUME					3.00	(4.78)
OHR × Ln(MARKET_CAP)					12.9	(2.47)
OHR × VOLATILITY					-1.98	(-1.16)
OHR × Ln(PRICE)					-6.33	(-0.90)
OHR × Ln(VOLUME)					-10.9	(-2.99)
OHR × RELATIVE_VOLUME					2.50	(1.60)
N	3,600		3,600		3,600	
T	21		21		21	
R^2	0.04		0.04		0.05	
Stock FE	X		X		X	
Year-month FE	X		X		X	

Table 8: Underpricing Pooled Difference-in-Differences Regressions Sample Splits

This table reports coefficients (t-statistics) from difference-in-differences regressions of UNDERPRICING on firm and offer characteristics and the OHR status of the stock being issued for companies with market capitalizations and average daily 1996 dollar volume traded below and above the sample median, respectively. All other details are as per Table 6.

Panel A: Market Cap	Low Market Cap				High Market Cap			
	(1)		(2)		(3)		(4)	
INTERCEPT	4.84	(9.87)			2.15	(7.82)		
Ln(MARKET_CAP)			-2.11	(-1.60)			-0.52	(-1.03)
RELATIVE_SIZE			2.01	(0.67)			0.59	(0.75)
VOLATILITY			0.36	(1.26)			0.05	(0.40)
Ln(PRICE)			-0.56	(-0.48)			-0.17	(-0.40)
Ln(VOLUME)			0.45	(0.90)			0.13	(0.57)
CLOSE_BID_DIFF			0.29	(0.97)			0.89	(7.99)
OHR	-1.62	(-2.23)	-3.35	(-2.29)	-1.06	(-3.28)	-0.88	(-1.94)
N	98		98		98		98	
Fixed Effects	None		PI-Date & OHR		None		PI-Date & OHR	

Panel B: Dollar Volume	Low Dollar Volume				High Dollar Volume			
	(1)		(2)		(3)		(4)	
INTERCEPT	4.29	(8.95)			2.76	(7.59)		
Ln(MARKET_CAP)			-1.26	(-1.13)			-1.00	(-2.03)
RELATIVE_SIZE			1.72	(0.58)			-0.53	(-0.54)
VOLATILITY			0.58	(1.38)			0.18	(1.13)
Ln(PRICE)			-1.03	(-0.88)			-0.96	(-1.74)
Ln(VOLUME)			0.23	(0.42)			0.39	(1.13)
CLOSE_BID_DIFF			0.56	(1.95)			0.69	(4.11)
OHR	-1.06	(-1.45)	-0.66	(-0.44)	-1.64	(-4.03)	-2.44	(-2.62)
N	98		98		98		98	
Fixed Effects	None		PI-Date & OHR		None		PI-Date & OHR	

Appendix

Figure A.1: Number of Stocks Included by Phase-in Date

This figure plots the number of Nasdaq stocks newly included in the OHR at each of the 22 phase-in dates. Each point on the plot depicts how many stocks that previously did not trade under the OHR but, that following the phase-in date, did then trade under the OHR.

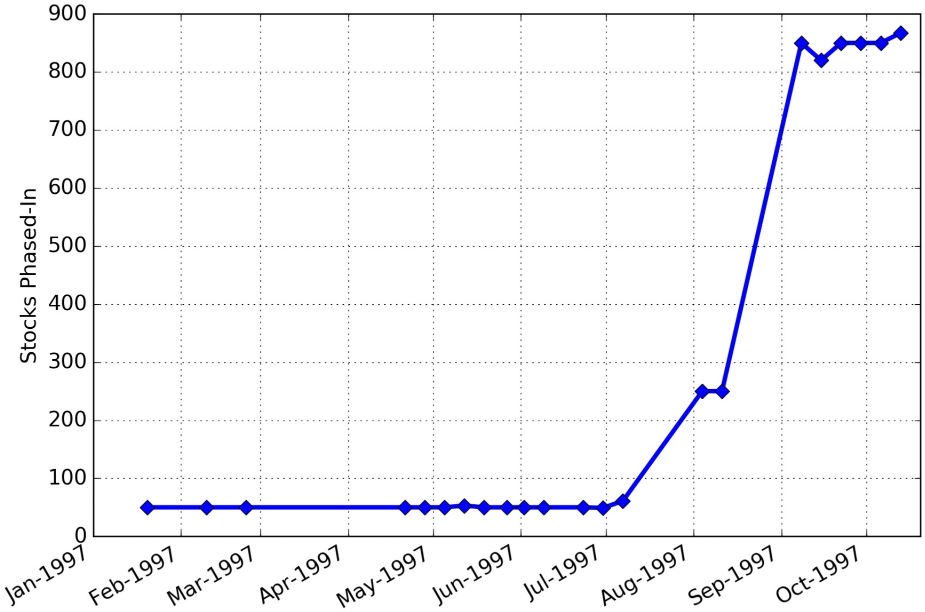


Table A.1: OLS Underpricing Regressions around Regulation NMS

This table reports coefficients (t-statistics) from an OLS regression of UNDERPRICING on firm and offer characteristics of the stock being issued in the one year prior and one year subsequent to the official implementation dates of Reg NMS as reported in Securities and Commission (2006). All other details are as per Table 3.

	Reg NMS	
INTERCEPT	3.00	(0.76)
Ln(MARKET_CAP)	0.40	(0.83)
RELATIVE_SIZE	2.76	(0.94)
VOLATILITY	0.94	(4.02)
Ln(PRICE)	-0.45	(-0.95)
Ln(VOLUME)	-0.25	(-0.71)
NYSE	0.54	(1.36)
POST	-0.14	(-0.37)
N	278	
R^2	0.16	

Table A.2: Underpricing Pooled Difference-in-Differences Regressions Post-Reg M and Tick-Size Changes

This table reports coefficients (t-statistics) from difference-in-differences regressions of UNDERPRICING on firm and offer characteristics and the OHR status of the stock being issued using only SEOs that occur after the implementation of the change in tick-size to sixteenths on the Nasdaq (and also the implementation of Regulation M by the SEC in March 1997). All five specifications discussed in Section 5 are presented and all other details are as per Table 6.

	(1)		(2)		(3)		(4)		(5)	
	Model A		Model B		Model C		Model D		Model E	
INTERCEPT	4.32	(7.92)	7.39	(2.97)						
Ln(MARKET_CAP)			-0.02	(-0.04)	-0.09	(-0.15)	-0.36	(-0.51)	-0.19	(-0.27)
RELATIVE_SIZE			1.17	(0.63)	1.15	(0.62)	1.45	(0.75)	1.50	(0.79)
VOLATILITY			0.18	(0.82)	0.21	(0.92)	0.25	(1.14)	0.29	(1.29)
Ln(PRICE)			-1.34	(-1.87)	-1.19	(-1.72)	-0.93	(-1.05)	-1.19	(-1.56)
Ln(VOLUME)			-0.17	(-0.57)	-0.18	(-0.60)	-0.18	(-0.50)	-0.12	(-0.36)
CLOSE_BID_DIFF									0.40	(1.20)
OHR	-2.20	(-3.55)	-1.76	(-2.58)	-1.95	(-2.66)	-2.94	(-3.28)	-2.68	(-2.75)
N	111		111		111		111		111	
R^2	0.12		0.24		0.28		0.40		0.42	
Fixed Effects	None		None		Month		PI-Date & OHR		PI-Date & OHR	

Table A.3: Underpricing Pooled Difference-in-Differences Regressions without Technology Stocks

This table reports coefficients (t-statistics) from difference-in-differences regressions of UNDERPRICING on firm and offer characteristics and the OHR status of the stock being issued, excluding SEOs from companies in industries 32, 35 and 36 in the Fama-French 48 Industry Portfolios. All five specifications discussed in Section 5 are presented and all other details are as per Table 6.

	(1) Model A		(2) Model B		(3) Model C		(4) Model D		(5) Model E	
INTERCEPT	3.49	(10.7)	9.47	(4.69)						
Ln(MARKET_CAP)			-0.65	(-1.55)	-0.61	(-1.31)	-0.65	(-1.30)	-0.54	(-1.04)
RELATIVE_SIZE			0.27	(0.21)	0.96	(0.70)	0.44	(0.35)	-0.75	(-0.59)
VOLATILITY			0.11	(0.54)	0.12	(0.61)	0.28	(1.15)	0.30	(1.29)
Ln(PRICE)			-1.16	(-1.79)	-1.32	(-2.17)	-1.22	(-1.73)	-1.46	(-2.22)
Ln(VOLUME)			0.11	(0.42)	0.24	(0.94)	0.06	(0.22)	0.24	(0.92)
CLOSE_BID_DIFF									0.60	(3.36)
OHR	-1.46	(-3.21)	-1.47	(-3.32)	-1.80	(-2.62)	-2.69	(-3.20)	-2.49	(-3.06)
N	139		139		139		139		139	
R^2	0.06		0.24		0.31		0.44		0.50	
Fixed Effects	None		None		Month		PI-Date & OHR		PI-Date & OHR	

Table A.4: Corwin (2003) OLS Underpricing Regressions

This table lists coefficients (t-statistics) from OLS regressions of UNDERPRICING on the main covariates used by Corwin (2003). All variables are defined as per Table 2 other than CAR(+) and CAR(-) which are the signed average excess returns over the CRSP value weighted portfolio in the three days prior to the offer date and NYSE which is a dummy variable for issues on the New York Stock Exchange. Model B includes VOLATILITY but excludes CLOSE_BID_DIFF. Model C includes both VOLATILITY and CLOSE_BID_DIFF. Model D is the same as Model C but CLOSE_BID_DIFF is interacted with exchange dummies (NASDAQ or NYSE). The sample includes all SEOs on either the Nasdaq or the NYSE between January and October 1997 that have undergone an IPO before the beginning of the sample period. Standard errors and associated t-statistics are estimated using White's heteroskedasticity-robust estimator.

	(1)		(2)		(3)		(4)	
	Model A		Model B		Model C		Model D	
INTERCEPT	4.50	(3.43)	3.78	(2.76)	3.48	(2.53)	3.45	(2.50)
Ln(MARKET_CAP)	0.00	(0.01)	0.02	(0.09)	0.05	(0.22)	0.05	(0.23)
RELATIVE_SIZE	1.16	(1.31)	1.19	(1.34)	1.08	(1.16)	1.02	(1.10)
CAR(+)	0.04	(0.95)	0.04	(0.89)	0.04	(1.05)	0.04	(1.06)
CAR(-)	-0.11	(-2.34)	-0.10	(-2.13)	-0.10	(-2.19)	-0.10	(-2.12)
Ln(PRICE)	-1.18	(-3.02)	-1.16	(-3.06)	-1.16	(-3.18)	-1.18	(-3.26)
NYSE	-0.45	(-1.27)	-0.32	(-0.92)	-0.23	(-0.63)	0.03	(0.07)
VOLATILITY			0.17	(1.48)	0.18	(1.61)	0.18	(1.67)
BIDASK	0.47	(2.98)	0.51	(3.16)	0.30	(1.59)	0.32	(1.71)
CLOSE_BID_DIFF					0.49	(2.08)		
NASDAQ $\times$ CLOSE_BID_DIFF							0.52	(2.04)
NYSE $\times$ CLOSE_BID_DIFF							0.22	(0.89)
R^2	0.23		0.24		0.27		0.28	
N	294		294		294		294	

Table A.5: Corwin (2003) OLS Gross Spreads Regressions

This table lists coefficients (t-statistics) from OLS regressions of GROSS_SPREAD on the main covariates used by Corwin (2003). All other details are as per Tables 3 and A.4.

	(1) Model A		(2) Model B		(3) Model C		(4) Model D	
INTERCEPT	8.32	(22.3)	8.29	(20.0)	8.32	(20.0)	8.33	(20.1)
Ln(MARKET_CAP)	-0.64	(-7.98)	-0.64	(-7.89)	-0.65	(-7.94)	-0.65	(-7.94)
RELATIVE_SIZE	-0.37	(-1.30)	-0.37	(-1.29)	-0.36	(-1.25)	-0.32	(-1.14)
CAR(+)	-0.02	(-1.36)	-0.02	(-1.36)	-0.02	(-1.39)	-0.02	(-1.42)
CAR(-)	0.00	(-0.07)	0.00	(-0.04)	0.00	(-0.01)	0.00	(-0.16)
Ln(PRICE)	0.15	(1.26)	0.15	(1.26)	0.15	(1.27)	0.16	(1.35)
NYSE	-0.60	(-5.08)	-0.59	(-5.06)	-0.60	(-5.07)	-0.74	(-5.54)
VOLATILITY			0.01	(0.21)	0.01	(0.20)	0.00	(0.06)
BIDASK	0.09	(3.11)	0.09	(2.93)	0.11	(3.19)	0.10	(2.92)
CLOSE_BID_DIFF					-0.04	(-1.41)		
NASDAQ $\times$ CLOSE_BID_DIFF							-0.06	(-1.98)
NYSE $\times$ CLOSE_BID_DIFF							0.10	(1.91)
R^2	0.66		0.66		0.66		0.67	
N	294		294		294		294	

Table A.6: Butler et al. (2005) OLS Regressions

This table lists coefficients (t-statistics) from OLS regressions of UNDERPRICING and GROSS_SPREAD on the main covariates used by Butler et al. (2005). All variables are defined as per Tables 3, A.4 and A.5, respectively, except for ISSUE_SIZE which is the total dollar value of the issue, as per Butler et al. (2005). Column 1 contains parameter estimates where the dependent variable is GROSS_SPREAD. Column 2 contains parameter estimates where the dependent variable is UNDERPRICING. The sample includes all SEOs on either the Nasdaq or the NYSE between January and October 1997 that were listed before the beginning of the sample period. Standard errors and associated t-statistics are estimated using White's heteroskedasticity-robust estimator.

	(1)		(2)	
	GROSS_SPREAD		UNDERPRICING	
INTERCEPT	7.81	(15.8)	5.03	(3.26)
Ln(MARKET_CAP)	-0.51	(-6.29)	-0.09	(-0.37)
Ln(ISSUE_SIZE)	-0.19	(-1.85)	-0.08	(-0.36)
Ln(PRICE)	0.11	(0.94)	-1.16	(-3.04)
VOLATILITY	0.00	(0.15)	0.22	(1.87)
NYSE	0.58	(4.70)	0.19	(0.55)
BIDASK	0.07	(2.12)	0.54	(3.13)
R^2	0.67		0.21	
N	294		294	