Stock Liquidity and Issuing Activity

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Abstract

Issuing activity does not result in superior post-issue liquidity. New issues are just as liquid as their peer non-issuers. Even the kinds of new issues that are supposed to be more liquid than others (IPOs backed by venture capital, new issues with high-prestige underwriters, severely underpriced IPOs) have the same liquidity as other similar issuers. The paper thus refutes the existing liquidity-based explanations of the new issues puzzle. The paper also shows that the low-minus-high (LMH) turnover factor seems to explain the new issues puzzle and related anomalies only because it picks up volatility risk.

Keywords: New issues puzzle, Liquidity, Stock issuance, Volatility risk, Turnover

JEL Codes: G12, G13, G32, E44

1 Introduction

Improved liquidity and increased investor attention has long been considered one of the important benefits of issuing activity. For example, a poll of CEOs and CFOs conducted by Brau and Fawcett (2006) indicates that the majority of them view liquidity provision as "important" or "very important" when selecting an underwriter. The attention given to post-issue liquidity by CEOs and CFOs is not surprising: first, a long literature started by Amihud and Mendelson (1986) suggests that higher liquidity implies a lower cost of capital.[1] Second, higher liquidity can be helpful in other aspects: for example, Butler, Grullon, and Weston (2005) show that higher liquidity leads to lower expenses when raising additional capital.

Liquidity can be broadly defined as the ease of trading of a security, and in the asset-pricing literature (see, e.g., Amihud and Mendelson, 1986; Acharya and Pedersen, 2005; Amihud, Mendelson, and Pedersen, 2005; Goyenko, Holden, and Trczinka, 2009) a more liquid security is defined as one with lower trading costs. Firms with high effective bid-ask spread and/or high price impact are deemed illiquid, and vice versa. Other variables that are plausibly related to liquidity, such as trading volume and turnover, need validation in the form of an empirical link with trading cost measures.

While the aforementioned reasons for why issuers care about post-issue liquidity imply that issuers will care about post-issue liquidity in several years following the issue, the literature on post-issue liquidity focuses on the liquidity in the first several months after the issue. Part of the literature (e.g., Boehmer and Fishe, 2000; Corwin, Harris, and Lipson, 2004) focuses on the role of the underwriter in providing liquidity and thus understandably

[1]For more recent studies confirming this result, see Amihud (2002), Easley *et al.* (2002), and Hasbrouck (2009).

looks at the first post-issue month. Similarly, more recent studies like He, Wang, and Wei (2014) look at 60 trading days after the SEO issue, while Qian (2011) considers SEO liquidity in the first post-issue year. Even papers that test the hypothesis of Booth and Chua (1996) that underpricing of IPOs results in increased breadth of ownership and thus higher liquidity (e.g., Pham, Kalev, and Steen, 2003; Zheng and Li, 2008) focus on liquidity in the first few post-issue months, even though the breadth of ownership argument is likely to remain valid beyond that period.

The few exceptions focus exclusively on either turnover (trading volume over shares outstanding) or volume-related liquidity measures. Reese (1998) and Eckbo and Norli (2005) look at turnover and observe that IPOs are more actively traded than matching firms in the several years after the issue. Butler and Wan (2010) show that in their 1975–1999 sample, debt issuers have a lower Amihud (2002) measure than their matches. Bilinski, Liu, and Strong (2012) find similar evidence for SEOs in a 1970–2004 sample using both turnover and the Amihud measure.[2] Boehme and Çolak (2012) find that IPOs have higher turnover, but also a higher Amihud measure.

Eckbo and Norli (2005) and Butler and Wan (2010) hypothesize that the higher liquidity of new issues should imply lower expected returns, and find that the LMH turnover factor that buys low turnover firms and shorts high turnover firms can explain the negative post-issue alphas of IPOs, SEOs, and debt issuers.[3] The LMH factor is based on the finding of Datar, Naik, and Radcliffe (1998) that low turnover firms have significantly

[2]Bilinski *et al.* (2012) also find that SEOs have a lower LM12 measure from Liu (2006), which is a linear combination of the number of no-trade days and the inverse of turnover.

[3]This conclusion is further supported by Carter, Dark, Floros, and Sapp (2011), who find that the LMH factor trumps other suggested risk factors in explaining the new issues puzzle. However, Butler and Wan (2010) find that a similar liquidity factor that buys/shorts firms with low/high Amihud measure instead of turnover does not explain the alphas of convertible debt issuers and seems unrelated to their returns, while Eckbo and Norli (2005) find that exposures to the Pastor and Stambaugh (2003) liquidity risk factor are not significantly different for issuers and non-issuers.

higher alphas than high turnover firms. In the sample used in this paper (1986–2017), the CAPM and Fama and French (1993) alphas of LMH are both at about 48 bp per month, with t-statistics exceeding 2.7.[4]

This paper leans on the finding of Barinov (2014) that turnover is largely unrelated to liquidity measures that directly measure bid-ask spread or price impact. The (missing) relation between turnover and liquidity is the product of two forces: some firms are actively traded because they are liquid, while for other firms higher turnover is created by disagreement (as in Harris and Raviv, 1993), and disagreement creates illiquidity.

Hence, the evidence that new issues have higher post-issue turnover than otherwise similar non-issuers does not, in fact, contain any information on whether new issues are indeed more liquid than peers, and more direct evidence is needed. This paper tests the hypothesis of superior post-issue liquidity using a battery of alternative liquidity measures. I find that no liquidity measure, including several measures of effective bid-ask spread and price impact, clearly and consistently indicates that new issues are more liquid than their peer firms with similar size, book-to-market, and other firm characteristics that drive liquidity and trading activity. Economically, the difference in trading costs between issuers and their peers is rather small: e.g., in the second half of my sample (2002–2017), the difference in effective bid-ask spread is between -15.2 bp and 16.3 bp, or between -4.0% and 4.3% of the quintile spread from the sorts of all firms on the bid-ask spread.

Taking my analysis further, I test whether there are any groups of issuing firms that

[4] The ability of the LMH factor to explain the alphas of new issues implies that those alphas could represent compensation for allegedly superior liquidity of new issues, but not lower liquidity risk of new issues. Liquidity risk, as, e.g., Acharya and Pedersen (2005) explain, refers to covariance of stock returns with changes in market liquidity (or, additionally, it can refer to covariance between changes in stock liquidity and market returns/changes in market liquidity), while the LMH factor simply captures return differential between firms with allegedly different liquidity (proxied by turnover). This return differential may or may not be related to changes in market liquidity.

do witness superior liquidity after the issue. In particular, I test whether IPOs can "buy" post-issue liquidity by underpricing, as Booth and Chua (1996) hypothesize. The evidence my tests produce is mixed: according to some trading cost measures, underpriced IPOs are more liquid than peers, while using other measures (most notably all my bid-ask spread measures) produce the opposite conclusion. My finding thus extends the empirical literature that tests the Booth and Chua (1996) hypothesis in the first several months after the issue and suggests that liquidity gains created by underpricing are short-lived.

I also test whether issues backed by more reputable underwriters or by venture capital (VC) become more liquid than their peers. Panel regressions of liquidity measures on a VC-backing dummy variable and firm characteristics driving liquidity present an even split of coefficients suggesting that VC-backed IPOs are more/less liquid than other IPOs. The case of new issues (IPOs, SEOs, and equity of convertible debt issuers) with high-prestige underwriters is similar to the case of underpriced IPOs: different trading cost measures yield opposing results, with the majority suggesting higher trading costs for issuers that use high-prestige underwriters, as compared to issuers with similar firm characteristics.

The second part of this paper deals with the new issues puzzle, i.e., the negative alphas of issuing firms in the first three years after the issue. In my sample period (1986–2017), equal-weighted CAPM and Fama and French (1993) alphas of IPOs, SEOs, and convertible debt issuers range between -34 bp and -68 bp per month, all statistically significant.[5]

Turning to the apparent ability of the LMH turnover factor of Eckbo and Norli (2005) to explain the new issues puzzle and employing the evidence in Barinov (2014) that the turnover effect is explained by volatility risk, I hypothesize that the ability of the LMH

[5] Value-weighted CAPM and Fama-French alphas of SEOs and convertible debt issuers fall into a tight range between -48 bp and -54 bp per month, with t-statistics exceeding -2.7 by absolute magnitude. Value-weighted alphas of IPOs are not statistically significant, but the CAPM alpha is still -36 bp per month.

turnover factor to explain the new issues puzzle stems exclusively from the fact that LMH picks up volatility risk rather than liquidity.

The economic mechanism behind this hypothesis is the following. First, turnover is strongly related to disagreement, because, as Harris and Raviv (1993) argue, investors have an incentive to trade more when they disagree more. Barinov (2014) confirms, using cross-sectional regressions, that turnover is strongly and positively related to measures of firm-specific volatility, analyst disagreement, etc.

Second, as Barinov (2013) shows, high disagreement firms are hedges against increases in market volatility, controlling for their market beta.[6] The cause of the hedging ability is that average disagreement in the economy increases when market volatility increases (see, e.g., Barinov, 2013; Duarte *et al.*, 2012, for evidence), and higher disagreement, all else equal, improves the value of option-like equity (Grullon *et al.*, 2012) and diminishes its risk (Johnson, 2004). Thus, high disagreement firms, and in particular high turnover firms and new issues, are hedges against volatility increases. As Campbell (1993) and Chen (2002) show, good performance in periods of high volatility is desirable, as higher market volatility (and average disagreement) predicts lower future consumption and higher future volatility, making investors cut current consumption for consumption-smoothing and precautionary savings reasons. Ang *et al.* (2006) confirm that sorting firms on historical loadings on market volatility change reveals significantly lower expected returns of firms with more positive reaction to volatility increases.

I present two pieces of evidence in favor of the view that the LMH turnover factor picks

[6] In a two-factor model with the market factor and the volatility risk factor, FVIX, high disagreement firms load positively on the market and negatively on FVIX. Since market return and market volatility are negatively correlated, high disagreement firms lose when volatility goes up, FVIX posts a positive return, and the market goes down, but a market-neutral position in high disagreement firms is a hedge against increases in market volatility.

up volatility risk rather than liquidity. First, I show that the volatility risk factor, FVIX, can explain LMH, but not vice versa: the alpha of LMH controlling for FVIX is -5.4 bp per month, whereas the alpha of FVIX controlling for LMH is -37.8 bp per month, t-statistic 4.45. Second and most importantly, I show that LMH is related in a counterintuitive fashion to the cross-section of the new issues puzzle. LMH seems to explain why smaller issuers have more negative CAPM alphas, but in doing so it ascribes particularly negative loadings to small issuers, which would be suggestive of their high liquidity (or at least high turnover). Inconsistent with that, if one looks at average and median liquidity measures of small issuers, they expectedly turn out to be significantly less liquid than large issuers. Even turnover, which is the basis of LMH, is lower for small issuers. On the other hand, FVIX can explain the more negative CAPM alphas of smaller issuers both empirically (the alphas drop from between -50 bp and -76 bp per month to between -2.5 bp and -22 bp per month) and theoretically: smaller issuers face higher levels of disagreement, and, as Barinov (2013) shows, in the cross-section, disagreement is negatively related to volatility risk. Thus, the puzzling ability of LMH to explain the more negative CAPM alphas of smaller issuers can be explained by the fact that LMH picks up volatility risk, not liquidity.

The closest papers to this study are Barinov (2014) and Barinov (2012). Barinov (2014) finds that in the cross-section, turnover is largely unrelated to measures of effective bid-ask spread and price impact, and thus high turnover firms are not necessarily more liquid. This result implies that the existing evidence that new issues have higher turnover than their peers (see, e.g., Eckbo and Norli, 2005; Boehme and Çolak, 2012) does not send us any signal about whether new issues are more or less liquid than peers.

This paper therefore contributes to the literature on post-issue liquidity by presenting evidence that new issues are no more liquid than their peers. Moreover, my findings raise doubts about important additional hypotheses that in the long-run, issuers can become more liquid than their peers by underpricing their shares, by engaging high-prestige underwriters, or gaining support of venture capital firms.[7] Lastly, my paper presents strong evidence that refutes the liquidity explanation of the new issues puzzle provided in the literature and favors volatility risk explanation instead.

Barinov (2012) finds that volatility risk explains the new issues puzzle. That by itself does not rule out the liquidity explanation, which may run parallel to the volatility risk explanation or overlap with it. This paper expands the time period in Barinov (2012) by 50%, thus including the post-2006 high volatility episodes, adds convertible debt issuers to the analysis, and shows that the apparent success of the LMH turnover factor in explaining the new issues puzzle is fully due to the fact that the turnover factor picks up volatility risk rather than liquidity.

The result that LMH mirrors the volatility risk factor is also interesting, because the volatility risk factor I use is based on the VIX index, and thus unavailable prior to 1986. The results in this paper suggest that at least when it comes to explaining the new issues puzzle, one can replace the volatility risk factor by LMH (and then interpret positive loadings on LMH as volatility risk rather than evidence of higher liquidity).

2 Data

The paper covers the sample period from January 1986 to December 2017. The starting date is determined by the availability of the VIX index, which is the basis of the volatility risk factor in the second part of the paper.

I obtain dates and identities of new issues (IPOs, SEOs, and convertible debt issues)

[7] Gao and Ritter (2010) provide evidence of a short-run effect of using an underwriter for SEOs that choose the bookbuilding route rather than the accelerated offer route.

from the SDC database. My new issues portfolios are rebalanced monthly and include new issues performed from 2 to 37 months ago.[8] I exclude the first month after the issue to eliminate the effects of price support provided by the underwriter. The results are robust to keeping the first month in the sample. The new issues obtained from SDC cover the period between December 1982 and November 2017.[9] I include in my sample only new issues listed on NYSE/AMEX/NASDAQ after the issue and exclude units issues and private placements. I also keep only common shares in my sample and exclude ADRs by requiring shrcd code from the CRSP events file to be either 10 or 11. I match new issues to CRSP returns data by six-digit CUSIP, requiring at least one valid return observation in the three years after the issue. When I look at the new issues puzzle in different size and market-to-book portfolios, I measure size and market-to-book of new issues using the after-issue market capitalization and total common equity values from SDC.

To measure the innovations to expected market volatility, I use daily changes in the old version of the VIX index (current ticker VXO) calculated by CBOE and available from WRDS. The VIX index measures the implied volatility of the at-the-money options on the S&P100 index. Using the old version of VIX provides longer coverage. The results in the paper are robust to using the new version of VIX.

I form a factor-mimicking portfolio that tracks daily changes in VIX by regressing them on daily excess returns to the base assets. The base assets are five quintile portfolios sorted on the past return sensitivity to VIX changes, as in Ang *et al.* (2006):

$$\begin{aligned}\Delta VIX_t = \; & \underset{(0.019)}{0.060} - \underset{(0.074)}{0.052} \cdot (VIX1_t - RF_t) - \underset{(0.156)}{0.611} \cdot (VIX2_t - RF_t) - \underset{(0.113)}{0.376} \cdot (VIX3_t - RF_t) \\ & - \underset{(0.386)}{0.679} \cdot (VIX4_t - RF_t) + \underset{(0.143)}{0.194} \cdot (VIX5_t - RF_t), \quad R^2 = 0.474 \qquad (1)\end{aligned}$$

[8]Huang and Ritter (2020) observe that the new issues puzzle is limited to months 7–36 after the issue.
[9]New issues in 1983 enter the new issues portfolio in 1986 as two- to three-year-old issues.

where $VIX1_t, \ldots, VIX5_t$ are the VIX sensitivity quintiles described in the next paragraph, with $VIX1_t$ being the quintile with the most negative sensitivity. The fitted part of the regression above less the constant is my volatility risk factor (FVIX factor).

The return sensitivity to VIX changes ($\gamma_{\Delta VIX}$) I use to form the base assets is measured separately for each firm-month by regressing daily stock excess returns in the past month on daily market excess returns and the VIX index change using daily data (at least 15 non-missing returns are required):

$$Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \gamma_{\Delta VIX} \cdot \Delta VIX_t. \tag{2}$$

By construction, FVIX is the portfolio that tends to earn positive returns when expected market volatility increases, and hence FVIX is a hedge against aggregate volatility risk. Therefore, when FVIX is used in factor models, a negative FVIX beta indicates exposure to aggregate volatility risk, and portfolios with positive FVIX betas are deemed hedges against volatility risk.

Turnover is trading volume divided by shares outstanding (both from CRSP). Following Gao and Ritter (2010), the NASDAQ turnover is adjusted to eliminate double-counting. I divide the NASDAQ turnover by 2.0 prior to January 2001, by 1.8 for the rest of 2001, by 1.6 for 2002–2003, and leave it unchanged thereafter. Firms are classified as NASDAQ firms if the exchcd historical listing indicator from the CRSP events file is equal to 3. The turnover factor (LMH) is the arbitrage portfolio that buys firms in the bottom turnover quintile and shorts firms in the top turnover quintile (NYSE quintile breakpoints are used).

IPO underpricing is defined as the first-day return, $\dfrac{P-O}{O}$, where P is the first-day closing price and O is offer price.

Underwriter reputation rankings are from the website of Jay Ritter at http://bear.warrington.ufl.edu/ritter/ipodata.htm. The ranks are from 1 to 9 with 9 being the most reputable. In the case of multiple underwriters, the rank of the lead underwriter is used. All other variables are described in online Data Appendix.[10]

3 Does Issuing Activity Create Superior Liquidity?

3.1 Liquidity and Issuing Activity: Literature Review

The existing liquidity explanations of the new issues puzzle (Eckbo and Norli, 2005; Butler and Wan, 2010; Carter *et al.*, 2011) argue that the issuing process makes new issues more liquid than matching firms by attracting investors' attention to the firm and broadening its ownership. The empirical evidence presented is the fact that new issues have significantly higher turnover than size and book-to-market matched firms.[11]

The literature on post-issue liquidity, outside of a few papers, focuses on the first few months after the issue. For example, Kothare (1997) finds that SEOs, in contrast to rights issues, have lower bid-ask spread in the first 100 days after the issue than in the 100 days preceding the issue. Corwin *et al.* (2004) find that IPOs, and especially underpriced IPOs, enjoy abnormally high market depth, but only in the first month after the issue. Qian (2011) compares SEO liquidity relative to the liquidity of peer firms in 12 months before and 12 months after the issue, while He *et al.* (2014) look at trading costs of SEOs estimated from high-frequency data in the first 60 trading days after the issue.[12]

The short post-issue period covered by the previous studies makes them largely irrel-

[10]Available at https://www.dropbox.com/s/fplwh7h2os7uqx3/Data%20Appendix%20QJF.pdf?dl=0

[11]Butler and Wan (2010) show that debt issuers have a lower Amihud measure, but turnover and the Amihud measure are mechanically negatively related through trading volume, since turnover is volume over shares outstanding and the Amihud measure is the average of absolute return over volume daily ratios.

[12]Other studies of post-issue liquidity, discussed in the Section 3.3 below, do not compare liquidity of new issues directly with that of similar firms, but are dedicated to testing the relation between IPO liquidity and underpricing. The post-issue time span of these studies is again several months.

evant for validating the liquidity explanation of the new issues puzzle. Indeed, the new issues puzzle lasts for at least three years, with no underpricing at all in the first few months after the issue ("honeymoon period"). Hence, in order for the liquidity explanation of the new issues puzzle to be valid, new issues have to be more liquid than peers for at least three years, and they do not actually have to be more liquid than peers during the "honeymoon period."

The only liquidity studies that look at long-run post-issue liquidity are Reese (1998) and Boehme and Çolak (2012), which focus on IPOs only, and Bilinski *et al.* (2012), which deals only with SEOs. Reese (1998) uses trading volume scaled by float as his only liquidity measure, which makes his evidence similar to the turnover-based evidence in Eckbo and Norli (2005). Boehme and Çolak (2012) use turnover and the Amihud (2002) price impact measure and arrive at the mixed result that IPOs have higher turnover than the median CRSP firm, but also higher price impact. Bilinski *et al.* (2012) add to that a modified zero-return frequency measure, LM12, from Liu (2006), which is a linear combination of the number of no-trade days and the inverse of turnover. They find that SEOs have a higher turnover, a lower Amihud measure, and a lower LM12 measure than size and book-to-market matches.

Barinov (2014) shows that turnover is largely unrelated to trading cost-based measures of liquidity. To put it differently, for an average firm turnover is an uninformative signal about its liquidity. Thus, the higher turnover of new issues does not tell us anything about whether new issues are in fact more liquid than their matches or not. Consequently, measures that are mechanically correlated with turnover, such as the Amihud ratio and LM12, can also create a false impression that high turnover firms are more liquid. In order to conclude whether the necessary condition for the liquidity explanation of the new issues puzzle is true or not, we have to look at several alternative trading cost measures in the long-run.

3.2 Are New Issues More Liquid than Their Peers?

Table 1 performs regressions of turnover and several trading costs measures on control variables and a dummy variable for issuing activity (1 if a firm has performed an IPO (Panel A1), SEO (Panel A2) or issued convertible debt (Panel A3) in the past three years). Following Peterson (2009), Table 1 performs one panel regression using all firm-year-months in the sample and clustering standard errors by firm-year-month. The regressions in Table 1 include industry-year fixed effects (industries are based on the two-digit SIC codes), but the results are qualitatively similar if I do not use fixed effects.

The trading costs measures in Table 1 include three measures of effective bid-ask spread: the Roll (1984) measure, the Corwin and Schultz (2012) effective spread estimate, and the effective tick estimate of Holden (2009). Also included are the price impact measure of Amihud (2002)[13] and the zero-return frequency measure from Lesmond *et al.* (1999), who suggest that zero-return frequency is a good proxy for total trading costs (investors choose not to trade and return is zero if trading costs are higher than the benefits from trading).

Panel A of Table 1 only uses size, market-to-book (and pre-issue liquidity for SEOs and convertible debt issuers) as controls. To make sure that past liquidity is pre-issue liquidity for SEOs and convertible debt issuers and to put issuers and other firms on the same footing, I use the corresponding liquidity measure (turnover if the left-hand side variable is turnover, the Amihud measure if the left-hand side variable is the Amihud measure,

[13] The Amihud measure, by definition, is average ratio of absolute daily return to daily trading volume (in millions of dollars). Thus, the Amihud measure is mechanically negatively related to turnover (ratio of trading volume to shares outstanding), which works against me finding either no relation or a positive relation between the Amihud measure and the new issue dummies.

etc.) lagged by three years.

Panel A finds that, consistent with Eckbo and Norli (2005) and Boehme and Çolak (2012), issuers have higher turnover, on average, in the three post-issue years. The rest of the liquidity measures deliver a split message both within each class of issuers and across the three classes. For example, for SEOs (Panel A2), the Amihud measure suggests that SEOs are more liquid post-issue than peer companies, the Roll measure suggests the opposite, and other measures record no significant liquidity change. Focusing on, for example, the Holden (2009) effective tick measure, one would conclude that post-issue IPOs are more liquid than their peers, convertible debt issuers are less liquid than their peers, and SEOs have the same liquidity as their peers.

In Panel B of Table 1, I follow Chordia *et al.* (2007) who look at variables driving trading activity[14] and use (in addition to market-to-book, size, and past liquidity already controlled for in Panel A), the level of stock price, return volatility, firm leverage, and contemporary gains (stock return if it is positive, 0 otherwise) and losses (stock return if it is negative, 0 otherwise), as well as age (months on CRSP) and market beta, with the latter two used for SEOs and convertible debt issuers only.[15]

Adding more controls erodes significance of the issuing dummies. In Panel B, I find that IPOs have higher post-issue bid-ask spreads than comparable firms according to all three spread measures, and no-trade days, price impact, and turnover do not significantly differ post-issue from IPOs' peers. Panel B also suggests that bid-ask spreads of convertible

[14] I use the same set of controls in the panel regressions with trading costs measures on the left-hand side, since Chordia *et al.* controls also turn out to be significantly related to liquidity in the expected manner (e.g., smaller firms and firms with lower price are less liquid, firms with higher leverage are less liquid, etc.)

[15] I drop the analyst following variable used in Chordia *et al.* (2007), since many IPOs do not join the IBES sample in their first years, and it is unclear, given their small size, whether that implies no analyst coverage or is due to small firms being underrepresented in the IBES sample.

debt issuers are similar to spreads of comparable firms, price impact for convertible debt issuers is smaller (probably mechanically so due to higher turnover), and the number of no-trade days for them is higher. Overall, the picture is similar in Panel A and Panel B: there is no agreement between liquidity measures that would indicate that either one of IPOs, SEOs, or convertible debt issuers has superior liquidity post-issue, or that all issuers have superior post-issue liquidity across some dimension (e.g., bid-ask spread).

A big event during the sample period is the decimalization that happened in early 2001 and dramatically reduced the minimum tick size and, consequently, reduced bid-ask spread and increased trading activity. In 1986–2001, zero-return frequency and the Amihud measure were an order of magnitude greater than in 2002–2017, the effective tick of new issues was roughly six time larger, and turnover was about three times lower. Since the changes in the dependent variables are so dramatic, Panels C and D split the sample into those two subperiods and re-estimate the regressions from Panel B.[16]

I find that full-sample results are rather close to 1986–2001 results, especially in Panels B1 and C1 (IPOs) and Panels B2 and C2 (SEOs), which is consistent with early years dominating the full sample due to higher issuing volume. I also find that the slopes are generally smaller and less significant in Panel D (2002–2017) than in Panel C (1986–2001), consistent with trading costs declining sharply after decimalization.

Looking at Panel D more closely, I find that my main conclusion that issuing activity has an ambiguous impact on trading costs still holds. For example, Panel D1 finds that IPOs have higher Roll measures post-issue than similar non-issuing firms, but Panels D2 and D3 do not confirm this result for SEOs and convertible debt issuers. Panel D2 finds

[16] Another benefit of splitting the sample is that the first half of the sample may play a disproportionate role in estimation results due to the large amount of new issues in the 1980s and 1990s. While portfolio analysis in the rest of the paper (from Table 3 on) weighs each month equally, panel regressions in Tables 1 and 2 weigh each new issue equally and thus assign more weight to more distant years.

that post-issue SEOs have lower effective tick measure, but higher effective spread measure from Corwin and Schultz (2012), etc.

The split sample also makes evaluating economic significance of the slopes easier. For example, Panel D2 finds that in 2002–2017, compared to other firms with similar firm characteristics, SEOs see monthly turnover that is by 4.9% of shares outstanding higher. According to Panel D2, SEOs' effective tick measure is by 15.2 bp lower, but SEOs' Corwin-Schultz measure is by 5.2 bp higher than that of comparable non-issuers. SEOs also have 32.8 bp (per $1 million traded) lower price impact and witness roughly 7 (-0.029 times 250 trading days in a year) less no-trade days per year.

Most modern studies estimate the difference in cost of capital between top and bottom liquidity quintiles to be 2–3% per annum, and Butler *et al.* (2005) find a 21% difference in underwriting fees between issuers in top and bottom liquidity quintiles. To put the numbers in the previous paragraph into context, in Section 5 of online Robustness Appendix[17], I look at the quintile spread in the aforementioned trading costs measures for all listed firms. For the effective tick of Holden (2009), the difference between the 90th and 10th percentiles in 2002–2017 constitutes 382 bp (as compared to the 15.2 bp decline in effective tick for SEOs in Panel D2); for the Corwin-Schultz (2012) effective spread measure, the quintile spread is 158 bp (as compared to 5.2 bp increase in Panel D2); for the Amihud measure and zero-return frequency, the quintile spreads are 3.224% and 0.093 (about 23 trading days per year). I conclude that the slopes on the new issues dummies in Table 1 are economically small and unlikely to have a noticeable effect on cost of capital or future underwriting fees.

[17] Available at https://www.dropbox.com/s/8o9leram6jetnp7/Robustness%20QJF.pdf?dl=0

3.3 Does Venture Capital Help to Improve Post-Issue Liquidity?

Several papers on IPOs backed by venture capital (VC) find that VC improves issuing firms along several dimensions. For example, Chemmanur and Loutskina (2006) find that VC-backed IPOs have higher institutional ownership, more reputable underwriters, and better analyst coverage. Krishnan *et al.* (2011) find that more VC involvement improves corporate governance and long-run performance. The latter conclusion is also supported by Brav and Gompers (1997). While I am not aware of any study, theoretical or empirical, that links long-run post-issue liquidity to VC-backing, it is reasonable to expect that most changes above that VC-backing brings can cause higher liquidity. For example, better analyst coverage can reduce information asymmetry in the market and bring bid-ask spreads down, better corporate governance can make the firm more transparent, reduce information asymmetry, and thus create liquidity, etc.

Panel A of Table 2 restricts the sample to IPOs only and repeats the panel regressions in Panel B of Table 1 adding the VC dummy (1 for IPOs backed by venture capital, 0 for all other firms).[18] The results in the top row of Panel A are similar to the results in Table 1: VC-backed IPOs have higher turnover, but the evidence on whether this higher turnover creates extra liquidity is mixed. In the regressions with effective bid-ask spread measures on the left-hand side, two slopes on the VC dummy are positive and significant, suggesting higher trading costs for VC-backed IPOs, and one slope is negative, but insignificant. The slopes on the VC dummy from the regressions with price impact (the Amihud measure) on the left-hand side are negative.

In terms of economic significance, the slopes on the VC dummy are small and suggest

[18] As Section 2.4 of online Robustness Appendix shows, the results are qualitatively similar if I use the full sample and use VC dummy together with IPO dummy (focusing on the IPOs-only sample allows slopes on control variables to be different for IPOs and non-issuers).

that effective bid-ask spread for VC-backed IPOs is 13.5 bp smaller (the effective tick measure) or 13.4 bp larger (the Roll measure) than that of other IPOs. VC-backed IPOs also witness about 5 zero-return days less than an average IPO.[19]

VC backing of an IPO is not a random event, thus the rest of Panel A corrects for that first by adding inverse Mills ratio to controls (as in Krishnan *et al.*, 2011) and then, alternatively, by replacing the VC dummy by its expected value from a probit regression (as in Dai, 2007). Both the inverse Mills ratio and the expected value are from the same probit regression estimated separately each month: following Dai (2007), I use as determinants of VC backing log of post-issue market cap, log of idiosyncratic volatility in the first post-issue month, log of proceeds from the IPO, log of post-issue market-to-book, a dummy variable that equals 1 if the company reported negative earnings before depreciation in the year preceding the issue and 0 otherwise, and a trading cost measure (or turnover) from the first post-issue month as indicated in the heading of the column.[20] The trading cost measure in the probit regression explicitly controls for weaker companies with lower expected liquidity potentially seeking help of a VC investor.

The inverse Mills ratio in Panel A2 is significant in five regressions out of six, indicating that the selection bias is indeed present. After controlling for the inverse Mills ratio, slopes on the VC dummy in Panel A2 become more positive: the VC dummy is now positive and significant in regressions with all three bid-ask spread measures on the right-hand side, and the VC dummy stays negative, but becomes insignificant in regressions with either the Amihud measure or zero-return frequency as dependent variables.

[19] In the more recent sample (2002–2017), these effects are roughly three times smaller.

[20] That is, in the column of Panel A labeled EffTick the probit regression used to produce either the inverse Mills ratio or the expected probability of VC backing includes the effective tick measure of Holden (2009) as one of the regressors, and in the column labeled Amihud the inverse Mills ratio and the expected probability of VC backing come from a slightly different probit regression with the Amihud measure used instead of effective tick.

In regressions that use expected probability of VC backing instead of the VC dummy (Panel A3), VC-backed IPOs appear to have significantly higher Amihud measure (in addition to higher bid-ask spread measures), but significantly fewer no-trade days than peer IPOs.[21]

Overall, the conclusion from Panel A of Table 2 is that there is no consistent evidence that VC-backed IPOs enjoy additional liquidity compared to other IPOs: VC-backed IPOs have higher bid-ask spread than peer IPOs, but likely see less no-trade days, whereas the evidence on price impact is mixed. This result is in contrast to Boehme and Çolak (2012) who look only at turnover and the Amihud measure, and conclude, consistent with the evidence in the top row of Panel A on those two variables, "VC backing alleviates the future liquidity frictions of an IPO" (p. 308).[22]

The fact that VC-backing does not appear to improve post-issue liquidity of IPOs does not imply that VC-backing is not useful, but rather that VC-backing is beneficial for reasons other than superior liquidity in the long-run.

3.4 Can IPOs Achieve Higher Liquidity through Underpricing?

The literature has long held the view that IPOs can "buy" post-issue liquidity by underpricing the issue. As first suggested by Booth and Chua (1996), underpricing allows to attract a greater number of investors, and broader ownership promotes liquidity. The argument in Booth and Chua (1996) is long-term in nature: there is nothing to suggest

[21] The slopes on the expected probability of VC backing in Panel A3 are several times larger than slopes on the VC dummy in Panel A2, because the expected probability of VC backing has much lower variance by construction.

[22] In Section 2.2 of online Robustness Appendix, I also use the matching firm technique to compare IPOs backed and not backed by venture capital to their matching firms. I find that only post-issue turnover of IPOs exceeds that of matching firms irrespective of whether IPOs are backed by venture capital or not. Other liquidity measures appear similar for IPOs and matching firms irrespective of VC-backing and the majority of point estimates suggests slightly lower liquidity of IPOs relative to their peers.

that broader ownership induced by underpricing will be short-lived (although part of it may be short-lived due to flipping). Yet, all empirical studies testing the Booth and Chua hypothesis choose to focus on the first month (or several months) after the issue.

For example, Corwin *et al.* (2004) use a relatively small sample of NYSE IPOs in 1995–1998 and find that severely underpriced IPOs enjoy greater market depth in the first month after the issue. Pham *et al.* (2003) find, using a small sample of Australian IPOs, that more underpricing means lower bid-ask spread and higher turnover between the fifth and thirtieth trading day after an IPO. Zheng and Li (2008) use a larger sample of US IPOs that occurred between 1993 and 2000, but still only look at liquidity in the first year after the issue. They find that underpricing is only related to trading volume, but not to other liquidity measures after controlling for breadth of ownership, and may be related to other liquidity measures through breadth of ownership.[23]

Panel B of Table 2 fills the void in the literature and tests the hypothesis of Booth and Chua using the data on liquidity in three years after the issue. The regressions are the same as in Panel A, with VC dummy replaced by the underpricing dummy, Under, and the sample is restricted to IPOs only.[24]

The underpricing dummy partitions all IPOs into two groups: those with above average underpricing ("Under" dummy variable equals 1) and those with below average underpricing or no underpricing at all (Under=0). Average underpricing is computed in the sample of IPOs that have positive first-day return (which is the measure of underpricing I use). In my sample, roughly one-quarter of IPOs are not underpriced, about one-third have above

[23]The argument of Booth and Chua (1996) and the evidence in the papers above is contested by Ellul and Pagano (2006), who suggest that firms might decide to underprice if they expect the post-issue market to be illiquid. In a sample of UK IPOs from 1998–2000, Ellul and Pagano do find that underpricing is greater for IPOs with lower predicted liquidity in the first month after the issue.

[24]As Section 2.4 of online Robustness Appendix shows, the results are qualitatively similar if non-issuers are included and the underpricing dummy is used along with the IPO dummy.

average underpricing, and the rest (42–45% of the sample) are mildly overpriced.[25]

Panel B1 of Table 2 presents evidence that is not consistent with underpricing alleviating liquidity in the long-run. Even though turnover is significantly higher for more underpriced IPOs, the sign split for trading cost measures is three-to-two in favor of the positive slopes (higher trading costs for more underpriced IPOs), with one positive and one negative slope insignificant.

In terms of economic significance, the slopes in Panel B2 are not large: Panel B2 finds that, according to all three effective spread measures, bid-ask spreads of underpriced IPOs are 7.4–17.8 bp per month higher than those of other IPOs, but underpriced IPOs witness roughly 5 no-trade days less. This is not a large difference compared to the top-minus-bottom quintile spread in no-trade days in the IPO subsample in 2002–2017 (19 days, see Section 5 of online Robustness Appendix).[26]

Panel B2 adds the inverse Mills ratio from the probit regression of the underwriting dummy on log market cap post-issue, log market-to-book and log leverage in the first post-issue year, log idiosyncratic volatility in the first post-issue month, as well as R&D-to-assets ratio and a liquidity measure in the first post-issue month as indicated in the heading of the column in Panel B2. The determinants of underpricing (except for liquidity) are from Pham *et al.* (2003).

Similar to Panel A2, the inverse Mills ratio is significant in five regressions out of six, indicating the presence of selection bias. Controlling for the inverse Mills ratio strengthens

[25]In untabulated analysis, I tried partitioning the sample into three groups: no underpricing, mild underpricing, and extreme underpricing. The results suggest that the liquidity of IPOs, as well as the liquidity of their peers, are very similar in the first two groups, so I chose to report IPOs with no underpricing and IPOs with small underpricing as one group.

[26]In Section 2.1 of online Robustness Appendix, I look at underpriced and non-underpriced IPOs separately and compare them to their size and market-to-book matches in each of the five years after the issue and observe little significant difference in post-issue liquidity between either group of IPOs and their matching firms.

positive loadings on the underpricing dummy (indicating higher post-issue trading costs for underpriced IPOs) and weakens negative loadings.

In Panel B3, I switch to two-stage estimation strategy that replaces the underpricing dummy by the estimated probability of underpricing (from the same probit model that delivers the inverse Mills ratio for Panel B2). The estimated probability of underpricing is significantly positively related to all five trading costs measures.

I conclude from my analysis that IPO underpricing does not appear to create additional liquidity in the long-run, contrary to what Booth and Chua (1996) predict and what subsequent studies find in the first months after the issue. In the three post-issue years, severely underpriced IPOs have higher bid-ask spreads than other IPOs with similar firm characteristics, potentially higher price impact, and the evidence on no-trade days is mixed.

As is the case with backing by venture capital, the lack of superior liquidity for underpriced IPOs does not imply that they should not have underpriced their shares, but rather that underpricing is motivated by reasons other than achieving better long-run liquidity post-issue.

3.5 Does Underwriter Reputation Matter for Long-Run Post-Issue Liquidity?

Underwriter reputation can also potentially be related to post-issue liquidity in the long-run. On the one hand, top underwriters can successfully screen for "good" companies, and their definition of "good" is likely to include post-issue liquidity. If this is the case, parsing the new issues sample based on underwriter's reputation will elicit that new issues with high-prestige underwriters are more liquid than other new issues, but not necessarily more liquid than their peers.

On the other hand, underwriters are definitely taking a more active stance in providing liquidity in the price support period, and remain the main dealer in the issue for several years after an IPO. Underwriters also select the level of post-issue ownership dispersion through book building, and are likely to provide issuers with valuable analyst services (Loughran and Ritter, 2004). Hence, it is possible that a higher-quality underwriter can make the issuing company stocks more liquid than peer stocks.

Underpricing and VC-backing are characteristics that are specific to IPOs; in contrast, all new issues (IPOs, SEOs, and convertible debt issues) can and almost always do have an underwriter. Following the literature, I use the underwriter reputation data set on the website of Jay Ritter at http://bear.warrington.ufl.edu/ritter/ipodata.htm and define high-reputation underwriters as underwriters with reputation ranks 8 and 9.[27] The ranking mechanism is described in more detail in Loughran and Ritter (2004) and Carter and Manaster (1990).

Panels C–E of Table 2 consider liquidity of new issues with high-prestige underwriters and introduce the Rank dummy (1 for high-prestige underwriters, 0 otherwise). Panel C looks at IPOs. In the top row (dubbed Panel C1), the signs of the slope on Rank are positive for all trading costs measures (insignificant for the Amihud measure and no-trade days), suggesting that IPOs with high-prestige underwriters have higher trading costs and thus lower liquidity.

Panel C2 adds the inverse Mills ratio that is significant in five out of six regressions. Controlling for the inverse Mills ratio makes all slopes numerically smaller, but the positive slope from the regression of no-trade days on Rank becomes significant. The inverse Mills ratio comes from the probit regression for the Rank dummy. The probit regression follows

[27] For convertible debt issues, this definition results in too few observations in the rest of the sample, and for this type of issuers I re-define high-reputation underwriters as underwriters with reputation rank equal to 9.

Fernando *et al.* (2005) and uses log of post-issue market cap, log of idiosyncratic volatility in the first post-issue month, log of proceeds from the IPO, VC dummy, and dummy for loss (negative net income) in the pre-issue quarter, as well as the liquidity measure in the first post-issue month as indicated in the column heading.[28]

Replacing the Rank dummy with expected probability from the probit regression results in the positive link between underwriter rank and the Amihud measure becoming significance, but now the relation between no-trade days and underwriter rank loses significance. Overall, Panel C presents consistent evidence that underpriced IPOs have higher bid-ask spreads than IPOs with similar firm characteristics, but it is unclear if they have higher price impact or more no-trade days.[29]

Panel D looks at SEOs and finds an even stronger preponderance of positive slopes: either before or after controlling for endogeneity, both bid-ask spread and number of no-trade days are significantly higher for SEOs with higher-ranked underwriters than for SEOs with comparable size, market-to-book, analyst coverage, etc. The relation between the Amihud measure and Rank is insignificant with or without the inverse Mills ratio control, but becomes positive and significant when the Rank dummy is replaced with its expected value from the first-stage probit regression.

Panel E looks at convertible debt issuers: Panels E2 and E3 that correct for endogeneity find consistently positive relation between bid-ask spread and Rank, while the relation is weaker in Panel E1 before the endogeneity control. With or without endogeneity control,

[28]Since pre-issue stock prices are available for SEOs and convertible debt issuers, I use market cap, idiosyncratic volatility, and liquidity in the pre-issue year when I perform similar probit regressions for Panel D and E.

[29]As in the rest of Table 2, the sample in Panels C–E includes only issuing firms. In Section 2.4 of online Robustness Appendix, I include all firms in the sample and use two dummies (one for issuing, another for using a high-prestige underwriter), I find that all slopes in all panels are significantly positive (indicating lower liquidity for all issuers with a high-prestige underwriter).

there seems to be no relation between post-issue Amihud measure or zero-return days and the decision of convertible debt issuers to engage or not to engage a high-prestige underwriter.

In matching firm analysis reported in Section 2.3 of online Robustness Appendix, I find that prior to controlling for size, new issuers with high-prestige underwriters are indeed significantly more liquid (and also have higher turnover) than new issuers with low-prestige underwriters. However, the same is true for their matching firms, and therefore new issuers with high-prestige underwriters are not more liquid than their peers. This conclusion extends Zheng and Li (2008), who find similar evidence looking at the first post-issue year of IPOs only.

Overall, the evidence in Panels C–E of Table 2 and the matching firm analysis suggest that high-prestige underwriters only perform the screening function in terms of post-issue liquidity. They tend to select firms that are likely to be more liquid in the long-run, but they do not provide additional liquidity compared to peer firms and firms with a high-prestige underwriter can even have higher bid-ask spread post-issue.

4 Why Does Turnover Factor Seem to Explain the New Issues Puzzle?

4.1 Turnover and Volatility Risk Factors Both Explain the New Issues Puzzle

In Table 3, I reproduce the results in Eckbo and Norli (2005) and Butler and Wan (2010) by regressing monthly returns to portfolios of new issues on asset-pricing factors, including the low-minus-high (LMH) turnover factor, and recording the monthly alphas.[30] The new

[30]Butler and Wan (2010) focus on the Amihud measure in their analysis of convertible debt issuers' liquidity, but then find that only the turnover factor can explain the alphas of convertible debt issuers, while a similar long-short factor based on the Amihud ratio is unrelated to convertible debt issuers' returns

issues portfolios contain all the firms that have performed the respective issue (IPO, SEO, convertible debt) in the past three years.[31]

The first two columns of Panels A–C in Table 3 confirm the existence of the new issues puzzle in my sample period (1986–2017), which updates the sample in Butler and Wan (1975–1999) and Eckbo and Norli (1972–1998). My sample period starts later due to my use of the FVIX factor, available starting in 1986. In the updated sample, the new issues puzzle is as strong as ever: the Fama-French model estimates it at -34 bp per month for IPOs, at -42 bp per month for SEOs, and at -68 bp per month for convertible debt issuers. That is essentially an out-of-sample test for the new issues puzzle, which was initially discovered in the 1970–1990 data. In my sample period, the underperformance of convertible debt issuers is even stronger than the underperformance of IPOs and SEOs, whereas in the initial studies (Spiess and Affleck-Graves, 1999; Loughran and Ritter, 1995; Ritter, 1991; Lee and Loughran, 1998) the reverse was true.[32]

The third column of Panels A–C in Table 3 extends the study of Barinov (2012) who uses the two-factor ICAPM with the market factor and the volatility risk factor (FVIX) to explain the new issues puzzle in 1986–2006. Compared to Barinov (2012), I add 11 more years to the sample, which include the high-volatility episode of the most recent financial crisis and increase the sample period by 50%. I also extend the analysis to convertible debt issues, while Barinov (2012) deals only with IPOs and SEOs.[33]

and does not impact their alphas.

[31]Spiess and Affleck-Graves (1999) document that issuers of straight debt also underperform, but in my sample period I do not observe this underperformance and estimate the post-issue CAPM/Fama-French alphas of straight debt issuers to be at most 10 bp away from zero.

[32]In untabulated results, I split my sample period in two halves and find that the new issues puzzle is weaker, but still significant in 2002–2017, with SEO alphas at -30 to -46 bp per month, convertible debt issuers alphas at -45 to -77 bp per month, and only IPO alphas between -3 and -22 bp per month and insignificant.

[33]Section 4.5 of the online Robustness Appendix and Table 7 below show that FVIX can also explain the recent frequent issuers puzzle from Huang and Ritter (2020).

I show that for IPOs and SEOs, the two-factor ICAPM of Barinov (2012) works equally well in the updated sample. Panels A and B of Table 3 show that the IPO alpha flips its sign and becomes positive and insignificant, the SEO alpha changes to -8 bp per month after controlling for volatility risk, and the FVIX betas of IPOs and SEOs are both positive and significant, indicating relatively good performance of IPOs and SEOs when market volatility increases (i.e., their hedging ability against volatility risk).[34]

The economic intuition for this result is that IPOs and SEOs are primarily small growth firms. As Brav *et al.* (2000) show, 50% of IPOs and 25% of SEOs come from only one portfolio in the five-by-five sorts on size and market-to-book, namely the portfolio of firms with the lowest size and highest market-to-book. All else equal, growth options, as all options, react positively to volatility increases, which makes growth firms a hedge against volatility risk (see Barinov and Chabakauri, 2019, for the model and empirical evidence). New issues are also growth firms, so they are also hedges against volatility risk, and even more so because new issues are small firms. Small firm are normally highly volatile and thus their volatility can increase more and have a larger (positive) effect on firm value in volatile periods of time.

In the third column of Panel C, I show that volatility risk can largely explain the underperformance of convertible debt issuers. After controlling for FVIX, their alpha declines to -33 bp per month, t-statistic -1.65, and their positive and significant FVIX beta, comparable to those of IPOs and SEOs, indicates that convertible debt issuers are also good hedges against volatility risk.

The last column in all panels reports results from the "liquidity CAPM" with the

[34]Section 6.1 of the online Robustness Appendix contains more details on descriptive statistics of FVIX as compared to standard asset-pricing factors. See also the Data section above for details on how FVIX is constructed and Table 4 below for its risk premium and exposure to other factors.

market factor and LMH, the return differential between low and high turnover firms. One can observe that in the updated sample LMH works as well as it worked in the original studies by Eckbo and Norli (2005) and Butler and Wan (2010), and also that LMH works almost exactly as well as the volatility risk factor in the third column.

The negative turnover beta of new issues is interpreted by Eckbo and Norli (2005) and Butler and Wan (2010) as evidence that new issues are high-liquidity firms, and their high liquidity is the explanation of their low expected returns. The previous section, however, revealed that post-issue liquidity is similar to liquidity of peer firms.

Thus, the only thing we can conclude from the negative turnover betas of new issues is that new issues are similar to high turnover firms. Why, then, do high turnover firms earn low expected returns and why does LMH explain the new issues puzzle, if not because it captures liquidity? The rest of this section will provide an answer to that.[35]

4.2 Turnover Factor and Volatility Risk Factor: A Horse Race

Table 4 performs a horse race between LMH and FVIX by regressing them one on the other. Panel A shows that LMH has significantly positive alphas of 48.1 bp and 47.5 bp per month in the CAPM and Fama-French model, but adding FVIX to the CAPM (Fama-French model) reduces the alpha to -5 bp and 11 bp per month. The FVIX beta of LMH is negative and significant, indicating that the positive CAPM/Fama-French alphas

[35] An important difference between the volatility risk explanation and liquidity explanation of the new issues puzzle is that the former is a "firm-type" explanation and the latter is a "risk-shifting" explanation. Eckbo and Norli (2005) and Butler and Wan (2010) suggest that the event of issuing changes the firm by attracting more attention to it, broadening ownership and thereby making the firm more liquid and its expected return smaller. The volatility risk explanation leans on the Brav *et al.* (2000) finding that it is small growth firms that issue equity. The volatility risk explanation shows that small growth firms are hedges against volatility risk, and thus new issues are hedges too: not because issuing changes the firm, but because a certain type of firms choose to issue. Bessembinder and Zhang (2013) and Bessembinder *et al.* (2019) support the latter view coming from a different angle. They show that performance of new issues is no different than performance of non-issuing firms comparable in terms of a number of characteristics, including market-to-book and idiosyncratic volatility.

of LMH can be explained by the tendency of LMH to perform worse than expected when expected market volatility (VIX) increases.

According to Barinov (2014), the negative FVIX beta of LMH is caused by the fact that high turnover firms are high disagreement firms, and high disagreement firms are hedges against volatility risk. When market volatility increases, average disagreement in the economy also increases (see Barinov, 2013) and higher disagreement makes option-like equity more valuable (Grullon *et al.*, 2012) and less risky (Johnson, 2004). These effects are naturally stronger for high disagreement firms. Thus, high disagreement firms, and in particular high turnover firms, are hedges against volatility risk. The LMH factor shorts those firms and therefore is exposed to volatility risk.

In Panel B of Table 4, I test whether LMH can explain FVIX returns. This is essentially a "covariance vs. characteristic" test: if there is a factor structure in returns due to (mis)pricing of high turnover firms, and FVIX somehow picks up this factor structure, FVIX will explain LMH and vice versa.[36] Panel B, however, shows that it is not the case: adding LMH to either CAPM or Fama-French model reduces the alpha of FVIX by 7–12 bp per month and leaves it statistically significant.

I conclude from Table 4 that FVIX wins the horse race with LMH: volatility risk can explain the alpha of LMH, but not the other way around. Interpreting Table 4 as a spanning test in the spirit of Barillas and Shanken (2017), I conclude that volatility risk is a broader phenomenon, and the alpha of LMH is just one of its manifestations. I also conclude that LMH is unlikely to pick up liquidity pricing, since FVIX betas are unrelated to liquidity (Barinov, 2014), and hence, if there had been a liquidity component to LMH,

[36] A more traditional "covariance vs. characteristic" test is a horse race between turnover and FVIX beta in Fama-MacBeth regressions. Barinov (2014) performs this test and finds that FVIX beta wins the race.

FVIX would not have been able to explain the alpha of LMH completely, as it does in Panel A.[37]

4.3 Cross-Section of the New Issues Puzzle Refutes Its Liquidity Explanation

Several studies, starting with Loughran and Ritter (1997) and Eckbo *et al.* (2000), document that new issues performed by small firms and growth firms underperform more. This evidence seems to contradict the liquidity explanation of the new issues puzzle, because a priori one would expect smaller companies and growth firms to be less liquid than large and value firms. Even if small and growth new issues witness larger increases in liquidity (untabulated results show that they do not), factor models benchmark both large and small new issues against "equally risky firms." Hence, in order for a liquidity factor to explain why large new issues have less negative CAPM/Fama-French alphas than small new issues, small new issues have to be more liquid than large new issues, not only small new issues peers.

Table 5 sorts new issues into three size and three market-to-book groups (based on NYSE size and market-to-book breakpoints) and looks at median liquidity in each group using the trading costs measures from Tables 1 and 2. Expectedly, all liquidity measures unanimously agree than smaller new issues are less liquid. The difference is always highly significant both statistically and economically: new issues from the smallest size group (bottom 30% among NYSE firms) have 1.5 to 3 times larger zero-return frequency, roughly twice higher effective bid-ask spread, and almost two orders of magnitude greater price

[37]Sections 6.2 and 6.3 of the online Robustness Appendix also find similar evidence with FVIX and RMW: consistent with Barinov (2020), FVIX can explain RMW, but not the other way around. This overlap between FVIX and RMW is responsible for the success of the new five-factor Fama and French (2015) model in explaining alphas of IPOs and potentially SEOs (but alphas of not convertible debt issues, which remain unexplained).

impact.

The sorts on market-to-book also reveal that new issues by growth firms are less liquid than those by value firms, even though the liquidity gap is not as great as in the case of size sorts and is sometimes marginally significant or even insignificant. Taking IPOs as an example, growth IPOs have price impact about 80% higher than that of value IPOs, and effective bid-ask spread 36% to 70% higher, depending on the measure I use. The zero-return frequency, however, is slightly lower for growth IPOs, but the difference is marginally significant.

The conclusion from Table 5 is that small new issues are clearly the least liquid new issues, and growth new issues are also visibly less liquid than value new issues. Hence, a liquidity factor, if it indeed captures liquidity, cannot explain why small and growth new issues have the most negative alphas of all new issues. The prediction of the liquidity explanation of the new issues puzzle would be completely opposite: that value and large new issues should have the most negative alphas, contrary to what previous studies (Loughran and Ritter, 1997; Eckbo *et al.*, 2000; Brav *et al.*, 2000) find.

In addition, Table 5 also looks at turnover across size and market-to-book new issues groups and finds that median turnover of new issues is largely unrelated to either size or market-to-book. Hence, even if LMH is picking up some turnover-related factor structure in returns and uses it to explain the new issues puzzle, LMH should not help to explain the cross-section of the new issues puzzle.

In Table 6, I examine the cross-section of the new issues puzzle by first looking at CAPM monthly alphas in the same sorts of new issues on size and market-to-book. Consistent with the literature, I find that growth new issues indeed have more negative alphas than value new issues. The difference is at 68 bp (86 bp) per month, t-statistics 2.61 (2.13) for IPOs in Panel A (convertible debt issuers in Panel C), and the CAPM alpha of value IPOs and convertible debt issuers is close to zero and insignificant. For SEOs in Panel B, the pattern in the alphas is weaker, but still growth SEOs are the only ones that have a significantly negative alpha, which is more than double that of value SEOs.

In the size sorts, the pattern is not as strong. First, the CAPM alpha differential between small and large new issues is only significant for convertible debt issuers, but not for IPOs and SEOs. Yet, for SEOs one can discern a relation between alphas and size, because the CAPM alphas of large SEOs are marginally significant at the 10% level, while the CAPM alphas of small SEOs are highly significant. For IPOs though, the alphas are flat across the size groups.

In the next two rows of Table 6, I show that controlling for FVIX perfectly resolves the severe underperformance of small and growth new issues, largely explains the dependence of the new issues alphas on size and market-to-book, and reveals a strong pattern in FVIX betas. This suggests that small and growth new issues are significantly better hedges against volatility risk than other kinds of new issues.

The volatility risk explanation of the new issues puzzle can explain the evidence in Table 6. Barinov (2012) argues that volatile option-like firms are the best hedges against volatility risk, because higher average volatility in recessions, holding everything else fixed, improves the value of option-like equity and also reduces its systematic risk by making the option less responsive to the value of the underlying asset.[38] This effect is expectedly greater for high volatility firms: if volatility increases from tiny to small, it is unlikely to have an impact on the option-like equity's value and/or risk, but if volatility goes from high to huge, the effect will naturally be greater. Small new issues have higher volatility,

[38]The latter follows from the well-known result that the elasticity of an option value with respect to the value of the underlying asset decreases in volatility.

and growth new issues are more option-like, hence both have more negative CAPM alphas and more positive FVIX betas.

The last two rows in Table 6 consider the "liquidity CAPM" with the market factor and LMH and find that LMH works exactly as FVIX in explaining the cross-section of the new issues puzzle. Most strikingly, LMH is able to explain why the new issues puzzle is stronger for small and growth firms, and this ability comes from very negative LMH betas of small and growth new issues, which are significantly more negative than LMH betas of other new issues.

The extremely negative LMH betas of small/growth new issues suggest that small and growth new issues should be extremely high turnover (allegedly very liquid) firms. That is puzzling because Table 5 reveals that small and growth new issues are not high turnover firms. Further, small/growth new issues are relatively illiquid, and the liquidity interpretation of LMH suggested in the literature would interpret the negative LMH betas as evidence of "superior liquidity" of small and growth new issues.

To sum up, Table 6 shows that LMH mirrors the behavior of FVIX in explaining the cross-section of the new issues puzzle, but this mirroring produces LMH loadings that are inconsistent with either the liquidity interpretation of LMH or the evidence in Table 5 that small and growth new issues are relatively illiquid. Thus, it appears that the explanatory power of LMH stems from the fact that LMH picks up volatility risk rather than liquidity.

4.4 Liquidity Explanation for Related Puzzles?

Brav *et al.* (2000) point out that about one-half of IPOs and one-quarter of SEOs come from the smallest growth (SG) portfolio in the five-by-five sorts on size and market-to-book. SG portfolio is known since at least Fama and French (1993) to have very negative alphas (so-called small growth puzzle), and Brav *et al.* (2000) show that performance of IPOs and SEOs that fall into the SG portfolio does not differ from the performance of this portfolio as a whole. The top row of Table 7 starts with looking at CAPM alphas, Fama and French (1993) alphas, and Carhart (1997) alphas of SG and finds that in my sample period all of the alphas, except for equal-weighted Carhart alpha, are highly significant and range between -55 bp and -79 bp per month.

In Section 4.2 of online Robustness Appendix, I find that the SG portfolio consists of firms that are significantly less liquid than the average firm in the market, which implies, if LMH is a liquidity factor, that the SG portfolio should load positively on LMH and controlling for LMH will make the negative alpha of SG even worse. Yet, the top row in Table 7 shows that in the data SG loads negatively on LMH and controlling for LMH significantly reduces its alpha.

This result makes sense only if LMH is picking up FVIX, and indeed the top row in Table 7 that the ICAPM with the market factor and FVIX explains the alpha of SG. The FVIX beta of SG is large and positive, consistent with my argument that volatile growth firms provide a hedge against increases in market volatility.

Daniel and Titman (2006) show that issuing equity results in underperformance even if performed through other means than IPOs and SEOs, e.g., through stock grants. They sort firms on difference between growth in their log market cap in the past five years and their log cumulative return in the past five years, and show that firms with the most positive/negative values of this measure (routine equity issuers/retirers) have significantly negative/positive alphas.

In Section 4.2 of online Robustness Appendix, I observe that firms with high cumulative issuance (routine equity issuers) are significantly less liquid than routine equity retirers.

Again, if LMH is truly a liquidity factor, then the high-minus-low cumulative issuance portfolio (CumIss) capturing the cumulative issuance puzzle will load positively on LMH, and controlling for LMH will make the alpha of CumIss worse (more negative).

However, middle row of Table 7 shows that in the data the reverse is true: CumIss has negative LMH beta and controlling for LMH reduces the alpha of CumIss. The alpha of CumIss is reduced even more if I control for FVIX instead, and FVIX beta of CumIss is positive, consistent with routine issuers being small/volatile growth companies (as Barinov, 2012, shows) and thus serving as a hedge against volatility risk.

Similarly, if I form CumIss in different size groups, I find in Section 4.4 of online Robustness Appendix that the cumulative issuance puzzle is stronger for smaller firms, consistent with its volatility risk explanation: smaller issuers are even more volatile than an average issuer. The data support this view showing that FVIX beta of CumIss is more positive if CumIss is formed using smaller firms. However, LMH surprisingly also contributes to explaining the stronger cumulative issuance puzzle for smaller firms, with LMH beta of CumIss formed using smaller firms only being particularly negative, as if small issuers are particularly liquid (which they are not).

Huang and Ritter (2020) look at firms that used external financing at least three times in the past three years and find that such frequent issuers underperform even more than ordinary new issuers, most of which issue equity or debt just once. In the bottom row of Table 7, I find that FVIX largely explains the alpha of frequent issuers. Section 4.5 of online Robustness Appendix also shows that the CAPM alpha of frequent issuers is more negative in the small firms subsample, and that FVIX can also explain the latter evidence.

In the bottom row of Table 7, I also find that in this case LMH again substitutes for FVIX: while its ability to explain the frequent issuers puzzle is weaker than that of

FVIX, LMH betas of frequent issuers are large and negative despite frequent issuers having significantly higher trading costs than a representative Compustat firm. In in Section 4.5 of online Robustness Appendix, the LMH betas of frequent issuers become particularly negative in the small firms subsample.

4.5 New Issues Puzzle, Related Anomalies, and Liquidity Risk

Eckbo and Norli (2005) attempt using Pastor and Stambaugh (2003) tradable liquidity risk factor to explain IPO and SEO alphas in their 1964-1997 sample. They find that SEOs, but not IPOs load significantly on the Pastor-Stambaugh (PS-T) factor, but the loadings of either IPOs or SEOs are no different from those of their size-BM matches. The magnitude of the PS factor betas in Eckbo and Norli (2005) is also economically small, so controlling for the PS-T factor does not have a large effect on the alpha.

Table 8 extends this analysis by looking at all anomalies considered in the paper and including in the analysis several liquidity factors, alone and together with FVIX. The four liquidity factors I use are the tradable PS-T factor used by Eckbo and Norli (return differential between firms with most negative and most positive reaction to increases in market illiquidity), the non-tradable PS-NT factor (innovation to aggregate liquidity series from Pastor and Stambaugh, 2003), and two non-tradable liquidity risk factors from Sadka (2006): one capturing the permanent effect of price impact (S-PV) and the other capturing the transitory effect (S-TF). Positive loadings on all factors mean liquidity risk.

Panel A looks at the Pastor-Stambaugh factors and finds that while the loadings are usually positive, they are never significant. When the liquidity risk factors are used together with FVIX, neither FVIX betas nor liquidity risk betas materially change, suggesting little overlap between FVIX and the liquidity risk factors. It is also interesting that the Pastor-Stambaugh factors reveal no exposure of LMH to liquidity risk.

Panel B looks at the two Sadka factors and arrives to very similar conclusions, with two exceptions: first, LMH seems exposed to liquidity risk according to both factors; second, SG1 is exposed to the transitory (S-TF) liquidity risk factor. Again, FVIX betas do not change much once the liquidity factors are controlled for, so I conclude that there is little overlap between FVIX and liquidity risk.

5 Conclusion

The paper fills an important void in the literature by looking at long-run post-issue liquidity of IPOs, SEOs, and convertible debt issuers and showing that new issues liquidity does not differ from liquidity of non-issuers with similar firm characteristics. I conclude that issuing activity does not result in superior liquidity, thus refuting the liquidity explanation for the new issues puzzle suggested in the literature. I find that the main oversight the liquidity explanation literature makes is taking higher turnover of new issues as evidence that new issues are more liquid. Barinov (2014) shows that turnover is unrelated to liquidity in the full CRSP-Compustat sample.

I also consider other potential ways that issuing firms might use to improve post-issue liquidity, such as underpricing the IPO or engaging a more reputable underwriter. I find that, controlling for drivers of liquidity/trading activity, underpricing or using a high-prestige underwriter does not appear to create additional liquidity, either compared to other new issues or non-issuing firms. My evidence raises doubts about the hypothesis of Booth and Chua (1996) that underpricing makes the issue more liquid by increasing the breadth of ownership, and suggests that the existing evidence supporting Booth and Chua (1996) is likely to be limited to only a few months after the issue.

Lastly, I find strong evidence that the low-minus-high turnover factor (LMH), used by Eckbo and Norli (2005) and Butler and Wan (2010) to explain the new issues puzzle, picks up volatility risk rather than liquidity. In addition to the evidence that new issues are not more liquid than their peers despite having higher turnover, I present four more pieces of evidence supporting my conclusion.

First, the volatility risk factor (FVIX) explains the new issues puzzle just as well as LMH. Second, controlling for FVIX explains the alpha of LMH, but controlling for LMH does not explain the alpha of FVIX. Third, while FVIX can explain why the new issues puzzle is stronger for small and growth firms (prior research, e.g., Barinov, 2013, shows that high disagreement option-like firms are the best hedges against volatility risk, and small/growth new issues are exactly that), LMH is able to do the same, which is counterintuitive. Small/growth new issues are less liquid than large/value new issues, and LMH betas suggest the opposite. Fourth, LMH explains several related puzzles, such as the small growth puzzle and the cumulative issuance puzzle, in the same counterintuitive fashion, suggesting that small growth firms and routine equity issuers are particularly liquid (and they are not). FVIX can also explain those puzzles, but its explanatory power stems from the established fact that small growth firms and routine equity issuers are high disagreement option-like firms, and such firms are hedges against volatility risk.

In other words, I find that the liquidity explanation of the new issues puzzle goes against the direct evidence on liquidity of new issues and seems to work only because LMH picks up volatility risk rather than liquidity. The ability of the turnover factor to pick up volatility risk also has an interesting implication that one can use LMH as a volatility risk factor in the pre-1986 or international samples, for which a reliable measure of expected market volatility (such as VIX) is not available.

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Table 1. Liquidity of Stock and Debt Issuers: Panel Regressions

Panel A presents the slope (B) on one of the IPOs/SEOs/ convertible issuers dummy (IPO equals 1 for three years after IPO, 0 otherwise; SEO and Conv dummies are similarly defined) from panel regressions of liquidity measures on the dummy, as well as size, market-to-book, and industry-year fixed effects (industries are based on the two-digit SIC codes) as controls:

$$Liq_t = a + B \cdot \{IPO;\ SEO;\ Conv\} + C \cdot Size_{t-1} + D \cdot MB_{t-1} + FE \tag{3}$$

Each column presents the slope B on the issuer dummy, the top row labels the columns by which variable is used as the dependent variable, starting with turnover in the first column and then changing to each of five trading cost measures. Turnover is monthly trading volume over shares outstanding. Zero-return frequency is the fraction of days with no price change and zero trading volume in a year. Amihud (2002) measure estimates price impact (in percent of stock price per $1 million trade) by dividing absolute daily return by trading volume and averaging the ratio within a firm-year. Roll (1984) measure, effective bid-ask spread measure of Corwin and Schultz (2012), and effective tick of Holden (2009) estimate effective bid-ask spread (in percent of stock price).

Panels B-D present the slope (B) on the issuer dummy from similar panel regressions with a standard set of liquidity/trading activity drivers from Chordia *et al.* (2007) as controls: in addition to size, market-to-book, and industry-year fixed effects (industries are based on the two-digit SIC codes), the controls include leverage, stock price, current positive and negative returns, as well as beta and age (for SEOs and convertible debt issuers).

$$Liq_t = a + B \cdot \{IPO;\ SEO;\ Conv\} + C \cdot Size_{t-1} + D \cdot MB_{t-1} + E \cdot Controls_{t-1} + FE \tag{4}$$

Detailed definitions of the controls are in online Data Appendix. The t-statistics use standard errors clustered by firm-year-month. The sample period for the regressions in Panels A and B is from January 1986 to December 2017, Panel C (D) re-runs Panel B in the January 1986 to December 2001 (January 2002 to December 2017) subsample.

Panel A. Size and MB as Controls

Panel A1. Post-Issue Liquidity of IPOs

Liq=	**Turn**	**Roll**	**Spread**	**EffTick**	**Amihud**	**Zero**
IPO	0.037	-0.570	0.843	-0.437	-3.860	-0.021
***t*-stat.**	*14.1*	*-6.89*	*18.4*	*-5.79*	*-9.52*	*-6.90*

Panel A2. Post-Issue Liquidity of SEOs

Liq=	**Turn**	**Roll**	**Spread**	**EffTick**	**Amihud**	**Zero**
SEO	0.056	-0.009	0.476	0.025	-1.280	-0.002
***t*-stat.**	*14.3*	*-0.16*	*14.4*	*0.69*	*-5.63*	*-1.49*

Panel A3. Post-Issue Liquidity of Convertible Debt Issuers

Liq=	**Turn**	**Roll**	**Spread**	**EffTick**	**Amihud**	**Zero**
Conv	0.064	0.713	0.455	0.037	-0.018	0.028
***t*-stat.**	*8.57*	*5.29*	*7.90*	*0.49*	*-0.05*	*8.66*

Panel B. Common Set of Controls

Panel B1. Post-Issue Liquidity of IPOs

Liq=	**Turn**	**Roll**	**Spread**	**EffTick**	**Amihud**	**Zero**
IPO	-0.002	0.300	0.457	0.296	-0.075	0.005
***t*-stat.**	*-0.85*	*4.93*	*13.1*	*11.60*	*-0.57*	*2.08*

Panel B2. Post-Issue Liquidity of SEOs

Liq=	**Turn**	**Roll**	**Spread**	**EffTick**	**Amihud**	**Zero**
SEO	0.021	-0.332	-0.014	0.029	-0.473	-0.011
***t*-stat.**	*8.54*	*-8.81*	*-0.64*	*1.92*	*-8.60*	*-9.74*

Panel B3. Post-Issue Liquidity of Convertible Debt Issuers

Liq=	**Turn**	**Roll**	**Spread**	**EffTick**	**Amihud**	**Zero**
Conv	0.034	-0.063	-0.075	-0.042	-0.298	0.007
***t*-stat.**	*4.32*	*-0.93*	*-1.92*	*-1.83*	*-4.69*	*3.30*

Panel C. Full Set of Controls: Early years, 1986–2001

Panel C1. Post-Issue Liquidity of IPOs

Liq=	**Turn**	**EffTick**	**Roll**	**Spread**	**Amihud**	**Zero**
IPO	0.003	0.282	0.506	0.308	-0.129	0.005
***t*-stat.**	*1.95*	*4.28*	*10.6*	*8.55*	*-0.70*	*2.53*

Panel C2. Post-Issue Liquidity of SEOs

Liq=	**Turn**	**EffTick**	**Roll**	**Spread**	**Amihud**	**Zero**
SEO	0.027	-0.310	-0.028	0.031	-0.827	-0.015
***t*-stat.**	*16.4*	*-5.35*	*-0.86*	*1.31*	*-7.98*	*-8.94*

Panel C3. Post-Issue Liquidity of Convertible Debt Issuers

Liq=	**Turn**	**EffTick**	**Roll**	**Spread**	**Amihud**	**Zero**
Conv	0.028	-0.250	-0.194	-0.101	-0.544	0.008
***t*-stat.**	*6.74*	*-2.47*	*-3.73*	*-3.00*	*-4.33*	*2.82*

Panel D. Full Set of Controls: Recent Years, 2002–2017

Panel D1. Post-Issue Liquidity of IPOs

Liq=	**Turn**	**EffTick**	**Roll**	**Spread**	**Amihud**	**Zero**
IPO	-0.034	-0.016	0.163	0.124	-0.254	-0.002
***t*-stat.**	*-5.80*	*-0.44*	*4.66*	*7.24*	*-1.86*	*-3.11*

Panel D2. Post-Issue Liquidity of SEOs

Liq=	**Turn**	**EffTick**	**Roll**	**Spread**	**Amihud**	**Zero**
SEO	0.049	-0.152	0.006	0.052	-0.328	-0.029
***t*-stat.**	*8.29*	*-5.98*	*0.24*	*4.86*	*-1.73*	*-6.25*

Panel D3. Post-Issue Liquidity of Convertible Debt Issuers

Liq=	**Turn**	**EffTick**	**Roll**	**Spread**	**Amihud**	**Zero**
Conv	0.132	-0.059	0.050	0.070	-0.207	-0.001
***t*-stat.**	*5.21*	*-1.35*	*1.15*	*3.30*	*-2.57*	*-1.09*

Table 2. Additional Liquidity Drivers: Venture Capital, Underpricing, and Underwriters

Using the IPOs-only subsample, top rows of Panels A–C present slopes from monthly panel regressions of liquidity measures on the dummy for venture-capital backed IPOs (VC, 1 if the issue is backed by a venture capital firm according to the SDC flag, 0 otherwise), or the dummy for strong underpricing (Under, 1 if the first-day return exceeds the median return among all issues with a positive first-day return, 0 otherwise), or the dummy for a highly reputable underwriter (Rank, 1 if the underwriter's rank is 8 and above in Jay Ritter's data, 0 otherwise), with the Chordia *et al.* (2007) controls (see Table 1) and industry-year fixed effects (industries are based on the two-digit SIC codes):

$$Liq_t = a + B \cdot \{VC;\ Under;\ Rank\} + C \cdot Size_{t-1} + D \cdot MB_{t-1} + E \cdot Controls_{t-1} + FE \quad (5)$$

The middle two rows of each panel augment the panel regression with the inverse Mills ratio from probit regressions (run separately each month) of the dummies on determinants of VC-backing/underpricing/involvement of a high-prestige underwriter. The bottom row of each panel uses, instead of the dummy, the fitted value from the probit regression. Panels D, E present similar slopes on the Rank dummy from the same panel regressions as above performed in SEOs-only subsample and convertible debt issuers-only subsample, respectively. The panel regressions are run for the five liquidity measures defined in the header of Table 1, as well as turnover. All liquidity measures are defined in the header of Table 1, all controls are listed in the header of Table 1 and defined in more detail in online Data Appendix. The t-statistics use standard errors clustered by firm-year-month. The sample period for the regressions is from January 1986 to December 2017.

Panel A. Role of Venture Capitalists for IPOs

Panel A1. Regression on VC Dummy

Liq=	Turn	EffTick	Roll	Spread	Amihud	Zero
VC	0.023	-0.135	0.134	0.216	-0.562	-0.018
***t*-stat.**	*5.04*	*-1.30*	*2.12*	*4.68*	*-2.20*	*-4.89*

Panel A2. Regression with Inverse Mills Ratio

Liq=	Turn	EffTick	Roll	Spread	Amihud	Zero
Mills	-0.031	1.422	0.103	-0.179	1.403	0.047
***t*-stat.**	*-4.96*	*8.18*	*1.12*	*-3.06*	*2.16*	*6.68*
VC	0.016	0.285	0.171	0.196	-0.152	-0.004
***t*-stat.**	*3.71*	*2.48*	*2.34*	*3.75*	*-0.57*	*-1.07*

Panel A3. Regression on Estimated VC Backing Probability

Liq=	Turn	EffTick	Roll	Spread	Amihud	Zero
E(VC)	0.041	0.604	1.499	0.559	2.495	-0.043
***t*-stat.**	*4.75*	*2.77*	*10.8*	*5.27*	*3.78*	*-5.17*

Panel B. Role of Underpricing for IPOs

Panel B1. Regression on Underpricing Dummy

Liq=	Turn	EffTick	Roll	Spread	Amihud	Zero
Under	0.013	0.074	0.163	0.178	-0.186	-0.023
***t*-stat.**	*2.96*	*0.84*	*2.95*	*5.17*	*-1.25*	*-6.79*

Panel B2. Regression with Inverse Mills Ratio

Liq=	Turn	EffTick	Roll	Spread	Amihud	Zero
Mills	-0.034	0.770	0.237	-0.028	1.093	0.040
***t*-stat.**	*-4.67*	*4.17*	*2.49*	*-0.46*	*2.89*	*5.37*
Under	0.010	0.257	0.253	0.204	0.047	-0.013
***t*-stat.**	*1.81*	*2.30*	*3.34*	*4.70*	*0.33*	*-3.07*

Panel B3. Regression on Estimated Underpricing Probability

Liq=	Turn	EffTick	Roll	Spread	Amihud	Zero
E(Under)	0.029	1.667	1.369	0.600	3.169	0.025
***t*-stat.**	*2.20*	*5.92*	*7.83*	*5.60*	*5.48*	*2.59*

Panel C. Role of High-Prestige Underwriters for IPOs

Panel C1. Regression on High-Prestige Dummy

Liq=	Turn	EffTick	Roll	Spread	Amihud	Zero
Rank	-0.010	0.734	0.419	0.166	0.129	0.004
***t*-stat.**	*-2.40*	*6.84*	*6.41*	*3.94*	*0.66*	*0.96*

Panel C2. Regression with Inverse Mills Ratio

Liq=	Turn	EffTick	Roll	Spread	Amihud	Zero
Mills	0.030	-0.092	0.200	0.219	1.025	-0.013
***t*-stat.**	*5.78*	*-0.60*	*2.02*	*2.35*	*2.63*	*-2.24*
Rank	-0.011	0.410	0.188	0.060	-0.084	0.010
***t*-stat.**	*-2.22*	*5.50*	*4.36*	*2.20*	*-1.31*	*4.24*

Panel C3. Regression on Estimated High-Prestige Probability

Liq=	Turn	EffTick	Roll	Spread	Amihud	Zero
E(Rank)	0.011	2.064	1.517	0.900	2.728	0.000
***t*-stat.**	*1.39*	*10.2*	*11.8*	*8.57*	*4.57*	*-0.02*

Panel D. Role of High-Prestige Underwriters for SEOs

Panel D1. Regression on High-Prestige Dummy

Liq=	Turn	EffTick	Roll	Spread	Amihud	Zero
Rank	-0.011	0.410	0.188	0.060	-0.084	0.010
t-stat.	*-2.22*	*5.50*	*4.36*	*2.20*	*-1.31*	*4.24*

Panel D2. Regression with Inverse Mills Ratio

Liq=	Turn	EffTick	Roll	Spread	Amihud	Zero
Mills	0.056	-0.549	0.207	0.288	0.231	-0.066
t-stat.	*3.86*	*-6.43*	*2.88*	*4.31*	*2.13*	*-10.9*
Rank	0.002	0.708	0.290	0.249	0.055	0.008
t-stat.	*0.25*	*9.08*	*6.53*	*6.85*	*1.00*	*2.21*

Panel D3. Regression on Estimated High-Prestige Probability

Liq=	Turn	EffTick	Roll	Spread	Amihud	Zero
E(Rank)	0.015	1.859	0.948	0.514	1.166	0.021
t-stat.	*1.14*	*10.6*	*11.1*	*9.34*	*4.10*	*3.59*

Panel E. Role of High-Prestige Underwriters for Convertible Debt Issuers

Panel E1. Regression on High-Prestige Dummy

Liq=	Turn	EffTick	Roll	Spread	Amihud	Zero
Rank	-0.002	0.137	0.057	0.090	-0.010	0.006
t-stat.	*-0.17*	*1.38*	*0.97*	*2.66*	*-0.40*	*1.31*

Panel E2. Regression with Inverse Mills Ratio

Liq=	Turn	EffTick	Roll	Spread	Amihud	Zero
Mills	0.010	-0.006	0.032	0.053	0.004	-0.003
t-stat.	*2.56*	*-0.24*	*2.04*	*4.33*	*1.30*	*-2.43*
Rank	0.055	0.665	0.280	0.317	-0.039	0.004
t-stat.	*2.85*	*2.92*	*2.24*	*3.27*	*-0.65*	*0.38*

Panel E3. Regression on Estimated High-Prestige Probability

Liq=	Turn	EffTick	Roll	Spread	Amihud	Zero
E(Rank)	0.134	0.803	0.641	0.602	0.046	-0.026
t-stat.	*4.46*	*3.35*	*3.89*	*6.16*	*1.82*	*-1.90*

Table 3. New Issues Puzzle: Volatility Risk and Liquidity Explanations

The table reports the results of fitting several time-series asset-pricing models to monthly returns of the new issues portfolios. The models include the CAPM, the Fama-French model (FF), the CAPM augmented with FVIX (ICAPM), and the CAPM augmented with liquidity factor, LMH (LCAPM).

$$\text{CAPM}: \quad Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) \tag{6}$$

$$\text{FF}: \quad Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t \tag{7}$$

$$\text{ICAPM}: \quad Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{FVIX} \cdot FVIX_t \tag{8}$$

$$\text{LCAPM}: \quad Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{LMH} \cdot LMH_t \tag{9}$$

The new issues portfolios include firms that performed an IPO (Panel A), SEO (Panel B), or issued convertible debt (Panel C) 2 to 37 months ago. FVIX is the factor-mimicking portfolio that tracks the daily changes in VIX. LMH is the portfolio that buys firms in the bottom 20% and shorts firms in the top 20% in terms of turnover. The t-statistics use the Newey-West (1987) correction for autocorrelation and heteroskedasticity. The sample period for the asset-pricing models is from January 1986 to December 2017 (new issues are from December 1982 to November 2017).

	Panel A. IPOs				**Panel B. SEOs**				**Panel C. Convertible Debt**			
	CAPM	**FF**	**ICAPM**	**LCAPM**	**CAPM**	**FF**	**ICAPM**	**LCAPM**	**CAPM**	**FF**	**ICAPM**	**LCAPM**
$\boldsymbol{\alpha}$	-0.494	-0.340	0.109	-0.171	-0.447	-0.419	-0.083	-0.179	-0.607	-0.683	-0.328	-0.357
$\boldsymbol{t}$**-stat.**	*-2.06*	*-2.22*	*0.46*	*-0.77*	*-2.79*	*-4.02*	*-0.47*	*-1.29*	*-3.32*	*-4.98*	*-1.65*	*-2.22*
$\boldsymbol{\beta_{MKT}}$	1.393	1.183	3.166	0.974	1.339	1.214	2.394	0.992	1.380	1.328	2.189	1.057
$\boldsymbol{t}$**-stat.**	*19.4*	*21.6*	*6.35*	*16.0*	*29.7*	*29.1*	*10.0*	*25.4*	*23.7*	*27.4*	*12.5*	*21.9*
$\boldsymbol{\beta_{SMB}}$		1.058				0.845				0.652		
$\boldsymbol{t}$**-stat.**		*9.31*				*9.45*				*8.89*		
$\boldsymbol{\beta_{HML}}$		-0.489				-0.085				0.250		
$\boldsymbol{t}$**-stat.**		*-3.52*				*-0.95*				*3.25*		
$\boldsymbol{\beta_{FVIX}}$			1.338				0.797				0.611	
$\boldsymbol{t}$**-stat.**			*3.88*				*4.53*				*4.66*	
$\boldsymbol{\beta_{LMH}}$				-0.674				-0.558				-0.519
$\boldsymbol{t}$**-stat.**				*-6.59*				*-10.1*				*-9.40*

Table 4. Volatility Risk Factor vs. Turnover-Based Liquidity Factor

Panel A explains monthly returns to the LMH factor using the CAPM, Fama-French models, and their versions augmented with FVIX.

$$\text{CAPM}: \quad LMH_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) \tag{10}$$
$$\text{FF}: \quad LMH_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t \tag{11}$$

Panel B explains monthly returns to the FVIX factor using the CAPM, Fama-French models, and their versions augmented with LMH.

$$\text{CAPM}: \quad FVIX_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) \tag{12}$$
$$\text{FF}: \quad FVIX_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t \tag{13}$$

FVIX is the factor-mimicking portfolio that tracks the daily changes in VIX. LMH is the portfolio that buys/shorts firms in the bottom/top turnover quintile (NYSE quintile breakpoints are used). The t-statistics use the Newey-West (1987) correction for autocorrelation and heteroscedasticity. The sample period is from January 1986 to December 2017.

	Panel A. LMH on FVIX				**Panel B. FVIX on LMH**			
	CAPM	**+FVIX**	**FF**	**+FVIX**	**CAPM**	**+LMH**	**FF**	**+LMH**
$\boldsymbol{\alpha}$	0.481	-0.054	0.475	0.111	-0.463	-0.378	-0.439	-0.375
***t*-stat.**	*2.79*	*-0.32*	*2.99*	*0.74*	*-4.73*	*-4.45*	*-4.00*	*-3.83*
$\boldsymbol{\beta_{MKT}}$	-0.622	-2.181	-0.544	-1.694	-1.325	-1.432	-1.358	-1.430
***t*-stat.**	*-10.0*	*-9.95*	*-9.34*	*-7.02*	*-37.0*	*-55.0*	*-35.2*	*-46.2*
$\boldsymbol{\beta_{SMB}}$			-0.571	-0.425			0.170	0.095
***t*-stat.**			*-9.04*	*-5.99*			*4.94*	*2.52*
$\boldsymbol{\beta_{HML}}$			0.015	-0.046			-0.073	-0.071
***t*-stat.**			*0.17*	*-0.48*			*-1.41*	*-1.35*
$\boldsymbol{\beta_{FVIX}}$		-1.176		-0.847				
***t*-stat.**		*-7.27*		*-5.03*				
$\boldsymbol{\beta_{LMH}}$						-0.172		-0.133
***t*-stat.**						*-6.58*		*-5.47*

Table 5. New Issues Liquidity in Cross-Section

The table presents median liquidity of IPOs, SEOs, and stocks of convertible debt issuers across size and market-to-book groups. The liquidity measures are averaged each month for all issuers that issued stock or convertible debt less than 36 months ago. The size and market-to-book groups are the top 30%, the middle 40%, and the bottom 30%. The market-to-book and size are measured in the month after the issue using SDC data. The size and market-to-book breakpoints are from the NYSE (exchcd=1) population. Sorting on size is conditional on market-to-book. The p-values use the Newey-West (1987) correction for autocorrelation and heteroscedasticity. The sample period for the asset-pricing models is from January 1986 to December 2017 (new issues are from December 1982 to November 2017).

Panel A. Liquidity of IPOs Across Size and Market-to-Book Sorts

	Small	**Med**	**Big**	**S-B**	***p*-value**		**Value**	**Neut**	**Growth**	**G-V**	***p*-value**
Turn	0.092	0.104	0.129	0.037	0.074	**Turn**	0.072	0.089	0.105	0.033	0.013
Amihud	0.329	0.020	0.022	-0.307	0.054	**Amihud**	0.166	0.184	0.303	0.137	0.174
Zero	0.126	0.116	0.082	-0.044	0.002	**Zero**	0.133	0.135	0.116	-0.017	0.074
Roll	2.241	1.414	1.256	-0.985	0.000	**Roll**	1.532	1.905	2.288	0.756	0.000
Spread	1.410	0.900	0.710	-0.700	0.000	**Spread**	0.872	1.151	1.482	0.610	0.000
EffTick	2.995	1.815	1.435	-1.560	0.001	**EffTick**	2.281	2.571	3.091	0.809	0.020

Panel B. Liquidity of SEOs Across Size and Market-to-Book Sorts

	Small	Med	Big	S-B	*p*-value		Value	Neut	Growth	G-V	*p*-value
Turn	0.119	0.142	0.132	-0.014	0.085	**Turn**	0.099	0.118	0.146	-0.047	0.000
Amihud	0.104	0.008	0.002	0.101	0.000	**Amihud**	0.034	0.030	0.021	0.013	0.086
Zero	0.111	0.077	0.056	0.055	0.000	**Zero**	0.110	0.094	0.081	0.029	0.005
Roll	1.908	1.254	1.016	0.892	0.000	**Roll**	1.343	1.326	1.658	-0.315	0.039
Spread	1.223	0.718	0.574	0.648	0.000	**Spread**	0.743	0.754	1.071	-0.328	0.001
EffTick	2.337	1.173	0.817	1.520	0.000	**EffTick**	1.666	1.442	1.588	0.078	0.291

Panel C. Liquidity of Convertible Debt Issuers Across Size and Market-to-Book Sorts

	Small	Med	Big	S-B	*p*-value		Value	Neut	Growth	G-V	*p*-value
Turn	0.170	0.183	0.153	0.017	0.442	**Turn**	0.153	0.153	0.182	-0.028	0.045
Amihud	0.076	0.006	0.001	0.075	0.031	**Amihud**	0.032	0.023	0.010	0.022	0.078
Zero	0.114	0.079	0.048	0.067	0.002	**Zero**	0.102	0.094	0.075	0.027	0.021
Roll	1.747	1.265	1.038	0.709	0.000	**Roll**	1.408	1.241	1.398	0.010	0.924
Spread	1.017	0.769	0.596	0.421	0.000	**Spread**	0.810	0.705	0.816	-0.006	0.917
EffTick	2.269	1.237	0.744	1.525	0.001	**EffTick**	1.727	1.541	1.320	0.407	0.027

Table 6. New Issues Puzzle in Cross-Section

The table presents the results of estimating various asset-pricing models for the IPO and SEO portfolios in different size and market-to-book groups. The models are fitted to monthly returns and include the CAPM, the CAPM augmented with FVIX (ICAPM), and the CAPM augmented with liquidity factor, LMH (LCAPM):

$$\begin{aligned} \text{CAPM}: \quad Ret_t - RF_t &= \alpha_{CAPM} + \beta_{MKT} \cdot (MKT_t - RF_t) && (14) \\ \text{ICAPM}: \quad Ret_t - RF_t &= \alpha_{ICAPM} + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{FVIX} \cdot FVIX_t && (15) \\ \text{LCAPM}: \quad Ret_t - RF_t &= \alpha_{LCAPM} + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{LMH} \cdot LMH_t && (16) \end{aligned}$$

FVIX is the factor-mimicking portfolio that tracks the daily changes in VIX. LMH is the portfolio that buys/shorts firms in the bottom/top turnover quintile (NYSE quintile breakpoints are used). The IPO and SEO portfolios include the returns to all IPOs/SEOs performed 2 to 37 months ago. The size and market-to-book groups are the top 30%, the middle 40%, and the bottom 30%. The market-to-book and size are measured in the month after the issue using SDC data. The size and market-to-book breakpoints are from the NYSE (exchcd=1) population. Sorting on size is conditional on market-to-book. The t-statistics use the Newey-West (1987) correction for autocorrelation and heteroscedasticity. The sample period for the asset-pricing models is from January 1986 to December 2017 (new issues are from December 1982 to November 2017).

Panel A. Performance of IPOs Across Size and Market-to-Book Sorts

	Small	Med	Big	S-B		Value	Neut	Growth	G-V
α_{CAPM}	-0.518	-0.648	-0.526	0.008	α_{CAPM}	-0.025	-0.249	-0.704	-0.679
t-stat.	*-1.99*	*-2.62*	*-2.14*	*0.02*	t-stat.	*-0.12*	*-1.07*	*-2.39*	*-2.61*
α_{ICAPM}	0.108	-0.077	-0.300	0.408	α_{ICAPM}	0.269	0.216	0.033	-0.237
t-stat.	*0.41*	*-0.33*	*-1.22*	*1.37*	t-stat.	*1.16*	*0.87*	*0.11*	*-0.93*
β_{FVIX}	1.375	1.305	0.529	0.846	β_{FVIX}	0.719	1.009	1.625	0.906
t-stat.	*3.85*	*4.18*	*1.90*	*1.50*	t-stat.	*3.08*	*4.69*	*3.81*	*3.57*
α_{LCAPM}	-0.194	-0.320	-0.339	0.145	α_{LCAPM}	0.197	0.051	-0.354	-0.551
t-stat.	*-0.80*	*-1.43*	*-1.62*	*0.45*	t-stat.	*1.00*	*0.24*	*-1.29*	*-2.17*
β_{LMH}	-0.674	-0.683	-0.389	-0.285	β_{LMH}	-0.462	-0.625	-0.728	-0.267
t-stat.	*-6.46*	*-5.18*	*-4.75*	*-2.03*	t-stat.	*-5.19*	*-6.90*	*-6.49*	*-3.82*

Panel B. Performance of SEOs Across Size and Market-to-Book Sorts

	Small	Med	Big	S-B		Value	Neut	Growth	G-V
$\boldsymbol{\alpha_{CAPM}}$	-0.497	-0.367	-0.236	-0.261	$\boldsymbol{\alpha_{CAPM}}$	-0.220	-0.276	-0.536	-0.316
***t*-stat.**	*-2.53*	*-2.33*	*-1.68*	*-1.35*	***t*-stat.**	*-1.11*	*-1.52*	*-2.70*	*-1.32*
$\boldsymbol{\alpha_{ICAPM}}$	-0.070	-0.025	-0.184	0.113	$\boldsymbol{\alpha_{ICAPM}}$	-0.084	-0.069	0.003	0.087
***t*-stat.**	*-0.33*	*-0.14*	*-1.12*	*0.48*	***t*-stat.**	*-0.39*	*-0.37*	*0.01*	*0.33*
$\boldsymbol{\beta_{FVIX}}$	0.923	0.742	0.123	0.800	$\boldsymbol{\beta_{FVIX}}$	0.313	0.456	1.173	0.860
***t*-stat.**	*4.32*	*3.63*	*0.56*	*2.21*	***t*-stat.**	*2.47*	*3.01*	*4.02*	*2.65*
$\boldsymbol{\alpha_{LCAPM}}$	-0.212	-0.101	-0.089	-0.123	$\boldsymbol{\alpha_{LCAPM}}$	-0.022	-0.056	-0.225	-0.203
***t*-stat.**	*-1.17*	*-0.77*	*-0.67*	*-0.61*	***t*-stat.**	*-0.11*	*-0.34*	*-1.25*	*-0.82*
$\boldsymbol{\beta_{LMH}}$	-0.593	-0.552	-0.305	-0.288	$\boldsymbol{\beta_{LMH}}$	-0.412	-0.458	-0.647	-0.235
***t*-stat.**	*-9.4*	*-9.07*	*-4.30*	*-2.99*	***t*-stat.**	*-5.61*	*-9.81*	*-8.75*	*-2.88*

Panel C. Performance of Convertible Debt Issuers Across Size and Market-to-Book Sorts

	Small	Med	Big	S-B		Value	Neut	Growth	G-V
$\boldsymbol{\alpha_{CAPM}}$	-0.760	-0.688	-0.162	-0.598	$\boldsymbol{\alpha_{CAPM}}$	-0.056	-0.256	-0.921	-0.865
***t*-stat.**	*-2.79*	*-3.16*	*-0.95*	*-2.27*	***t*-stat.**	*-0.13*	*-1.03*	*-4.66*	*-2.13*
$\boldsymbol{\alpha_{ICAPM}}$	-0.336	-0.300	-0.106	-0.230	$\boldsymbol{\alpha_{ICAPM}}$	0.001	-0.085	-0.534	-0.535
***t*-stat.**	*-1.19*	*-1.19*	*-0.60*	*-0.74*	***t*-stat.**	*0.00*	*-0.34*	*-2.40*	*-1.48*
$\boldsymbol{\beta_{FVIX}}$	0.939	0.847	0.119	0.820	$\boldsymbol{\beta_{FVIX}}$	0.143	0.383	0.842	0.700
***t*-stat.**	*3.18*	*5.27*	*0.67*	*2.38*	***t*-stat.**	*0.40*	*1.62*	*4.90*	*1.82*
$\boldsymbol{\alpha_{LCAPM}}$	-0.514	-0.381	0.001	-0.515	$\boldsymbol{\alpha_{LCAPM}}$	0.121	-0.029	-0.660	-0.781
***t*-stat.**	*-2.03*	*-1.90*	*0.01*	*-1.96*	***t*-stat.**	*0.31*	*-0.13*	*-3.66*	*-2.00*
$\boldsymbol{\beta_{LMH}}$	-0.513	-0.638	-0.340	-0.173	$\boldsymbol{\beta_{LMH}}$	-0.368	-0.473	-0.542	-0.174
***t*-stat.**	*-5.36*	*-8.17*	*-4.37*	*-1.40*	***t*-stat.**	*-2.29*	*-5.05*	*-8.86*	*-0.99*

Table 7. Explaining Related Puzzles

The table presents alphas and FVIX/LMH betas from the following nine models (other betas are not reported for brevity):

$$\text{CAPM}: \quad Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) \tag{17}$$

$$\text{FF3}: \quad Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t \tag{18}$$

$$\text{Carh}: \quad Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t + \beta_{MOM} \cdot MOM_t \tag{19}$$

$$\text{ICAPM}: \quad Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{FVIX} \cdot FVIX_t \tag{20}$$

$$\text{Carh} + \text{V}: \quad Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t + \beta_{MOM} \cdot MOM_t + \beta_{FVIX} \cdot FVIX_t \tag{21}$$

$$\text{LCAPM}: \quad Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{LMH} \cdot LMH_t \tag{22}$$

The dependent variables in the models are returns to portfolios indicated in the first column of each panel. *SG* is the intersection of bottom size quintile and top market-to-book quintile. *CumIss* is the portfolio that in the top 30% and shorts firms in the bottom 30% in terms of cumulative issuance. Cumulative issuance is the log market value growth minus the cumulative log return in the past five years. *FreqIss* is the portfolio of firms that have performed at least three issues of debt or equity in the past three years that exceed, in term of proceeds, 5% of total assets and 3% of market value of equity. *LMH* is the portfolio that buys firms in the bottom 20% and shorts firms in the top 20% in terms of turnover. When *Cumiss* is used as a dependent variable, RF is not deducted from its returns. FVIX is the factor-mimicking portfolio that tracks the daily changes in VIX. The t-statistics use the Newey-West (1987) correction for autocorrelation and heteroscedasticity. The sample period is from January 1986 to December 2017.

Panel A. Value-Weighted Returns

	α_{CAPM}	α_{FF3}	α_{Carh}	α_{ICAPM}	β_{FVIX}	α_{Carh+V}	β_{FVIX}	α_{LCAPM}	β_{LMH}
SG	-0.788	-0.631	-0.545	-0.065	1.580	-0.377	0.378	-0.498	-0.602
t-stat	*-3.15*	*-4.32*	*-3.71*	*-0.18*	*3.03*	*-2.55*	*4.01*	*-1.90*	*-4.50*
CumIss	-0.717	-0.654	-0.567	-0.474	0.539	-0.453	0.257	-0.548	-0.352
t-stat	*-6.11*	*-7.32*	*-6.76*	*-3.59*	*3.39*	*-4.70*	*2.36*	*-5.30*	*-11.55*
FreqIss	-0.350	-0.374	-0.221	-0.094	0.563	-0.088	0.298	-0.144	-0.451
t-stat	*-2.13*	*-2.34*	*-1.26*	*-0.53*	*4.41*	*-0.50*	*2.55*	*-1.00*	*-8.25*

Panel B. Equal-Weighted Returns

	α_{CAPM}	α_{FF3}	α_{Carh}	α_{ICAPM}	β_{FVIX}	α_{Carh+V}	β_{FVIX}	α_{LCAPM}	β_{LMH}
SG	-0.682	-0.551	-0.256	-0.007	1.488	-0.073	0.412	-0.311	-0.773
t-stat	*-2.24*	*-2.59*	*-0.99*	*-0.02*	*3.94*	*-0.28*	*2.62*	*-1.01*	*-5.24*
CumIss	-0.740	-0.610	-0.469	-0.341	0.869	-0.331	0.312	-0.512	-0.475
t-stat	*-4.27*	*-4.99*	*-3.84*	*-1.62*	*3.12*	*-2.53*	*2.55*	*-3.09*	*-6.24*
FreqIss	-0.664	-0.681	-0.422	-0.210	0.996	-0.332	0.200	-0.333	-0.728
t-stat	*-2.50*	*-3.51*	*-2.17*	*-0.73*	*4.10*	*-1.75*	*1.19*	*-1.42*	*-9.34*

Table 8. New Issues Puzzle, Related Anomalies, and Liquidity Risk

The table presents FVIX betas and loadings on liquidity risk factors from the following nine models:

$$\text{Model1}: \quad Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{FVIX} \cdot FVIX_t \tag{23}$$
$$\text{Model2}: \quad Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{PS-T} \cdot PS - T_t \tag{24}$$
$$\text{Model3}: \quad Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{FVIX} \cdot FVIX_t + \beta_{PS-T} \cdot PS - T_t \tag{25}$$
$$\text{Model4}: \quad Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{PS-NT} \cdot PS - NT_t \tag{26}$$
$$\text{Model5}: \quad Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{FVIX} \cdot FVIX_t + \beta_{PS-NT} \cdot PS - NT_t \tag{27}$$
$$\text{Model6}: \quad Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{S-PV} \cdot S - PV_t \tag{28}$$
$$\text{Model7}: \quad Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{FVIX} \cdot FVIX_t + \beta_{S-PV} \cdot S - PV_t \tag{29}$$
$$\text{Model8}: \quad Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{S-TF} \cdot S - TF_t \tag{30}$$
$$\text{Model9}: \quad Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{FVIX} \cdot FVIX_t + \beta_{S-TF} \cdot S - TF_t \tag{31}$$

PS-T (PS-NT) is Pastor and Stambaugh (2003) tradable (non-tradable) factor, S-PV is Sadka (2006) permanent-variable factor, S-TF is Sadka (2006) transitory-fixed factor. The number of the model where the betas come from is indicated in the top row of each panel. The dependent variables in the models are returns to portfolios indicated in the first column of each panel. *SG* is the intersection of bottom size quintile and top market-to-book quintile. *IPO/SEO/Conv* is a portfolio of firms that performed an IPO/SEO/issued convertible debt 2 to 37 months ago. *CumIss* is the portfolio that in the top 30% and shorts firms in the bottom 30% in terms of cumulative issuance. Cumulative issuance is the log market value growth minus the cumulative log return in the past five years. *FreqIss* is the portfolio of firms that have performed at least three issues of debt or equity in the past three years that exceed, in term of proceeds, 5% of total assets and 3% of market value of equity. *LMH* is the portfolio that buys firms in the bottom 20% and shorts firms in the top 20% in terms of turnover. When *Cumiss* and *LMH* are used as dependent variables, RF is not deducted from their returns. FVIX is the factor-mimicking portfolio that tracks the daily changes in VIX. The t-statistics use the Newey-West (1987) correction for autocorrelation and heteroscedasticity. The sample period is from January 1986 to December 2017.

Panel A. Pastor-Stambaugh Liquidity Risk Factors

	1	2	3		4	5	
	β_{FVIX}	β_{PS-T}	β_{FVIX}	β_{PS-T}	β_{PS-NT}	β_{FVIX}	β_{PS-NT}
SG	1.488	0.044	1.486	0.020	-1.178	1.495	-2.963
t-stat	*3.94*	*0.44*	*3.89*	*0.21*	*-0.21*	*3.98*	*-0.53*
IPO	1.338	0.038	1.336	0.016	-0.161	1.342	-1.716
t-stat	*3.88*	*0.46*	*3.86*	*0.19*	*-0.04*	*3.91*	*-0.40*
SEO	0.797	0.034	0.794	0.022	-0.784	0.801	-1.774
t-stat	*4.53*	*0.58*	*4.45*	*0.38*	*-0.21*	*4.67*	*-0.49*
Conv	0.508	0.013	0.517	0.003	-1.152	0.512	-1.761
t-stat	*3.56*	*0.23*	*3.39*	*0.05*	*-0.32*	*3.57*	*-0.51*
CumIss	0.869	0.027	0.867	0.013	-0.908	0.873	-2.004
t-stat	*3.12*	*0.50*	*3.07*	*0.27*	*-0.33*	*3.14*	*-0.80*
FreqIss	0.996	0.026	0.995	0.012	1.242	0.996	0.107
t-stat	*4.10*	*0.29*	*4.01*	*0.14*	*0.26*	*4.15*	*0.02*
LMH	-0.342	-0.053	-0.337	-0.048	2.258	-0.348	2.684
t-stat	*-2.79*	*-1.31*	*-2.74*	*-1.26*	*0.80*	*-2.69*	*0.91*

Panel B. Sadka Liquidity Risk Factors

	1	6	7		8	9	
	β_{FVIX}	β_{S-PV}	β_{FVIX}	β_{S-PV}	β_{S-TF}	β_{FVIX}	β_{S-TF}
SG	1.488	0.215	1.607	-0.241	4.072	1.573	3.535
t-stat	*3.94*	*0.27*	*3.95*	*-0.29*	*2.02*	*3.79*	*2.21*
IPO	1.338	0.278	1.406	-0.128	2.370	1.387	1.884
t-stat	*3.88*	*0.43*	*3.72*	*-0.19*	*1.55*	*3.63*	*1.47*
SEO	0.797	0.365	0.790	0.145	0.866	0.790	0.602
t-stat	*4.53*	*0.95*	*4.71*	*0.37*	*0.94*	*4.73*	*0.80*
Conv	0.508	0.225	0.552	0.069	-0.278	0.558	-0.470
t-stat	*3.56*	*0.54*	*3.49*	*0.19*	*-0.40*	*3.53*	*-0.69*
CumIss	0.869	-0.276	0.979	-0.545	0.929	0.955	0.614
t-stat	*3.12*	*-0.67*	*3.28*	*-1.34*	*1.06*	*3.15*	*0.82*
FreqIss	0.996	0.722	1.009	0.435	3.624	1.000	3.281
t-stat	*4.10*	*1.31*	*4.56*	*0.82*	*2.40*	*4.39*	*2.67*
LMH	-0.342	0.477	-0.321	0.567	0.902	-0.308	1.007
t-stat	*-2.79*	*1.81*	*-2.37*	*2.35*	*2.39*	*-2.35*	*2.97*