Supplementary Tests for Stock Liquidity and Issuing Activity

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Abstract

This document collects robustness checks and supplementary tests for the paper "Stock Liquidity and Issuing Activity". Section 1 compares post-issue liquidity of issuing firms with liquidity of matching firms separately for each post-issue year. Section 2 does the same for several classes of new issues (underpriced and not underpriced IPOs, IPOs backed and not backed by venture capital, new issues with high-prestige underwriters). Section 3 looks at the role of market liquidity and price pressure of mutual funds on post-issue liquidity. Section 4 uses FVIX and the LMH turnover factor to explain the cumulative issuance puzzle, the small growth anomaly, and the recent frequent issuers anomaly from Huang and Ritter (2020). Section 5 looks at distribution of liquidity for new issues and all firms before and after decimalization. Section 6 explores the performance of the new issues puzzle in the five-factor Fama and French (2015) model and in the 21st century subsample. Section 6 also holds descriptive statistics of FVIX and other asset pricing and the horse race between FVIX and CMA/RMW.

1 Liquidity of New Issues vs. Matching Firms in Event Time

1.1 Baseline Result

In Table 1A, I look at median values of five liquidity measures (as well as turnover) for new issues (IPOs, SEOs, and convertible debt issuers) and their size, market-to-book, exchange and pre-issue liquidity matches. The matching is performed first on stock exchange, then on market-to-book and then on size: a non-issuing firm with the minimal difference in market-to-book from the issuing firm is selected and then the market capitalization of the match is required to be within 30% of that of the issuer.[1] The matching is performed once, using post-issue market capitalization and book value from SDC. The results in Table 1A are robust to additionally matching on two-digit SIC code and to using means instead of medians.

In the top left corner of each panel, I look at median turnover and observe that new issues indeed have higher turnover than their peers. The difference in turnover lacks statistical significance for IPOs, but is significant in for the first two post-issue years for SEOs, and is particularly large, though at most marginally significant at the 10% level for convertible debt issuers.

In the sub-panels to the right of the turnover sub-panels, I look at the frequency of non-trading days, i.e., the fraction of days in a year that record both zero return and zero trading volume. Lesmond et al. (1999) show that the zero-return frequency is a good proxy for total trading costs (investors choose not to trade if trading costs are higher than benefits from the trade). I find no significant evidence that zero-return frequency of new

[1] One matching firm can serve as a match for different issuers: for IPOs and convertible debt issuers, that hardly ever happens; for SEOs, about 15% of matches are re-used.

issues is higher than their peers; in fact, negative differences (implying that new issues witness 1 to 5 extra no-trade days per year) dominate the sample, and for IPOs, as well as some in later post-issue years for SEOs and convertible debt issuers, these differences are even statistically significant. [2]

The top right sub-panel looks at the Amihud (2002) measure that estimates price impact. The Amihud measure, by definition, is the average value of the ratio of absolute daily return to daily trading volume (in million dollars). Thus, the Amihud measure is mechanically negatively related to turnover (the ratio of trading volume to shares outstanding). Yet, despite the mechanical relation, I observe no statistically significant difference in the Amihud measures of issuers and their peers. Negative point estimates of the difference (suggesting higher price impact for issuers) are just as common than positive point estimates. This result updates Butler and Wan (2010), who find that convertible debt issuers have lower Amihud ratios than matching firms in 1975-1999, and Bilinski et al. (2012), who find the same for SEOs in 1970-2004 (without matching on exchange).

The bottom part of each panel looks at three measures of effective bid-ask spread: the Roll (1984) measure, the Corwin and Schultz (2012) spread estimate, and the effective tick estimate of Holden (2009). I find that IPOs and SEOs have higher rather than lower post-issue effective spreads, with the differences being statistically significant for IPOs and insignificant for SEOs and hovering around 0.1-0.4% of the stock price depending on the

[2]Liu (2006) suggests a modification of zero-return frequency (LM12 measure), which is a linear combination of zero-return frequency and an inverse of turnover. Since later research of Barinov (2014) shows that turnover is unrelated to liquidity, I refrain from using this modification in the main analysis. In untabulated results though, I find that for new issues LM12 is dominated by zero-return frequency and the results with LM12 measure are similar to the results with zero-return frequency in Table 1A: IPOs have higher average LM12 measure (lower liquidity) than matching firms, and SEOs and convertible debt issuers have average LM12 measure statistically indistinguishable for that of their peers. This evidence suggests that the result in Bilinski et al. (2012), who look only at SEOs in 1970-2004 and find that SEOs in this period do have lower LM12 that size and book-to-market matches, does not apply to IPOs and convertible debt issuers and does not hold for SEOs in the more modern 1986-2017 sample and when firms are additionally matched on stock exchange.

spread measure. For convertible issuers, the point estimates mostly suggest lower bid-ask spreads than those of matching firms, but the difference is never statistically significant.

Another argument against issuing activity resulting in superior liquidity is that one does not generally observe in Table 1A that the liquidity differentials between issuers and their peers become smaller as the issue ages. If issuing activity indeed improves liquidity by attracting more attention and more liquidity trading to the firm, the effect of issuing activity on liquidity should wear off with time.[3]

The totality of the evidence in Table 1A suggests that, outside of turnover, which is a flawed liquidity measure according to Barinov (2014), other liquidity measures do not reveal any consistent evidence that issuers' stock is more liquid than their peers; to the contrary, in most cases I observe somewhat lower liquidity of issuers' stock and this lower liquidity does not seem to be affected by issuing activity. That undermines the main argument in the liquidity explanation of the new issues puzzle in Eckbo and Norli (2005) and Butler and Wan (2010): despite having higher turnover, new issues are not more liquid, and therefore their low expected returns cannot be explained by their superior liquidity.

The economic magnitude of liquidity difference between issuers and their matches is also small. The point estimates in the majority of cases show that new issues are less liquid than matches; even if we purposefully pick a large positive difference (e.g., effective tick for SEOs in the first post-issue year), it results in at most 6% difference (and most liquidity differentials are within 3%). Benchmarking the liquidity differentials to top vs. bottom quintile spreads makes them appear even smaller: for example, the aforementioned difference in effective tick for SEOs, 9.5 bp, is very small compared to 275 bp spread in

[3]For example, Eckbo and Norli, 2005, use turnover as a measure of liquidity and find that in their sample superior turnover of IPOs compared to their peers lasts only three years, and state that this result is expected.

median effective tick between top and bottom effective tick quintiles. Such differences are very unlikely to lead to large differences in cost of capital or costs of raising additional equity: 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.

1.2 Robustness Checks

Table 2A additionally matches on exchange and, in the case of SEOs and convertible debt issuers, on the liquidity measure being compared from the last full year before the issue to exclude the possibility that they are less liquid before the issue than their peers and then become just as liquid, or vice versa. For example, when the post-issue Roll (1984) measures of SEOs and matches are being compared, the Roll measure of the matching firm is required to be within 10% of the Roll measure of the SEO in the pre-issue year; when Amihud (2002) measures are compared, the Amihud measure of the matching firm is required to be within 10% of the Roll measure of the SEO in the pre-issue year.

The results in Table 2A are similar to the ones in Table 1A, with an expected decline in significance due to matching on pre-issue liquidity. For example, both Tables 1A and 2A agree that new issues tend to have higher, not lower effective bid-ask spread than their peers according to all three measures of bid-ask spread. Table 2A, however, finds a lot less significant differences in this case than Table 1A. Similarly, Tables 1A and 2A agree that the frequency of zero-return days is, if anything, larger for new issues than matching firms, but while Table 1A does find several cases of this difference being significant, Table 2A finds almost none. Tables 1A and 2A do agree, however, than the difference in price impact between new issues and their matches is always insignificant and that new issues have significantly higher turnover (in the case of SEOs, the difference is significant).

Tables 3A and 4A split the sample into the pre-decimalization period (1986-2001, Table 3A) and post-decimalization period (2002-2017, Table 4A). Decimalization was completed by the end of January 2001 on NYSE and AMEX; by early April 2001, other exchanges followed. I add the whole 2001, the adjustment year, to the pre-decimalization period.

Splitting the sample is important, because, as the last section of this document records, average zero-return frequency and average Amihud measure are different by an order of magnitude between those two periods, average effective tick measure of Holden (2009) is different by a factor of six and average turnover is different by a factor of three; the same is true about medians and other percentiles.

Compared to the full sample analysis of Table 1A, in Table 3A (1986-2001) I get a cleaner message that new issues have higher, not lower effective bid-ask spread and higher zero-return frequency than their size and market-to-book matches. New issues still have higher turnover, and the difference in price impact is insignificant.

In Table 4A (2002-2017), the signs of the differences between new issues and matches are the same as in Tables 1A and 3A, with the only difference being the lack of significance of the difference in bid-ask spreads (the Roll, 1984, measure and the Corwin and Schultz, 2012, measure) between SEOs and convertible debt issuers vs. their matching non-issuing firms.

2 Do Subsets of New Issues Have Superior Liquidity?

2.1 Can IPOs Achieve Higher Liquidity through Underpricing?

Table 5A uses the data on liquidity in five years after the issue to test the hypothesis of Booth and Chua (1996) that IPOs can "buy" post-issue liquidity with underpricing the issue, since underpricing allows to attract a greater number of investors, and broader ownership promotes liquidity. In terms of underpricing, Table 5A partitions all IPOs in the sample into two groups: the ones with above average underpricing and the ones with below average underpricing or no underpricing at all. Average underpricing is computed in the sample of underpriced IPOs only, that is, in the sample of IPOs that have positive first day return (which is the measure of underpricing I use). In terms of the sample composition, roughly one-quarter of the IPOs in my sample are not underpriced (their first day return is negative), about one-third have above average underpricing, and the rest (42-45% of the sample) are mildly overpriced.[4]

Comparing median liquidity of IPOs in Panel A of Table 5A (extremely underpriced) and Panel B (the rest), I do find that severely underpriced IPOs are more liquid than the rest of IPOs. For example, in the five post-issue years, severely underpriced IPOs have more than twice lower frequency of zero-return days and 3 to 6 times lower price impact. The Roll (1984) measure and the effective bid-ask spread estimate of Corwin and Schultz (2012) do not reveal that severely underpriced IPOs are more liquid than other IPOs, but the effective tick measure of Holden (2009) suggests that severely underpriced IPOs have effective bid-ask spread that is roughly 30% lower than that of the rest of IPOs.

Interestingly enough, when I compare severely underpriced IPOs to the other IPOs, turnover and liquidity measures agree: severely underpriced IPOs, in addition to being more liquid, also have almost twice higher turnover. This is another piece of evidence that supports the argument that if IPOs have higher turnover than peers and turnover is unrelated to liquidity in the full cross-section of stocks, one cannot conclude whether

[4]In untabulated analysis, I tried partitioning the sample into three groups: no underpricing, mild underpricing, and extreme underpricing, but the results suggested 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.

IPOs will be more, less, or equally liquid compared to their peers, and running the tests presented in the paper is necessary.

The main message of Table 5A though is that while it is true that severely underpriced IPOs are more liquid than the rest of IPOs, the difference between liquidity of matching firms in these two IPO subsamples is equally great. As a result, Panel A shows that severely underpriced IPOs are almost exactly as liquid as their matches, and the point estimates of the liquidity differentials almost unanimously suggest that severely underpriced IPOs are somewhat less liquid than their peers, even though no liquidity differential in Panel A is significant (for example, the Roll measure suggests that the effective bid-ask spread of severely underpriced IPOs is by roughly 20% greater than that of their peers, and the effective tick measure places the similar difference at about one-third).

I conclude from Table 5A that IPO underpricing does not create additional liquidity in the long-run, contrary to what Booth and Chua (1996) predict and what the studies discussed above find in the first few months after the issue. Rather, more liquid firms (presumably, larger firms and growth companies) tend to self-select into the extreme underpricing group. Their post-issue liquidity is then similar or slightly below liquidity of their size and book-to-market matches.

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

Table 6A repeats Table 5A by splitting the sample of IPOs into those backed by venture capital, VC, (Panel A) and those that are not (Panel B). I do find traces of evidence that VC-backed IPOs are slightly more liquid than the rest of IPOs (zero-return frequency, the Amihud measure, and effective tick suggest that, while the Roll measure and the Corwin-Schultz measure disagree). However, the liquidity differential between VC-backed IPOs and other IPOs is much smaller than the differential between severely underpriced IPOS and other IPOs observed in Table 2.

Similar to Table 5A, Table 6A finds that VC-backed IPOs are not significantly more liquid than their peers despite having significantly higher turnover. The only possible exception is zero-return frequency, which is somewhat smaller for VC-backed IPOs than for matching firms, with the differential (marginally statistically significant) suggesting three to six extra zero-return days per year for matching firms. The point estimates for the effective bid-ask spread differential (statistically insignificant) lean towards the opposite conclusion that VC-backed IPOs are slightly less liquid than their peers.

Overall, the message from Table 6A is similar to the one from Table 5A: even if VC-backed IPOs are somewhat more liquid than other IPOs, this liquidity differential is there because VC-backed IPOs are more liquid types of firms, not because VC-backing makes them more liquid.

This conclusion is in contrast to Boehme and Çolak (2012) who look only at turnover and the Amihud measure and observe similar evidence to the one presented in Table 6A, but conclude that "VC backing alleviate future liquidity frictions of an IPO" (p. 308), because they compare VC-backed IPOs and the other IPOs, but do not contrast either type of IPOs with matching firms.

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

Table 7A splits the sample of new issues according to the underwriter's reputation. Underpricing and VC-backing are characteristics that are specific to IPOs; in contrast, all new issues (IPOs, SEOs, and convertible debt issues) can and usually 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 rank 8 and 9.[5] The ranking mechanism is described in more detail in Loughran and Ritter (2004) and Carter and Manaster (1990).

Panels A and B of Table 7A consider the liquidity of IPOs with high-prestige and low-prestige underwriters, respectively. Similar to Table 5A, I find that while IPOs with high-prestige underwriters are indeed significantly more liquid (and also have higher turnover) than IPOs with low-prestige underwriters, the same is true for their matching firms, and therefore IPOs with high-prestige underwriters are not more liquid than their peers. I conclude that more liquid firms are coupled with high-prestige underwriters, but issuing equity does not make those firms more liquid - their liquidity stays at the same level as the liquidity of their peers. This conclusion extends Zheng and Li (2008), who find similar evidence looking at the first post-issue year of IPOs.

A similar picture emerges when I look at Panels C and D of Table 7A, which consider liquidity of SEOs with high- and low-prestige underwriters, respectively. The former SEOs are more liquid than the latter by about a third, if one looks at the measures of effective bid-ask spread and zero-return frequency, and an order of magnitude more liquid if one looks at price impact. Yet, the difference in liquidity between SEOs with high- and low-prestige underwriters is similar in the year before the issue. Also, the post-issue (and pre-issue) liquidity of their matching firms differs by almost as much, suggesting that SEOs backed by high-prestige underwriters are more liquid not because being backed by high-prestige underwriters increases liquidity of the firm's shares, but because firms that engage high-prestige underwriters are larger and more liquid to start with.

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

The difference of Panels C and D from Panels A and B is that in Panel C I do observe, in some instances (zero-return frequency, the Amihud measure, the Corwin-Schultz effective bid-ask spread) that SEOs backed by high-prestige underwriters are more liquid than matching firms. However, the difference in liquidity is usually marginally significant and is much weaker in magnitude than the difference between SEO liquidity in Panel C versus Panel D. In several instances, a similar marginally significant difference is observed for SEOs with low-prestige underwriters as well (Panel D: the Corwin-Schultz effective bid-ask spread, zero-return frequency in the first two post-issue years and the Amihud measure). I conclude therefore that while some weak post-issue liquidity improvement is observed for SEOs, it is unrelated to the underwriter's reputation, and SEOs backed by underwriters with better reputation are more liquid than other SEOs only because high-prestige underwriters are engaged by more liquid firms.

Turning to Panels E and F of Table 7A that treat convertible debt issuers with high- and low-prestige underwriters, respectively, I observe that neither of them have higher liquidity than their peers after the issue. I also observe, as in the previous pairs of panels, that convertible debt issuers backed by high-prestige underwriters are significantly more liquid than convertible debt issuers backed by low-prestige underwriters both pre-issue and post-issue. The magnitude of the difference is comparable to what I observe for SEOs and IPOs. I arrive at the same conclusion that post-issue liquidity of convertible debt issuers does not depend on the issuing activity or the choice of underwriter, but rather, larger and more liquid issuers use higher-prestige underwriters.

Overall, the evidence in Table 7A suggests that high-prestige underwriters only perform the screening function in terms of post-issue liquidity. They do select firms that are likely to be more liquid in the long-run, but they do not provide additional liquidity in the long-run (despite them often being the market maker and also providing analyst coverage) and do not make new issues more liquid than matching firms.

Lastly, it is interesting to observe turnover in the top left corner of each panel. First, turnover largely agrees with liquidity measures when it comes to comparing new issues backed by high- and low-prestige underwriters (with the possible exception of the comparison between Panels E and F), indicating that some high turnover firms are indeed more liquid, and thus higher post-issue turnover of new issues may or may not mean higher post-issue liquidity even if turnover is unrelated to liquidity in the full sample of CRSP firms.

Second, in all panels of Table 7A new issues witness a significant post-issue increase in turnover, which, as we discussed above, is not translated into a post-issue increase in liquidity. Thus, my main conclusion that higher post-issue turnover of new issues should not be interpreted as higher liquidity as a result of the issuing activity, holds not only for all new issues, but also in their various subsamples, including those in which a post-issue increase in liquidity would be most likely.

2.4 Alternative Cross-Sectional Regressions

Table 1 in the paper summarizes the analysis in Tables 1A-4A by performing panel regressions of liquidity measures on either market-to-book and size or standard liquidity drivers from Chordia et al. (2007). Table 2 similarly summarizes the analysis in Tables 5A-7A by performing, in IPO-only/SEO-only/convertible debt issues-only sample, similar panel regressions of liquidity measures (only with Chordia et al., 2007, controls) on dummies for VC-backing/underpricing/high-prestige underwriters in the case of IPOs and only the high-prestige underwriter dummy in the case of SEOs and convertible debt issuers.

In Table 8A, I make two changes to the research design in Table 2 in the paper: first, I use the full sample of issuers and non-issuers, regressing liquidity measures on the new issue dummy and one of the dummies for VC-backing/underpricing/high-prestige underwriters. Second, I also report results with only size and market-to-book controls, since most new issues puzzle studies compare liquidity of issuers to their size and market-to-book peers.

Panels A1 and B1 of Table 8A repeat the panel regressions in Table 1 in the paper adding the VC dummy (1 for IPOs backed by venture capital, 0 for all other firms). Since VC-baked IPOs are a subset of all IPOs, the slope on the VC dummy in the presence of the IPO dummy captures incremental long-run liquidity associated with VC-backing. Similar to Table 1 in the paper, Panel A1 of Table 8A uses as controls size and market-to-book only, while Panel B1 adds other controls from Chordia et al. (2007).

The results in Panels A1 and B1 of Table 8A are also similar to the results in Table 2 in the paper: VC-backed IPOs have higher turnover, but the evidence on whether this higher turnover creates extra liquidity is mixed. Four out of six slopes on the VC dummy in the regressions with effective bid-ask spread measures on the left-hand side are positive, even though only one of them is statistically significant. The point estimates from the regressions with price impact (the Amihud measure) on the left-hand side are positive, but, on the other hand, the next column shows that VC-backed IPOs have significantly less no-trade days.

Overall, the conclusion from Panels A1 and B1 is that there is no consistent evidence that VC-backed IPOs enjoy additional liquidity compared to other IPOs. This conclusion is in contrast to Boehme and Çolak (2012) who look only at turnover and the Amihud measure, but conclude that "VC backing alleviate future liquidity frictions of an IPO" (p. 308). Boehme and Çolak compare VC-backed and non-VC-backed IPOs without controlling for any other firm characteristics (such as size, market-to-book, volatility, etc.) and look at average liquidity ranking rather than liquidity itself.

Panels A2 and B2 of Table 8A test the hypothesis of Booth and Chua (1996) using the data on liquidity in three years after the issue. In terms of underpricing, Panels A2 and B2 partition all IPOs in the sample into two groups: the ones with above average underpricing ("Under" dummy variable equals to 1) and the ones with below average underpricing or no underpricing at all (Under=0). Average underpricing is computed in the sample of underpriced IPOs only, that is, in the sample of IPOs that have positive first day return (which is the measure of underpricing I use). In terms of the sample composition, roughly one-quarter of the IPOs in my sample are not underpriced (their first day return is negative), about one-third have above average underpricing, and the rest (42-45% of the sample) are mildly overpriced.[6]

Panels A2 and B2 of Table 8A present evidence that does not seem consistent with underpricing alleviating liquidity in the long-run. Even though turnover is significantly higher for more underpriced IPOs, as both Panel A2 and Panel B2 show, Panel A2, with only size and market-to-book used as controls, presents an even split between negative coefficients on the Under dummy (which imply positive effect of underpricing on liquidity) and positive coefficients. The split is 3 to 2 in favor of the negative slopes, but one of the negative slopes is minuscule and the significance of positive slopes is better. Panel B2, with additional controls, reports positive slopes (less liquidity after more underpricing) throughout, with the exception of the negative slope from the regression with no-trade days (Zero variable) on the left-hand side.

[6] In untabulated analysis, I tried partitioning the sample into three groups: no underpricing, mild underpricing, and extreme underpricing, but the results suggested 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.

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 the studies discussed in the paper find in the first few months after the issue. As 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.

Panels A3 and B3 of Table 8A consider the liquidity of new issues with high-prestige underwriters and introduce the Rank dummy (1 for high-prestige underwriters, 0 otherwise). The first two rows look at IPOs and the signs of the slope on Rank are evenly split: if one looks only at statistically significant slopes, the split is 4 to 4. In the other rows that look at SEOs and convertible debt issuers, the slopes are uniformly positive, suggesting that, all else equal, issuers with high-prestige underwriters have lower, not higher liquidity after the issue.

Overall, the evidence in Panels A3 and B3 of Table 8A and the matching firm analysis suggest that high-prestige underwriters only perform the screening function in terms of post-issue liquidity. They do select firms that are likely to be more liquid in the long-run, but they do not provide additional liquidity in the long-run (despite them often being the market maker and also providing analyst coverage) and do not make new issues more liquid than matching firms.

Lastly, in all parts of Table 8A new issues witness a significant post-issue increase in turnover, which, as discussed above, is not translated into a post-issue increase in liquidity. Thus, my main conclusion that higher post-issue turnover of new issues should not be interpreted as higher liquidity as a result of the issuing activity, holds not only for all new issues, but also in their various subsamples, including those in which a post-issue increase in liquidity would be most likely.

3 Do Market Liquidity and Price Pressure Matter?

Hanselaar et al. (2019) show that issuing activity is positively related to market level of liquidity, measured as market-wide average of individual firms' Amihud ratio. It may be the case that the lack of superior post-issue liquidity is coming from liquid periods, when many firms go public and trading costs for all firms, including issuers, are low, so a significant difference in those does not emerge.

This reasoning is likely to explain why the link between liquidity and issuing is weak, not why it is negative (as it is, e. g., for IPOs in Panel B1). Still, Panel A of Table 9A repeats Panel B of Table 1 in the paper adding the dummy for liquid market (1 if the market-wide average Amihud measure is out of the top quintile in 1986-2017 sample, 0 otherwise) and the product of the dummy for liquid market with the issuance dummy. Thus, the slope on the issuance dummy in Panel A of Table 9A measures the incremental liquidity of issuers in an illiquid market, and the slope on the product of the dummies shows whether this difference in liquidity between issuers and non-issuers is larger if the market is liquid.

Panel A1 (IPOs) finds that it is precisely in illiquid market, when liquidity is allegedly most important, that new issues tend to lack superior liquidity than their peers. All liquidity measures for IPOs suggest that in an illiquid market IPOs are less liquid than peers, though this liquidity differential shrinks as market liquidity improves (which can be partly mechanical: as trading costs become uniformly smaller for all firms, the difference in trading costs between different classes of firms will also likely shrink). For SEOs (Panel A2), positive slopes on the SEO dummy become more numerous and larger compared to

Panel B2 of Table 1 in the paper, but Panel A2 still delivers a mixed result on whether SEOs are more liquid than peers. The result that this difference is more in favor of SEOs in a more liquid market is more clear.

Panel A3, which looks at convertible debt issuers, finds that the slopes on the issuance dummy change in the opposite direction: compared to Panel B3 of Table 1 in the paper, these slopes in Panel A3 uniformly indicate that convertible debt issuers are more liquid than peers when the market as a whole is illiquid, but this superior liquidity generally dissipates as the market becomes more liquid.

Khan et al. (2012) show that firms engage in opportunistic SEOs when their stocks experience positive price pressure caused by inflows into mutual funds that are holding them. Under this scenario, managers are unlikely to be concerned about whether issuance will improve post-issue liquidity and may even accept lower post-issue liquidity if the gains from issuing overpriced equity and doing that fast are large enough. To make sure that my results in Table 1 are not affected by such firms, which can obscure the relation between issuing and post-issue liquidity, Panel B of Table 9A introduces a dummy variable for the firms in the top decile of net buying by mutual funds, as those firms are most likely to be issuing for opportunistic reasons and least likely to be concerned about post-issue liquidity.

In constructing the dummy, labeled *Pressure*, I start with mutual fund flows, defined the standard way, as the change in total net assets that cannot be attributed to returns, and assume that funds in the top flow decile engage in rushed buying and funds in the bottom decile engage in fire sales. Then the shares of the firm sold by funds in the bottom flow decile are deducted from the shares bought by funds in the top flow decile, and Pressure equals one if in the quarter immediately preceding the issue this resulting measure falls into the top decile among all firms (not only SEOs), and zero otherwise. The need for mutual fund flows data (from CRSP) restricts the sample period in Panel D to 1999-2017, and the need for pre-issue trading data excluded IPOs from the analysis.

The slopes on the interaction term of Pressure dummy with SEO dummy (Panel B1) and Conv dummy (Panel B2, convertible bond issues) suggest that opportunistic issuance indeed results in higher post-issue trading costs. Excluding the turnover column, nine out of ten slopes in the other five columns of Panel B of Table 9A are positive and six of them are significant at the 10% level.

In the presence of the interaction term (and with Pressure dummy controlled for), the slopes on the SEO and Conv dummies measure the impact of issuance on post-issue liquidity for those firms that are less likely to issue because of perceived overpricing. These slopes present the sign split just as, if not more ambiguous than that reported in Panel B of Table 1 in the paper. In terms of sign, the split is seven-to-three in favor of lower post-issue trading costs. If one counts only slopes that are significant at the 5% level, the split is four-to-two. In terms of consistency, both SEO and Conv dummies are significantly negative only in the regression with the effective tick measure on the left-hand side, whereas they are both significantly positive in the regression with the Roll measure (another measure of effective bid-ask spread) as the dependent variable.

4 Liquidity Explanation for Related Puzzles?

4.1 Definition of Related Puzzles

This section applies the LMH turnover factor to two puzzles related to the new issues puzzle - the small growth puzzle and the cumulative issuance puzzle - in an effort to corroborate the conclusion of the previous section that the turnover factor mirrors FVIX, the volatility risk factor, and is often related to liquidity in counterintuitive ways.

The small growth puzzle refers to the large and negative alphas of firms at the intersection of the bottom size quintile and the top market-to-book quintile (the smallest growth portfolio) and dates back to at least Fama and French (1993). The smallest growth portfolio since then became known as the most challenging portfolio for asset-pricing models to explain, and Brav et al. (2000) have established the overlap between the small growth puzzle and the new issues puzzle by pointing out that about one-half of IPOs and one-quarter of SEOs come from the smallest growth portfolio and that the performance of IPOs and SEOs that fall into this portfolio does not differ from the performance of this portfolio as a whole.

The cumulative issuance puzzle refers to the observation by Daniel and Titman (2006) that issuing equity results in underperformance even if performed through other means that IPOs and SEOs, e.g., through stock grants. Daniel and Titman sort firms on the 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.

Huang and Ritter (2020) show that frequent issuers of either debt or equity underperform especially severely. Huang and Ritter use cash flow data and look at change in debt and equity computed from Compustat data as the difference between cash flows from issuing and retiring debt and equity. A company is said to have issued debt/equity if change in debt/equity exceeds 5% of total assets in the beginning of the year and 3% of market value of equity in the beginning of the year. If change in debt/equity additionally exceeds 10% of total assets in the beginning of the year, then the firm is said to have performed a large issue of debt/equity. A firm that performed at least three (large) debt or equity issues in the past three years is dubbed frequent (large) issuer.

In this section, I will look at liquidity of small growth firms, routine equity issuers/retirers, and frequent debt/equity issuers and check whether LMH betas are consistent with the liquidity patterns I observe and whether LMH can and should explain the small growth and cumulative issuance puzzles.

4.2 Small Growth Firms, Cumulative Issuance, and Liquidity

In Panel A of Table 10A, I compare median liquidity of firms in the smallest growth portfolio (SG1) and firms in the second smallest growth portfolio (SG2, the intersection of the second size quintile and the top market-to-book quintile, formed using NYSE breakpoints) with median liquidity in the full CRSP-Compustat sample.

Expectedly enough, I find that the smallest growth portfolio consists of firms that are significantly less liquid than the median firm in the market. Effective bid-ask spread of firms in the smallest growth portfolio is at least twice higher than the median bid-ask spread in the market, price impact is ten times higher, and the zero-return frequency is more than twice higher. Firms in the smallest growth portfolio also have roughly three times lower turnover than the median firm in the market.

Because the size sorts use NYSE breakpoints, firms in the second smallest growth quintile (which also have negative CAPM/Fama-French alphas) are not that different from the median firm in the market. Panel A shows that those firms have effective bid-ask spread and turnover that are roughly the same as those of the median firm in the market, are more liquid than the median firm in the market in terms of price impact, but still have a higher frequency of zero-return days.

Overall, Panel A predicts that if the turnover factor picks up either liquidity or at least turnover, the smallest growth portfolio will load positively on LMH (and thus LMH will make its negative alpha worse), and the second smallest growth portfolio will not load significantly on LMH.

In Panel B of Table 10A, I turn to the sorts on cumulative issuance. I sort firms into three groups - top 30%, middle 40%, and bottom 30% - using NYSE breakpoints. All results are robust to sorting firms into five groups and/or using CRSP breakpoints.

Consistent with the evidence in Brav et al. (2000) that issuing firms tend to be small and more direct evidence in Barinov (2012) that cumulative issuance is strongly and negatively related to size, I observe in Panel B that firms with high cumulative issuance (routine equity issuers) are significantly less liquid than routine equity retirers: routine equity issuers have roughly twice higher median effective bid-ask spread, four times higher median price impact, and 20% higher zero-return frequency. However, routine equity issuers have significantly higher turnover, illustrating once again the disagreement between liquidity measures and turnover and also presenting an example of a sort, for which turnover and liquidity are negatively related despite no relation between them in the full cross-section.

Overall, Panel B predicts that cumulative issuance sorts would be another good example that would answer the question whether LMH picks up liquidity or not. 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).

4.3 Small Growth Puzzle and Cumulative Issuance Puzzle: Volatility Risk and Liquidity Explanations

In Table 11A, I look at the ability of FVIX and LMH to explain the small growth puzzle (Panels A and B) and the cumulative issuance puzzle (Panel C). The CAPM and Fama-French models reveal that the alphas of SG1 portfolio are at -79 bp and -63 bp per month, the alphas of SG2 portfolio are at -34 bp and -19 bp per month, and the cumulative issuance puzzle (measured as the alpha of the CumIss arbitrage portfolio) is at -74 bp and -61 bp per month, all statistically significant.

In the third column of each panel, I consider the two-factor ICAPM with the market and volatility risk factors and observe, consistent with the evidence in Barinov (2012), but in a 50% longer sample that includes the financial crisis of 2008, that the ICAPM completely explains the small growth puzzle and explains about one-half of the cumulative issuance puzzle, leaving the rest marginally insignificant.

The driving force behind the decline in the alphas are the positive FVIX betas that indicate, consistent with the view that high disagreement option-like firms are good hedges against volatility risk, that small growth firms and routine equity issuers perform relatively well in the periods of increasing market volatility. Since investors appreciate protection against such increases, investors are willing to tolerate relatively low returns (negative CAPM/Fama-French alphas) of small growth firms and routine equity issuers.

In the fourth column of each panel, I present the two-factor "liquidity CAPM" with the market factor and LMH. As the previous subsection states, if LMH is truly a liquidity factor, SG1 and CumIss portfolios (Panels A and C) will load positively on LMH (and thus LMH will only make their negative alphas worse), and SG2 (Panel B) will not load on LMH. IF LMH is picking up turnover-related factor structure in returns, then SG1 will still load positively on LMH, SG2 will have zero loading, and CumIss will load negatively. However, if the turnover factor picks up volatility risk, all portfolios in Table 11A will load negatively on LMH, because LMH has very negative FVIX beta (see Table 5).

Table 11A strongly confirms the latter prediction. LMH betas of all three portfolios are indeed large, negative, and significant, and controlling for LMH seems to significantly weaken the cumulative issuance puzzle and the alpha of the smallest growth portfolio, similar to what controlling for FVIX does.

The last column of each panel tries using LMH and FVIX together and find that their slopes are reduced in the presence of the other factor and, most importantly, that adding LMH to the ICAPM with FVIX does not improve the alphas at all, suggesting that the two factors have the same amount of information as FVIX alone has about the alphas of small growth firms and the cumulative issuance puzzle.

I conclude that Table 11A corroborates my conclusion that LMH picks up volatility risk rather than liquidity or any turnover-related effects.

4.4 Cross-Section of the Cumulative Issuance Puzzle Refutes Its Liquidity Explanation

In Table 12A, I explore the cross-sectional behavior of the cumulative issuance puzzle and report the alphas and betas of the high-minus-low cumulative issuance portfolio formed separately in each size and market-to-book group. In the first row, I look at the CAPM alphas of the high-minus-low portfolio and find that the cumulative issuance puzzle is significantly stronger for small and growth firms, even though it is present in all size and market-to-book groups.

In the next two rows, I consider the two-factor ICAPM with the market and volatility risk factors and find that controlling for volatility risk successfully explains why the cumulative issuance puzzle is significantly stronger for small and growth firms by revealing that the high-minus-low cumulative issuance portfolio has a better hedging ability against volatility risk for small and growth firms. This is not surprising: the volatility risk explanation of the cumulative issuance puzzle has it that routine issuers have negative CAPM/Fama-French alphas because they are primarily small growth firms, or, more generally, high disagreement option-like firms. Thus, the cumulative issuance puzzle should be driven by and be stronger for small and growth firms, and this pattern should be explained by volatility risk.

In the last two rows, I replace FVIX by LMH and observe how using LMH results in very similar reduction in the alphas, and in particular a similar reduction in the differential between the alphas of the high-minus-low cumulative issuance portfolio between small and large (growth and value) subsamples. The LMH betas also mirror FVIX betas, which is understandable if LMH picks up volatility risk, but very surprising under the liquidity interpretation of LMH. Indeed, if underperformance of routine issuers is due to their superior liquidity (which they do not actually possess, see Panel B of Table 10A), small and growth routine issuers should underperform less, not more, because they are less liquid than an average routine issuer.

Overall, I conclude from Table 12A that, as in the similar case with the new issues puzzle, the cross-section of the cumulative issuance puzzle and its relation with the turnover factor strongly favor the volatility risk interpretation of the turnover factor over its liquidity interpretation.

4.5 Frequent Debt and Equity Issuers

Panel A of Table 13A repeats Panel A of Table 10A and tabulates median liquidity of frequent (large) issuers along with liquidity of the median firm on Compustat and then compares the two. I find that frequent issuers do have higher turnover than the median Compustat firm, but they also have significantly higher effective bid-ask spread no matter which of the three spread measures I look at. The difference in the Amihud measure and zero-return frequency also seems to suggest that frequent issuers are less liquid than a representative Compustat firm, though those differences are insignificant (but the difference in the Amihud measure is relatively large at 20-30% of the Compustat median).

One can argue whether those differences in liquidity are economically meaningful, since they are 2-3 times smaller than the differences between extreme quintiles from sorts on the respective trading cost measure. E.g., the difference between the effective tick measure of frequent issuers and the median Compustat firm is 66 bp, while the difference between the 90th and 10th percentile of effective spread is, on average, 380 bp even in the later half of my sample. But in any case there is no case to be made that frequent issuers are more liquid (i.e., less costly to trade) than the representative Compustat firm.

Panels B and C of Table 13A perform factor regressions from Table 11A with returns to frequent issuers from Huang and Ritter (2020) as the left-hand side variable. Panel B deals with frequent issuers using 5% of total assets as a cut-off for issuing activity: the CAPM and three-factor Fama and French (1993) models estimate the value-weighted (equal-weighted) alphas of frequent issuers to be -35 to -37 bp (-66 to -68 bp) per month, close to what Huang and Ritter report for a longer 1974-2017 sample.

In Panel B, controlling for FVIX in the two-factor ICAPM with the market and FVIX reduces those alphas to -9 bp and -21 bp per month, respectively, both with t-statistics below 1 in absolute magnitude. FVIX betas of frequent issuers are positive and similar in magnitude to FVIX betas of new issues in Table 3 in the paper, and the t-statistics of FVIX betas of frequent issuers exceed 4. The positive FVIX betas of frequent issuers suggest that frequent issuers are hedges against increases in aggregate volatility, which seems to explain why their CAPM/FF alphas are negative.

Replacing FVIX with LMH also reduces the alphas to insignificance, but their point estimates are larger than when FVIX is used. LMH betas of frequent issuers are negative, suggesting that frequent issuers are high turnover and allegedly liquid firms: Panel A supports the former conclusion, but finds no evidence consistent with the latter, making it more likely that LMH is just picking up aggregate volatility risk.

Panel C of Table 13A looks at frequent large issuers, which raise at least 10% of assets at least three times in the past three years (as either debt or equity) and reaches conclusions very similar to Huang and Ritter (2020) and Panel B. Compared to Panel B, CAPM/FF alphas in Panel C are 2-3 times higher, just as Huang and Ritter (2020) find. The FVIX betas do not increase as much, and therefore the ICAPM alphas of frequent large issuers remain significant at least at the 10% level and economically large, but they do decline by 40-50% compared to the CAPM/FF alphas. Similar to Panel B, I also find that frequent large issuers have negative LMH betas despite being less liquid than the representative Compustat firm, which suggests that LMH is picking up aggregate volatility risk.

Table 14A looks at the relation between firm size and the magnitude of the frequent issuers puzzle of Huang and Ritter (2020). Table 14A sorts all frequent issuers into bottom 30%, middle 40%, and top 30% in terms of their market cap and looks at frequent issuers alphas and FVIX/LMH betas separately in each of the size groups.

The first novel piece of evidence in Table 14A is that the frequent issuers puzzle is significantly stronger for smaller firms - the difference in the CAPM alphas of small and large frequent issuers is 76 bp per month (53 bp in equal-weighted returns). The second new piece of evidence is that controlling for FVIX resolves the frequent issuers puzzle in all size groups and significantly reduces the above difference: in the ICAPM alphas, the difference between small and large frequent issuers is 23 bp per month in equal-weighted returns and 50 bp (t-statistic 1.75) in value-weighted returns. The FVIX betas of small and large frequent issuers are also significantly different by a factor of two. This is consistent with my aggregate volatility risk explanation of the new issues puzzle and related anomalies: growth firms are more likely to issue, and growth firms are also hedges against aggregate volatility risk, as growth options benefit from increases in volatility all else equal, as all options do. Small firms are particularly volatile, and hence their volatility is likely to increase more and impact the firm value more when aggregate volatility increases, making small growth firms (and small frequent issuers) particularly good hedges against aggregate volatility risk.

Table 14A also shows the same pattern in LMH betas: while LMH is expectedly weaker than FVIX and cannot explain the entirety of the frequent issuers puzzle, LMH betas of frequent issuers are more negative in small firms subsample, which under the liquidity interpretation of LMH would suggest that small frequent issuers are particularly high turnover/highly liquid firms, contrary to the strong negative association between size and either turnover or trading costs measures. Thus, Table 14A presents yet another confirmation that LMH is substituting for FVIX rather than picking up any liquidity effects.

5 Distribution of Trading Costs Measure Pre- and Post-Decimalization

The first half of my sample was the period of artificially high bid-ask spread: the minimum tick size at the time was 12.5 cents, or 1/8th of a dollar, but due to alleged collusion, the minimum bid-ask spread was 25 cents. The minimum tick size was reduced to 1/16th of a dollar (6.25 cents) in 1997, and then in 2001 the minimum tick size became 1 cent, which dramatically decreased observed bid-ask spreads and increased trading activity. The decimalization was completed by the end of January 2001 on NYSE/AMEX and by early April 2001 on other exchanges.

In Table 15A, I split the sample the same way I did previously in Tables 3A and 4A, into the pre-decimalization period (1986-2001) and post-decimalization period (2002-2017), and report the 10th, 25th, 50th, 75th, and 90th percentile point for firms in the IPO (SEO, convertible debt) portfolio. The new issues portfolios include all firms that performed an issue in the past 2 to 37 months. The percentile points are computed each month and then averaged over time across all months. Panels A4 and B4 additionally present the same percentiles for all CRSP firms.

Panel A presents the averages from the pre-decimalization period. I find that in 1986-2001 IPOs have median zero return frequency of 20.9%, and even the 10th percentile is at 9.8%. This is consistent with the evidence Lesmond, Ogden, and Trczinka (1999) present for earlier, 1963-1990 sample, in which firms in the bottom two size deciles (which is where about 75% of IPOs come from according to Brav, Geczy, and Gompers, 2000) have average zero return frequency of 36.6% and 31.1%, and even firms in the top size decile, on average, have zero return frequency of 11.9%. Panel B looks at the post-decimalization period and finds that percentage points for zero return frequency of IPOs declined by an order of magnitude, but the median is still at 2.1% (roughly 5 days per year) and even the 10th percentile is at 0.004 (1 day per year) rather than exact zero. Looking at SEOs and convertible debt issuers presents a similar picture: a median convertible debt issuer has roughly 3 zero return days per year post-decimalization, as compared to 15.7% of all trading days (roughly 38 days per year) in the pre-decimalization period.

Another measure that drops by an order of magnitude between 1986-2001 and 2002-2017 is the Amihud measure of price impact. Turnover, on the other hand, triples post-decimalization, and the effective tick measure drops by a factor of six. The Roll (1984) and Corwin and Schultz (2012) measures of effective bid-ask spread show a much smaller decline, dropping by about 40% for IPOs and by 25-30% (the Roll measure) or 10% (the Corwin-Schultz measure) for other issuers.

6 New Issues Puzzle in the Five-Factor Fama-French Model

6.1 Descriptive Statistics of Asset-Pricing Factors

Table 16A presents descriptive statistics of the five Fama-French factors, the momentum factor, and FVIX. By construction, the Fama and French (2015) factors and momentum have positive average returns, while FVIX has a negative average return: since FVIX is created as the combination of the base assets that has the maximum positive correlation with VIX changes, FVIX represents a valuable insurance against volatility increases.

The first column of Table 16A presents average returns and shows that FVIX return, by absolute magnitude, is 2-3 times greater than average returns to other factors (-1.36% per month for FVIX vs. 0.68% per month for the market factor and 0.52% for momentum). FVIX's standard deviation is also greater than those of the other factors, but the difference is smaller than the difference in the averages, which causes FVIX to have the largest by absolute magnitude Sharpe ratio too (-0.229 for FVIX vs. 0.155 for the market factor and 0.137 for RMW).

Since change in VIX and market return are tightly positively correlated (at daily frequency, the correlation in 1986-2017 is at -0.681), FVIX market beta is expectedly highly negative (Table 4 in the paper reports it as -1.325). The negative market beta of FVIX is responsible for most of the negative average return of FVIX: in column four of Table 16A, the CAPM alpha of FVIX is -46 bp per month, close in absolute magnitude to the alphas of CMA and RMW (50 bp and 38 bp per month) and behind the CAPM alpha of the momentum factor (65 bp per month). However, cleaning the market risk out of FVIX also dramatically decreases FVIX's volatility, so in the fifth column of Table 16A the appraisal ratio (the ratio of the CAPM alpha to the standard deviation of the CAPM residuals) of FVIX is larger, by absolute magnitude, than those of other factors (-0.337 for FVIX vs. 0.207 for RMW and 0.202 for CMA).

The last two columns of Table 16A look at skewness and kurtosis and find that FVIX has positive skewness (similar to CMA, but dissimilar to the market factor and momentum) and FVIX's kurtosis is right at the median of the group of the seven factors.

The overall conclusion from Table 16A is that FVIX earns a significant risk premium, which is, according to several measures, greater than that of other popular factors. Thus, FVIX captures an important risk and it is not surprising that controlling for FVIX resolves a number of anomalies, including the new issues puzzle.

6.2 Does the New Issues Puzzle Survive the Addition of CMA and RMW?

Fama and French (2016) show that the five-factor model with CMA and RMW is able to explain or alleviate several salient anomalies, and Hou et al. (2015) find the same about a closely related four-factor "Q-model". In Table 17A, I evaluate the ability of the new Fama-French factors, CMA and RMW, to explain the new issues puzzle.

The first columns of Panels A1 (IPOs), A2 (SEOs), and A3 (convertible debt issues) repeat the estimates of the three-factor Fama-French model from Table 4 in the paper. The second column of each panel in Table 17A adds CMA to the three-factor model and finds that the alphas of SEOs and convertible issues are barely affected and the alpha of IPOs declines by one-third and becomes insignificant, but the result is suspect since the t-statistic of the CMA beta of IPOs is only -1.60.

The third column adds RMW instead to the three-factor Fama-French model and finds that RMW has more success: the alpha of IPOs declines to - 7 bp per month, and the alpha of SEOs and convertible debt issues decline by roughly 35% and 20%, respectively, though both stay significant. The RMW betas of new issues are also significant in all panels.

In the rightmost column of each panel, I estimate the full five-factor Fama-French model, which makes the alphas of IPOs and SEOs insignificant, but the alpha of convertible debt issues survives at -50 bp per month, t-statistic -3.09. It is clear though that RMW does the heavy lifting in the five-factor model, somewhat contrary to Lyandres et al. (2008), who found that their version of the investment factor explains roughly 80% of IPOs and SEOs alphas. In untabulated results, I explored the sources of the difference and found that about a half of explanatory power of the Lyandres et al. investment factor comes from including changes in working capital into their definition of investment. Without that, even in the sample period of Lyandres et al. and with the exact same way of forming the investment factor as in the paper, the investment factor explains roughly 40% of IPOs and SEOs alphas and leaves the rest significant.

Panel B of Table 17A highlights the role of an important outlier: in January 2001, a brief bounce-back during the dot-com bubble burst happened, and IPOs/SEOs earned about 55%/40% in one single month. Excluding January 2001 from the sample restores the significance of SEOs alpha in the five-factor model and the significance of IPOs alpha in the three-factor model augmented with CMA.

6.3 On the Overlap between FVIX and the New Fama-French Factors

Barinov (2020) shows that FVIX can explain the profitability anomaly and the alpha of the RMW factor. The economic intuition is that low profitability firms tend to be distressed and their equity therefore is like a call option on the assets. The option-likeness of distressed equity makes it a hedge against volatility risk; since the RMW factor shorts unprofitable/distressed firms, RMW is exposed to volatility risk.

Panel A of Table 18A confirms the result in Barinov (2020) in my sample period: RMW has a CAPM/three-factor alpha of 50 bp/43 bp per month, with t-statistics exceeding 3. However, when FVIX is added to either CAPM or the three-factor Fama-French model, the alpha of RMW drops to 12 bp/18 bp per month and becomes insignificant. The role of FVIX in explaining the alpha of RMW is underscored by highly significant negative FVIX betas of RMW, which indicate the tendency of RMW to underperform when market volatility unexpectedly increases.

Panel B of Table 18A shows that while FVIX could explain the alpha of RMW, the reverse is not true: the alpha of FVIX is significantly negative in the CAPM/three-factor model, and adding RMW to either one reduces the alpha of FVIX by 9-14 bp and leaves it highly significant. Even in the new five-factor model the alpha of FVIX is -30.5 bp per month, t-statistic -3.73, which is not too far from its three-factor alpha (-43.9 bp per month).

Interpreting Panels A and B as a spanning test in the spirit of Barillas and Shanken (2017), I conclude that RMW is redundant given FVIX, i.e. RMW does not have significant information in addition to the information contained in FVIX. This conclusion is similar to the conclusion I draw from Table 4 in the paper, where I find that FVIX similarly spans

LMH and thus LMH merely substitutes for FVIX when LMH explains the new issues puzzle. The same is true about RMW: the only reason why the five-factor model and RMW in particular are able to (partly) explain the alphas of IPOs and SEOs in Table 17A is that RMW picks up volatility risk and substitutes for FVIX.

Panels C and D perform similar tests of CMA against FVIX and find little overlap between the two factors. Controlling for FVIX reduces the alphas of CMA by 5-10 bp per month, and controlling for CMA similarly reduces the alphas of FVIX by 3-5 bp per month. In both cases, the alphas remain significant, but since Table 17A establishes that it is RMW that does the heavy lifting in the five-factor explanation of the new issues puzzle, the lack of overlap between CMA and FVIX does not matter.

6.4 New Issues Puzzle in the 21st Century

Table 19A repeats Table 4 in the paper in the 2002-2017 subperiod, exactly the second half of my 1986-2017. The use of January 2002 as the cut-off date also removes from the sample the dot-com bubble and its immediate aftermath and makes sure that the whole subsample is in the post-decimalization period.

Panels A and D of Table 2R look at equal-weighted and value-weighted IPO returns and find that IPOs do not really have a negative alpha in 2002-2017: the CAPM and Fama-French alphas range from -3 bp to -22 bp per month and none of them is significant.[7]

However, the negative alphas of SEOs and convertible debt issuers are still there in 2002-2017. In value-weighted returns, alphas of SEOs (convertible debt issuers) are roughly

[7] FVIX betas of IPOs are still significantly positive, suggesting that the zero CAPM/FF alphas may still be disappointing performance that is tolerated by investors only because IPOs are hedges against volatility risk. One reason zero CAPM/FF alphas may be disappointing is that IPOs may be high-risk (or simply undesirable) across some other dimension, which makes their required return higher than what the CAPM/FF model would predict. Another reason could be that 2002-2017 is a period dominated by bad news, and if IPOs are hedges (as their FVIX beta suggests), they are supposed to beat the CAPM in such a period, but they do not.

-45 bp (-75 bp) per month, with t-statistics exceeding 2.7 in absolute magnitude. In equal-weighted returns, the CAPM alphas of SEOs and convertible debt issuers are shaky in terms of statistical significance, but still check in at -31 bp and -45 bp per month (that is, we cannot reject that the equal-weighted CAPM alpha of SEOs is 0, but we also cannot reject that it is -70 bp). The Fama-French alphas, however, are significant at -40.6 bp and -51.8 bp per month with t-statistics of -2.519 and -2.516.

The paper looks at the new issues puzzle as a whole, not limiting its attention to IPOs, but also bringing SEOs and convertible debt into the picture. The paper argues against the liquidity explanation of the new issues puzzle based on the LMH turnover factor (as suggested by Eckbo and Norli, 2005, for IPOs and SEOs, and by Butler et al., 2010, for convertible debt issuers). The paper also suggests FVIX/volatility risk as an alternative explanation of negative alphas of IPOs, SEOs, and convertible debt issuers.

Tables 18A finds that in the recent sample the IPO puzzle being the weakest of the three, but the similar puzzles involving SEOs and convertible debt issuers survive the use of value-weighted returns and/or limiting the attention to the second half of the sample. So the paper does have a puzzle to explain.

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Table 1A. Liquidity of Stock and Debt Issuers and Their Peers Matched on Size, Market-to-Book, Exchange, and Pre-Issue Liquidity

The table compares median liquidity of stock and debt issuers and matching firms in the first five full years after the issue. Matching firms are matched by market-to-book and then by size. The first column contains the year after the issue. Turnover is monthly trading volume over shares outstanding. Zero return frequency is the fraction of days with no price change (and no trade) 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). P-values use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The medians are from January 1986 to December 2017 (new issues are from December 1982 to November 2017).

Panel A. Post-Issue Liquidity of IPOs and Their Size-MB Matches

	Turnover				Zero Return Frequency				Amihud Measure, Price Impact			
Year	**Issuer**	**Match**	**I-M**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	0.089	0.093	-0.003	0.721	0.117	0.117	0.000	0.958	0.179	0.253	0.074	0.188
2	0.101	0.093	0.007	0.294	0.128	0.118	-0.010	0.049	0.244	0.228	-0.016	0.628
3	0.101	0.097	0.005	0.605	0.130	0.119	-0.011	0.002	0.284	0.342	0.058	0.302
4	0.102	0.094	0.007	0.258	0.132	0.119	-0.013	0.034	0.374	0.279	-0.095	0.256
5	0.103	0.094	0.009	0.082	0.130	0.114	-0.015	0.030	0.370	0.351	-0.019	0.798

	Roll Measure, Bid-Ask Spread				Effective Bid-Ask Spread				Effective Tick, Holden (2009)			
Year	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	1.997	1.753	-0.244	0.032	1.269	1.117	-0.152	0.011	2.511	2.450	-0.062	0.528
2	2.052	1.721	-0.331	0.004	1.273	1.082	-0.191	0.001	2.781	2.469	-0.311	0.029
3	2.013	1.787	-0.226	0.060	1.221	1.058	-0.163	0.002	2.829	2.508	-0.320	0.016
4	2.014	1.703	-0.311	0.002	1.200	1.040	-0.160	0.001	2.885	2.467	-0.418	0.002
5	1.913	1.709	-0.203	0.002	1.169	0.993	-0.176	0.005	2.788	2.353	-0.435	0.003

Panel B. Post-Issue Liquidity of SEOs and Their Size-MB Matches

	Turnover				Zero Return Frequency				Amihud Measure, Price Impact			
Year	**Issuer**	**Match**	**I-M**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	0.134	0.110	0.024	0.000	0.086	0.088	0.001	0.543	0.022	0.026	0.004	0.278
2	0.129	0.108	0.021	0.000	0.093	0.091	-0.002	0.338	0.023	0.030	0.008	0.320
3	0.124	0.105	0.020	0.000	0.096	0.088	-0.009	0.007	0.023	0.027	0.004	0.408
4	0.121	0.107	0.014	0.001	0.094	0.084	-0.010	0.009	0.019	0.030	0.010	0.267
5	0.122	0.109	0.013	0.010	0.089	0.077	-0.012	0.007	0.020	0.017	-0.002	0.388

	Roll Measure, Bid-Ask Spread				Effective Bid-Ask Spread				Effective Tick, Holden (2009)			
Year	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	1.487	1.345	-0.142	0.002	0.896	0.803	-0.093	0.007	1.492	1.429	-0.063	0.021
2	1.458	1.348	-0.110	0.011	0.879	0.783	-0.096	0.007	1.585	1.425	-0.160	0.001
3	1.404	1.310	-0.094	0.028	0.832	0.764	-0.068	0.017	1.619	1.410	-0.209	0.001
4	1.351	1.279	-0.072	0.145	0.795	0.742	-0.053	0.036	1.566	1.375	-0.191	0.002
5	1.367	1.259	-0.108	0.077	0.787	0.720	-0.067	0.013	1.496	1.244	-0.252	0.008

Panel C. Post-Issue Liquidity of Convertible Debt Issuers and Their Size-MB Matches

	Turnover				Zero Return Frequency				Amihud Measure, Price Impact			
Year	**Issuer**	**Match**	**I-M**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	0.175	0.121	0.054	0.005	0.078	0.074	-0.004	0.144	0.011	0.010	0.000	0.821
2	0.159	0.123	0.036	0.014	0.083	0.073	-0.010	0.023	0.014	0.011	-0.003	0.434
3	0.145	0.121	0.025	0.019	0.082	0.070	-0.012	0.010	0.014	0.010	-0.004	0.185
4	0.132	0.118	0.014	0.190	0.081	0.071	-0.010	0.084	0.012	0.009	-0.003	0.349
5	0.129	0.128	0.001	0.892	0.076	0.067	-0.010	0.048	0.009	0.009	0.000	0.932

	Roll Measure, Bid-Ask Spread				Effective Bid-Ask Spread				Effective Tick, Holden (2009)			
Year	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	1.414	1.224	-0.190	0.049	0.777	0.713	-0.063	0.025	1.360	1.138	-0.222	0.000
2	1.301	1.191	-0.110	0.058	0.749	0.693	-0.056	0.023	1.380	1.193	-0.187	0.001
3	1.237	1.170	-0.068	0.238	0.737	0.676	-0.061	0.007	1.433	1.153	-0.280	0.000
4	1.236	1.142	-0.094	0.132	0.701	0.682	-0.019	0.466	1.344	1.161	-0.183	0.020
5	1.229	1.210	-0.019	0.732	0.675	0.672	-0.003	0.895	1.262	1.067	-0.195	0.057

Table 2A. Liquidity of Stock and Debt Issuers and Their Peers Matched on Size, Market-to-Book, Exchange, and Pre-Issue Liquidity

The table compares median liquidity of stock and debt issuers and matching firms in the first five full years after the issue. Matching firms are matched by stock exchange, then by market-to-book and then by size. SEOs are convertible debt issuers are additionally matched on the liquidity measure being compared from the pre-issue year. The first column contains the year after the issue. The trading costs measures are defined in the header of Table 1A. P-values use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The medians are from January 1986 to December 2017 (new issues are from December 1982 to November 2017).

Panel A. Post-Issue Liquidity of IPOs and Their Size-MB-Exchange Matches

	Turnover				**Zero Return Frequency**				**Amihud Measure, Price Impact**			
Year	**Issuer**	**Match**	**I-M**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	0.091	0.089	0.002	0.801	0.117	0.117	0.000	0.854	0.175	0.259	0.084	0.189
2	0.100	0.093	0.007	0.338	0.129	0.119	-0.010	0.008	0.250	0.222	-0.029	0.460
3	0.105	0.092	0.013	0.180	0.131	0.119	-0.013	0.001	0.303	0.315	0.012	0.709
4	0.105	0.092	0.012	0.045	0.132	0.115	-0.017	0.004	0.349	0.250	-0.099	0.202
5	0.104	0.100	0.005	0.257	0.129	0.110	-0.019	0.003	0.390	0.326	-0.064	0.566

	Roll Measure, Bid-Ask Spread				**Effective Bid-Ask Spread**				**Effective Tick, Holden (2009)**			
Year	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	2.004	1.843	-0.161	0.073	1.268	1.189	-0.079	0.155	2.533	2.534	0.002	0.992
2	2.048	1.839	-0.209	0.064	1.263	1.132	-0.130	0.010	2.804	2.503	-0.301	0.116
3	2.026	1.836	-0.190	0.072	1.224	1.096	-0.129	0.004	2.881	2.469	-0.412	0.007
4	2.047	1.723	-0.324	0.000	1.196	1.042	-0.154	0.000	2.852	2.372	-0.480	0.000
5	1.953	1.722	-0.232	0.018	1.160	0.990	-0.170	0.000	2.756	2.273	-0.483	0.005

Panel B. Post-Issue Liquidity of SEOs and Their Size-MB-Exchange-Liquidity Matches

	Turnover				Zero Return Frequency				Amihud Measure, Price Impact			
Year	**Issuer**	**Match**	**I-M**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	0.132	0.106	0.026	0.000	0.0874	0.0912	0.0038	0.2244	0.0224	0.0267	0.0044	0.2371
2	0.126	0.106	0.021	0.009	0.0940	0.0909	-0.0030	0.1847	0.0256	0.0278	0.0022	0.6998
3	0.122	0.102	0.019	0.004	0.0958	0.0919	-0.0040	0.0009	0.0234	0.0224	-0.0010	0.5487
4	0.119	0.104	0.015	0.015	0.0966	0.0900	-0.0066	0.0038	0.0209	0.0227	0.0017	0.6915
5	0.119	0.105	0.014	0.002	0.0922	0.0841	-0.0081	0.0024	0.0235	0.0212	-0.0023	0.5741

	Roll Measure, Bid-Ask Spread				Effective Bid-Ask Spread				Effective Tick, Holden (2009)			
Year	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	1.473	1.424	-0.049	0.2360	0.843	0.835	-0.009	0.6726	1.462	1.557	0.095	0.2301
2	1.423	1.381	-0.042	0.3657	0.838	0.800	-0.038	0.1146	1.519	1.491	-0.028	0.5061
3	1.392	1.344	-0.049	0.3009	0.807	0.776	-0.032	0.1623	1.530	1.418	-0.112	0.0027
4	1.314	1.317	0.003	0.9387	0.773	0.744	-0.029	0.1936	1.513	1.433	-0.079	0.2687
5	1.321	1.293	-0.028	0.5724	0.791	0.748	-0.042	0.0805	1.375	1.305	-0.070	0.0865

Panel C. Post-Issue Liquidity of Convertible Debt Issuers and Their Size-MB-Exchange-Liquidity Matches

	Turnover				Zero Return Frequency				Amihud Measure, Price Impact			
Year	**Issuer**	**Match**	**I-M**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	0.182	0.140	0.042	0.0053	0.0891	0.0845	-0.005	0.2040	0.0168	0.0290	0.012	0.1172
2	0.163	0.143	0.020	0.0418	0.0952	0.0823	-0.013	0.0213	0.0302	0.0352	0.005	0.5014
3	0.148	0.134	0.014	0.1993	0.0961	0.0862	-0.010	0.0244	0.0547	0.0284	-0.026	0.2530
4	0.140	0.141	-0.001	0.9788	0.0931	0.0916	-0.001	0.7741	0.0682	0.0508	-0.017	0.2645
5	0.131	0.136	-0.005	0.4838	0.0908	0.0780	-0.013	0.0173	0.0624	0.0837	0.021	0.5459

	Roll Measure, Bid-Ask Spread				Effective Bid-Ask Spread				Effective Tick, Holden (2009)			
Year	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	1.3731	1.4724	0.099	0.3998	0.8735	0.9822	0.109	0.1178	1.4642	1.5429	0.079	0.5901
2	1.3211	1.4376	0.116	0.0884	0.8781	0.9579	0.080	0.1763	1.4488	1.4608	0.012	0.8727
3	1.3266	1.4828	0.156	0.1089	0.8612	0.8987	0.038	0.3841	1.6238	1.4421	-0.182	0.0344
4	1.2803	1.4127	0.132	0.1214	0.8222	0.9029	0.081	0.0668	1.5471	1.4634	-0.084	0.4601
5	1.5358	1.3190	-0.217	0.0808	0.8376	0.8944	0.057	0.3569	1.3977	1.5207	0.123	0.1780

Table 3A. Liquidity of Stock and Debt Issuers and Their Peers: 1986-2001 Subsample

The table compares median liquidity of stock and debt issuers and matching firms in the first five full years after the issue in the pre-decimalization sample. Matching firms are matched by market-to-book and then by size. The first column contains the year after the issue. The trading costs measures are defined in the header of Table 1A. P-values use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The medians are from January 1986 to December 2001 (new issues are from December 1982 to November 2001).

Panel A. Post-Issue Liquidity of IPOs and Their Size-MB Matches

	Turnover				Zero Return Frequency				Amihud Measure, Price Impact			
Year	**Issuer**	**Match**	**I-M**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	0.054	0.041	0.013	0.000	0.214	0.214	-0.001	0.900	0.343	0.496	0.154	0.124
2	0.049	0.040	0.009	0.000	0.234	0.218	-0.016	0.069	0.467	0.449	-0.018	0.798
3	0.046	0.037	0.009	0.003	0.238	0.221	-0.017	0.005	0.542	0.675	0.133	0.220
4	0.045	0.037	0.008	0.089	0.243	0.222	-0.020	0.061	0.730	0.539	-0.191	0.264
5	0.044	0.036	0.008	0.009	0.242	0.217	-0.025	0.059	0.744	0.712	-0.032	0.853

	Roll Measure, Bid-Ask Spread				Effective Bid-Ask Spread				Effective Tick, Holden (2009)			
Year	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	2.451	2.063	-0.388	0.056	1.491	1.239	-0.251	0.021	4.295	4.271	-0.024	0.897
2	2.518	2.060	-0.458	0.003	1.459	1.206	-0.252	0.000	4.739	4.313	-0.426	0.021
3	2.435	2.145	-0.290	0.099	1.378	1.188	-0.189	0.013	4.793	4.427	-0.366	0.036
4	2.431	1.989	-0.443	0.012	1.353	1.127	-0.226	0.013	4.945	4.316	-0.629	0.017
5	2.314	1.995	-0.319	0.017	1.340	1.062	-0.278	0.010	4.917	4.229	-0.689	0.006

Panel B. Post-Issue Liquidity of SEOs and Their Size-MB Matches

	Turnover				Zero Return Frequency				Amihud Measure, Price Impact			
Year	**Issuer**	**Match**	**I-M**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	0.076	0.052	0.024	0.000	0.157	0.162	0.006	0.158	0.042	0.049	0.007	0.308
2	0.070	0.052	0.018	0.001	0.170	0.169	-0.001	0.783	0.042	0.058	0.016	0.297
3	0.064	0.050	0.014	0.000	0.177	0.162	-0.014	0.010	0.044	0.052	0.008	0.407
4	0.063	0.051	0.011	0.000	0.172	0.156	-0.016	0.015	0.037	0.057	0.020	0.261
5	0.064	0.050	0.013	0.006	0.168	0.147	-0.021	0.001	0.039	0.034	-0.005	0.410

	Roll Measure, Bid-Ask Spread				Effective Bid-Ask Spread				Effective Tick, Holden (2009)			
Year	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	1.690	1.466	-0.223	0.002	0.968	0.786	-0.182	0.001	2.520	2.461	-0.058	0.301
2	1.580	1.461	-0.118	0.042	0.908	0.767	-0.141	0.000	2.669	2.462	-0.207	0.019
3	1.519	1.420	-0.099	0.039	0.842	0.736	-0.105	0.002	2.738	2.443	-0.295	0.008
4	1.519	1.393	-0.125	0.075	0.814	0.718	-0.096	0.003	2.687	2.387	-0.300	0.003
5	1.564	1.392	-0.173	0.072	0.815	0.694	-0.121	0.001	2.643	2.203	-0.440	0.004

Panel C. Post-Issue Liquidity of Convertible Debt Issuers and Their Size-MB Matches

	Turnover				Zero Return Frequency				Amihud Measure, Price Impact			
Year	**Issuer**	**Match**	**I-M**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	0.083	0.062	0.020	0.003	0.142	0.138	-0.004	0.382	0.020	0.020	-0.001	0.864
2	0.079	0.059	0.020	0.006	0.152	0.137	-0.016	0.034	0.028	0.022	-0.006	0.499
3	0.071	0.058	0.013	0.098	0.151	0.131	-0.020	0.011	0.027	0.020	-0.007	0.179
4	0.070	0.055	0.015	0.007	0.150	0.132	-0.017	0.095	0.024	0.018	-0.006	0.335
5	0.070	0.056	0.015	0.040	0.141	0.127	-0.015	0.109	0.019	0.018	0.000	0.940

	Roll Measure, Bid-Ask Spread				Effective Bid-Ask Spread				Effective Tick, Holden (2009)			
Year	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	1.504	1.400	-0.104	0.373	0.740	0.710	-0.030	0.321	2.307	1.997	-0.310	0.003
2	1.391	1.318	-0.073	0.390	0.718	0.697	-0.022	0.375	2.375	2.114	-0.261	0.010
3	1.386	1.367	-0.019	0.723	0.710	0.678	-0.032	0.221	2.497	2.042	-0.455	0.000
4	1.426	1.276	-0.150	0.105	0.708	0.687	-0.021	0.635	2.303	2.035	-0.268	0.064
5	1.360	1.302	-0.058	0.525	0.660	0.677	0.017	0.671	2.186	1.883	-0.303	0.131

Table 4A. Liquidity of Stock and Debt Issuers and Their Peers: 2002-2017 Subsample

The table compares median liquidity of stock and debt issuers and matching firms in the first five full years after the issue in the post-decimalization sample. Matching firms are matched by market-to-book and then by size. The first column contains the year after the issue. The trading costs measures are defined in the header of Table 1A. P-values use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The medians are from January 2002 to December 2017 (new issues are from December 1998 to November 2017).

Panel A. Post-Issue Liquidity of IPOs and Their Size-MB Matches

	Turnover				Zero Return Frequency				Amihud Measure, Price Impact			
Year	**Issuer**	**Match**	**I-M**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	0.125	0.144	-0.020	0.128	0.020	0.021	0.000	0.887	0.015	0.010	-0.006	0.076
2	0.152	0.147	0.005	0.696	0.022	0.018	-0.004	0.087	0.022	0.008	-0.014	0.262
3	0.157	0.157	-0.000	0.992	0.023	0.017	-0.006	0.104	0.026	0.008	-0.018	0.269
4	0.158	0.151	0.007	0.555	0.022	0.017	-0.005	0.005	0.018	0.019	0.001	0.849
5	0.158	0.148	0.010	0.334	0.024	0.018	-0.006	0.004	0.019	0.013	-0.006	0.161

	Roll Measure, Bid-Ask Spread				Effective Bid-Ask Spread				Effective Tick, Holden (2009)			
Year	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	1.544	1.444	-0.100	0.097	1.047	0.994	-0.053	0.410	0.727	0.628	-0.099	0.024
2	1.587	1.383	-0.204	0.060	1.087	0.958	-0.129	0.055	0.822	0.626	-0.197	0.199
3	1.590	1.428	-0.162	0.199	1.064	0.928	-0.136	0.048	0.864	0.590	-0.275	0.169
4	1.597	1.418	-0.178	0.033	1.047	0.953	-0.093	0.091	0.824	0.617	-0.207	0.063
5	1.536	1.442	-0.095	0.118	1.008	0.928	-0.080	0.034	0.791	0.594	-0.197	0.005

Panel B. Post-Issue Liquidity of SEOs and Their Size-MB Matches

	Turnover				Zero Return Frequency				Amihud Measure, Price Impact			
Year	**Issuer**	**Match**	**I-M**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	0.192	0.168	0.024	0.012	0.016	0.013	-0.003	0.057	0.003	0.003	0.000	0.497
2	0.188	0.164	0.024	0.006	0.016	0.013	-0.003	0.004	0.003	0.002	-0.001	0.497
3	0.185	0.159	0.025	0.000	0.016	0.013	-0.003	0.005	0.002	0.002	0.000	0.568
4	0.180	0.163	0.018	0.032	0.016	0.012	-0.004	0.000	0.002	0.002	0.000	0.680
5	0.177	0.164	0.013	0.152	0.015	0.012	-0.004	0.000	0.002	0.002	0.000	0.725

	Roll Measure, Bid-Ask Spread				Effective Bid-Ask Spread				Effective Tick, Holden (2009)			
Year	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	1.285	1.224	-0.061	0.333	0.825	0.821	-0.004	0.903	0.464	0.396	-0.068	0.025
2	1.337	1.235	-0.102	0.160	0.850	0.799	-0.050	0.348	0.501	0.388	-0.113	0.035
3	1.289	1.200	-0.089	0.292	0.822	0.792	-0.030	0.527	0.501	0.377	-0.123	0.034
4	1.184	1.165	-0.019	0.755	0.776	0.766	-0.010	0.786	0.444	0.363	-0.081	0.006
5	1.182	1.134	-0.048	0.537	0.760	0.745	-0.016	0.593	0.421	0.345	-0.076	0.002

Panel C. Post-Issue Liquidity of Convertible Debt Issuers and Their Size-MB Matches

	Turnover				Zero Return Frequency				Amihud Measure, Price Impact			
Year	**Issuer**	**Match**	**I-M**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	0.267	0.179	0.088	0.006	0.014	0.011	-0.003	0.022	0.001	0.001	0.000	0.332
2	0.238	0.187	0.051	0.060	0.013	0.009	-0.003	0.000	0.001	0.001	0.000	0.173
3	0.220	0.184	0.036	0.091	0.013	0.009	-0.003	0.004	0.001	0.000	0.000	0.084
4	0.194	0.181	0.013	0.545	0.012	0.010	-0.002	0.051	0.001	0.001	0.000	0.823
5	0.184	0.195	-0.012	0.495	0.016	0.011	-0.005	0.005	0.001	0.001	0.000	0.907

	Roll Measure, Bid-Ask Spread				Effective Bid-Ask Spread				Effective Tick, Holden (2009)			
Year	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	1.325	1.048	-0.277	0.034	0.814	0.717	-0.097	0.040	0.414	0.278	-0.135	0.000
2	1.210	1.064	-0.147	0.275	0.779	0.689	-0.090	0.081	0.385	0.272	-0.113	0.000
3	1.089	0.972	-0.117	0.297	0.764	0.673	-0.090	0.042	0.368	0.263	-0.105	0.000
4	1.045	1.007	-0.039	0.623	0.693	0.677	-0.016	0.565	0.385	0.287	-0.097	0.000
5	1.106	1.124	0.018	0.772	0.688	0.666	-0.022	0.401	0.395	0.302	-0.094	0.001

Table 5A. Liquidity of IPOs and Underpricing

The table compares median liquidity of IPOs and matching firms in the five years after the issue. IPOs are divided into two groups: with extreme underpricing (Panel A) and "little to no underpricing" (Panel B). Extreme underpricing is the situation when the first-day return is above the average positive first-day return (that is, the average is computed for positive first-day returns only). Matching firms are matched by market-to-book and then by size. The first column contains the year after the issue. Turnover is monthly dollar trading volume over market cap. Zero return frequency is the fraction of days with no price change (and no trade) 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). P-values use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The medians are from January 1986 to December 2017 (new issues are from December 1982 to November 2017).

Panel B. Liquidity of IPOs with Extreme Underpricing (1st day return > Average Underpricing)

	Turnover				**Zero Return Frequency**				**Amihud Measure, Price Impact**			
Year	**Issuer**	**Match**	**I-M**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	0.0819	0.0649	0.0170	0.3103	0.1349	0.1660	0.0311	0.0056	0.0681	0.0435	-0.0246	0.0823
2	0.0736	0.0643	0.0093	0.1047	0.1389	0.1532	0.0143	0.0596	0.0928	0.0472	-0.0456	0.3552
3	0.0712	0.0643	0.0069	0.0411	0.1270	0.1195	-0.0075	0.1153	0.0919	0.0490	-0.0430	0.6089
4	0.0892	0.0728	0.0164	0.0551	0.1062	0.0952	-0.0110	0.1131	0.0595	0.0317	-0.0278	0.4726
5	0.1033	0.0797	0.0236	0.0231	0.0968	0.0794	-0.0174	0.5762	0.0391	0.0321	-0.0070	0.4191

	Roll Measure, Bid-Ask Spread				**Effective Bid-Ask Spread**				**Effective Tick, Holden (2009)**			
Year	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	2.6232	2.2890	-0.3341	0.1244	1.7338	1.5631	-0.1707	0.2581	2.8940	2.6602	-0.2338	0.5545
2	2.7103	2.1236	-0.5867	0.1435	1.7355	1.4204	-0.3151	0.0570	3.6123	2.6194	-0.9929	0.2211
3	2.5038	2.0617	-0.4421	0.2254	1.5911	1.3860	-0.2050	0.3138	3.3608	2.4746	-0.8862	0.1373
4	2.2815	2.0569	-0.2246	0.1532	1.4958	1.2788	-0.2170	0.9989	2.8533	2.1924	-0.6610	0.2869
5	2.0725	1.8089	-0.2636	0.3618	1.3676	1.1752	-0.1925	0.2335	2.5464	1.9422	-0.6041	0.1161

Panel B. Liquidity of IPOs with Little to No Underpricing (1st day return < Average Underpricing)

	Turnover				Zero Return Frequency				Amihud Measure, Price Impact			
Year	**Issuer**	**Match**	**I-M**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	0.0454	0.0395	0.0059	0.8780	0.2937	0.3083	0.0146	0.0254	0.3605	0.2667	-0.0939	0.4010
2	0.0454	0.0402	0.0052	0.0091	0.2819	0.2964	0.0145	0.0858	0.3088	0.2585	-0.0503	0.2446
3	0.0464	0.0408	0.0056	0.0076	0.2757	0.2905	0.0148	0.0869	0.2907	0.2735	-0.0172	0.7952
4	0.0488	0.0394	0.0095	0.0198	0.2451	0.2648	0.0198	0.0052	0.2321	0.2359	0.0038	0.3192
5	0.0532	0.0412	0.0120	0.0178	0.2143	0.2323	0.0180	0.1019	0.1693	0.1979	0.0286	0.9211

	Roll Measure, Bid-Ask Spread				Effective Bid-Ask Spread				Effective Tick, Holden (2009)			
Year	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	2.3785	2.3179	-0.0606	0.4456	1.5350	1.5860	0.0511	0.1461	4.2700	4.2033	-0.0667	0.4421
2	2.4948	2.4057	-0.0891	0.1746	1.4623	1.5115	0.0493	0.0657	4.3461	4.1444	-0.2017	0.0527
3	2.4116	2.3716	-0.0400	0.1045	1.4223	1.4387	0.0164	0.2367	4.4023	4.1718	-0.2305	0.3923
4	2.4943	2.3794	-0.1149	0.4257	1.4215	1.4089	-0.0126	0.2181	4.2819	4.0580	-0.2238	0.7932
5	2.3426	2.2693	-0.0733	0.0928	1.3580	1.3485	-0.0095	0.4459	3.7889	3.6251	-0.1637	0.4421

Table 6A. Liquidity of IPOs and Venture Capital

The table compares median liquidity of IPOs and matching firms in the five years after the issue. IPOs are divided into two groups: the ones backed by a venture-capital firm (Panel A) and the ones that are not (Panel B). Matching firms are matched by market-to-book and then by size. The first column contains the year after the issue. Turnover is monthly dollar trading volume over market cap. Zero return frequency is the fraction of days with no price change (and no trade) 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). P-values use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The medians are from January 1986 to December 2017 (new issues are from December 1982 to November 2017).

Panel A. Liquidity of IPOs Backed by Venture Capitalists

	Turnover				**Zero Return Frequency**				**Amihud Measure, Price Impact**			
Year	**Issuer**	**Match**	**I-M**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	0.0984	0.0960	0.0024	0.7647	0.1690	0.1860	0.0170	0.0257	0.1741	0.1752	0.0011	0.3373
2	0.1127	0.0891	0.0235	0.0431	0.1785	0.1890	0.0105	0.1156	0.1650	0.1917	0.0267	0.2516
3	0.1152	0.0899	0.0252	0.0057	0.1800	0.1938	0.0138	0.0805	0.2028	0.3159	0.1131	0.2270
4	0.1283	0.0827	0.0457	0.0013	0.1743	0.1924	0.0180	0.0367	0.2025	0.4260	0.2235	0.1200
5	0.1258	0.0893	0.0364	0.0015	0.1604	0.1859	0.0255	0.0380	0.1330	0.4332	0.3003	0.0691

	Roll Measure, Bid-Ask Spread				**Effective Bid-Ask Spread**				**Effective Tick, Holden (2009)**			
Year	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	2.3797	2.3541	-0.0256	0.8118	1.5101	1.5260	0.0159	0.8157	2.9200	3.0562	0.1363	0.4707
2	2.3721	2.1701	-0.2020	0.1352	1.5689	1.4716	-0.0973	0.2561	3.3376	3.4078	0.0702	0.8023
3	2.3630	2.2949	-0.0681	0.6522	1.5038	1.4144	-0.0894	0.3363	3.4937	3.4481	-0.0456	0.8782
4	2.2664	2.2287	-0.0377	0.7646	1.4592	1.4205	-0.0386	0.6694	3.2207	3.5659	0.3452	0.3298
5	2.0980	2.1787	0.0807	0.6104	1.4043	1.4263	0.0220	0.8137	2.9106	3.4096	0.4990	0.1448

Panel B. Liquidity of IPOs Not Backed by Venture Capitalists

	Turnover				Zero Return Frequency				Amihud Measure, Price Impact			
Year	**Issuer**	**Match**	**I-M**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	0.0698	0.0868	-0.0171	0.0940	0.1802	0.1978	0.0177	0.0405	0.3155	0.3969	0.0813	0.1346
2	0.0698	0.0811	-0.0113	0.0852	0.1935	0.2032	0.0098	0.1137	0.5250	0.4380	-0.0871	0.0583
3	0.0755	0.0787	-0.0031	0.3689	0.2013	0.2004	-0.0009	0.8628	0.5112	0.5763	0.0650	0.4268
4	0.0757	0.0731	0.0025	0.5380	0.2027	0.2075	0.0048	0.1332	0.6435	0.6557	0.0123	0.9293
5	0.0807	0.0757	0.0050	0.2165	0.1897	0.1886	-0.0012	0.8234	0.8200	0.4177	-0.4022	0.1469

	Roll Measure, Bid-Ask Spread				Effective Bid-Ask Spread				Effective Tick, Holden (2009)			
Year	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	2.2092	2.3753	0.1662	0.0760	1.3293	1.5393	0.2100	0.0029	3.0169	3.5804	0.5634	0.0600
2	2.2896	2.4139	0.1243	0.1300	1.3338	1.5348	0.2010	0.0049	3.4987	3.7499	0.2512	0.2836
3	2.2738	2.3189	0.0451	0.5993	1.2632	1.4779	0.2147	0.0031	3.6056	3.8068	0.2013	0.3521
4	2.2903	2.2679	-0.0224	0.8410	1.2710	1.4108	0.1399	0.0206	3.6475	3.7468	0.0993	0.7025
5	2.3700	2.3683	-0.0017	0.9895	1.3218	1.4139	0.0921	0.2838	3.6102	3.6449	0.0347	0.8625

Table 7A. Liquidity of New Issues and Underwriter Reputation

The table compares median liquidity of stock and debt issuers and matching firms before and after the issue.Issuing firms are divided into two groups: the ones using high-prestige underwriters (reputation rank 8 and above for IPOs and SEOs, reputation rank equal to 9 for convertible debt issuers) and the ones that are not using high-prestige underwriters. The underwriter's reputation rank is from Jay Ritter's website. Matching firms are matched by market-to-book and then by size. The first column contains the year after the issue. Turnover is monthly dollar trading volume over market cap. Zero return frequency is the fraction of days with no price change (and no trade) 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). P-values use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The medians are from January 1986 to December 2017 (new issues are from December 1982 to November 2017).

Panel A. Liquidity of IPOs with High-Prestige Underwriters

	Turnover				Zero Return Frequency				Amihud Measure, Price Impact			
Year	**Issuer**	**Match**	**I-M**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	0.0888	0.1022	-0.0133	0.1203	0.1557	0.1735	0.0178	0.0280	0.1030	0.1032	0.0003	0.9863
2	0.0949	0.0955	-0.0005	0.9218	0.1673	0.1802	0.0130	0.0397	0.1281	0.1054	-0.0228	0.3418
3	0.0999	0.0898	0.0101	0.1344	0.1704	0.1812	0.0109	0.0839	0.1573	0.1513	-0.0061	0.8586
4	0.1057	0.0889	0.0168	0.0519	0.1731	0.1690	-0.0041	0.7597	0.3130	0.2025	-0.1105	0.3891
5	0.1097	0.0903	0.0195	0.0081	0.1596	0.1654	0.0058	0.4857	0.3356	0.1538	-0.1818	0.3768

	Roll Measure, Bid-Ask Spread				Effective Bid-Ask Spread				Effective Tick, Holden (2009)			
Year	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	2.0470	2.0690	0.0220	0.8275	1.2239	1.3271	0.1032	0.1491	2.4114	2.4428	0.0313	0.8353
2	2.0323	2.0476	0.0153	0.8966	1.2744	1.3185	0.0441	0.5502	2.6134	2.5898	-0.0235	0.8987
3	2.0598	2.0394	-0.0205	0.8637	1.2115	1.2883	0.0768	0.3548	2.8150	2.7192	-0.0958	0.6280
4	2.0591	2.0370	-0.0221	0.8332	1.2194	1.2671	0.0477	0.5584	2.7974	2.8291	0.0318	0.8874
5	2.0944	1.9723	-0.1221	0.5383	1.1973	1.2949	0.0976	0.3421	2.6305	2.6731	0.0426	0.8681

Panel B. Liquidity of IPOs with Low-Prestige Underwriters

	Turnover				Zero Return Frequency				Amihud Measure, Price Impact			
Year	**Issuer**	**Match**	**I-M**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	0.0591	0.0672	-0.0081	0.2993	0.2163	0.2268	0.0105	0.0583	0.8894	1.1461	0.2567	0.2094
2	0.0589	0.0629	-0.0041	0.4312	0.2245	0.2334	0.0090	0.1971	1.3351	1.2699	-0.0652	0.5843
3	0.0624	0.0666	-0.0042	0.6277	0.2252	0.2287	0.0035	0.6088	1.4882	1.4778	-0.0104	0.9719
4	0.0696	0.0592	0.0105	0.1395	0.2254	0.2341	0.0087	0.3039	1.2321	1.5106	0.2785	0.4022
5	0.0730	0.0592	0.0138	0.0864	0.2154	0.2208	0.0053	0.5218	1.4695	1.3386	-0.1309	0.7894

	Roll Measure, Bid-Ask Spread				Effective Bid-Ask Spread				Effective Tick, Holden (2009)			
Year	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
1	2.8657	2.9093	0.0436	0.5562	1.7556	2.0398	0.2841	0.0077	4.3053	5.3952	1.0899	0.0326
2	3.0191	2.9279	-0.0911	0.4006	1.7117	1.9435	0.2318	0.0451	4.9480	5.5879	0.6399	0.1038
3	3.1180	3.0212	-0.0969	0.4771	1.7066	1.7695	0.0629	0.4233	5.1966	5.4635	0.2669	0.4371
4	3.1272	2.8223	-0.3049	0.0526	1.6691	1.8222	0.1530	0.2166	4.9042	5.7425	0.8384	0.1598
5	2.9015	3.0511	0.1496	0.6466	1.6191	1.7748	0.1557	0.2512	4.6938	5.6465	0.9527	0.1394

Panel C. Liquidity of SEOs with High-Prestige Underwriters

	Turnover				Zero Return Frequency				Amihud Measure, Price Impact			
Year	**Issuer**	**Match**	**I-M**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
-1	0.0957	0.0987	-0.0030	0.6852	0.1049	0.1060	0.0011	0.7677	0.0456	0.0408	-0.0048	0.5950
0	0.1301	0.1095	0.0205	0.0008	0.0846	0.0985	0.0139	0.0167	0.0229	0.0352	0.0123	0.0812
1	0.1340	0.1032	0.0308	0.0000	0.0862	0.1040	0.0178	0.0066	0.0165	0.0396	0.0231	0.0518
2	0.1280	0.0993	0.0287	0.0000	0.0934	0.1050	0.0117	0.0590	0.0203	0.0361	0.0158	0.0867
3	0.1233	0.0958	0.0275	0.0000	0.0982	0.1052	0.0069	0.0962	0.0188	0.0314	0.0126	0.0389
4	0.1167	0.0926	0.0241	0.0000	0.0972	0.1016	0.0045	0.1828	0.0166	0.0323	0.0157	0.1076
5	0.1164	0.0918	0.0245	0.0000	0.0901	0.1007	0.0107	0.0308	0.0131	0.0310	0.0178	0.0989

	Roll Measure, Bid-Ask Spread				Effective Bid-Ask Spread				Effective Tick, Holden (2009)			
Year	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
-1	1.7625	1.7104	-0.0521	0.3655	0.9992	1.0989	0.0997	0.1089	2.0696	1.8044	-0.2652	0.0007
0	1.6373	1.6542	0.0169	0.6986	0.9765	1.0763	0.0998	0.0898	1.5748	1.6844	0.1096	0.0544
1	1.6218	1.6462	0.0244	0.4799	0.9712	1.0450	0.0737	0.1570	1.6207	1.6901	0.0695	0.1366
2	1.5491	1.5856	0.0365	0.5609	0.9382	1.0253	0.0871	0.0814	1.7092	1.6560	-0.0532	0.3722
3	1.4740	1.6025	0.1285	0.0253	0.8990	0.9949	0.0959	0.0925	1.7081	1.6194	-0.0887	0.1134
4	1.4300	1.5905	0.1605	0.0005	0.8665	0.9634	0.0969	0.0775	1.6095	1.5433	-0.0662	0.2646
5	1.4554	1.5568	0.1014	0.1483	0.8469	0.9772	0.1303	0.0477	1.5477	1.4346	-0.1131	0.0102

Panel D. Liquidity of SEOs with Low-Prestige Underwriters

	Turnover				Zero Return Frequency				Amihud Measure, Price Impact			
Year	**Issuer**	**Match**	**I-M**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
-1	0.0592	0.0610	-0.0018	0.7141	0.1469	0.1455	-0.0014	0.7943	0.5350	0.5026	-0.0324	0.6159
0	0.0931	0.0699	0.0231	0.0009	0.1283	0.1388	0.0105	0.0016	0.2115	0.4455	0.2340	0.0589
1	0.0946	0.0687	0.0259	0.0001	0.1262	0.1448	0.0186	0.0037	0.1949	0.4081	0.2132	0.0359
2	0.0863	0.0677	0.0187	0.0003	0.1392	0.1470	0.0079	0.0492	0.2228	0.3647	0.1418	0.0449
3	0.0825	0.0731	0.0095	0.0690	0.1397	0.1481	0.0084	0.1177	0.2749	0.4052	0.1303	0.1321
4	0.0820	0.0742	0.0078	0.2024	0.1423	0.1459	0.0036	0.4057	0.4499	0.4173	-0.0326	0.8435
5	0.0837	0.0711	0.0126	0.0414	0.1370	0.1377	0.0007	0.8326	0.9348	0.5013	-0.4335	0.4225

	Roll Measure, Bid-Ask Spread				Effective Bid-Ask Spread				Effective Tick, Holden (2009)			
Year	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
-1	2.4267	2.4196	-0.0071	0.9109	1.4937	1.5241	0.0304	0.5322	3.5642	3.4019	-0.1622	0.3451
0	2.2335	2.4049	0.1713	0.2260	1.3522	1.4576	0.1053	0.1995	2.8513	3.3466	0.4953	0.0800
1	2.0913	2.3308	0.2395	0.0624	1.2742	1.4422	0.1680	0.0468	2.7505	3.3645	0.6140	0.0160
2	2.0171	2.3408	0.3237	0.0597	1.2084	1.4279	0.2195	0.0564	2.9280	3.4316	0.5036	0.0877
3	1.9626	2.2399	0.2773	0.0296	1.2225	1.4028	0.1803	0.0590	3.0570	3.3003	0.2433	0.2467
4	1.9908	2.2311	0.2403	0.2131	1.1882	1.4251	0.2369	0.0334	2.9766	3.5173	0.5406	0.0445
5	2.0539	2.2997	0.2458	0.0565	1.1461	1.3681	0.2220	0.0182	2.8999	3.1476	0.2477	0.1576

Panel E. Liquidity of Convertible Debt Issuers with High-Prestige Underwriters

	Turnover				Zero Return Frequency				Amihud Measure, Price Impact			
Year	**Issuer**	**Match**	**I-M**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
-1	0.1999	0.1288	0.0710	0.0108	0.0683	0.0759	0.0076	0.2866	0.0058	0.0054	-0.0003	0.6480
0	0.2141	0.1371	0.0770	0.0101	0.0623	0.0762	0.0139	0.1379	0.0066	0.0064	-0.0002	0.7867
1	0.2144	0.1292	0.0852	0.0051	0.0705	0.0794	0.0089	0.0676	0.0056	0.0078	0.0021	0.1983
2	0.1902	0.1228	0.0674	0.0036	0.0767	0.0820	0.0052	0.2928	0.0082	0.0071	-0.0011	0.4765
3	0.1830	0.1230	0.0599	0.0055	0.0748	0.0849	0.0102	0.3102	0.0073	0.0125	0.0052	0.0769
4	0.1573	0.1177	0.0395	0.0213	0.0684	0.0864	0.0181	0.1363	0.0042	0.0104	0.0062	0.1512
5	0.1994	0.1146	0.0848	0.0236	0.0734	0.0836	0.0103	0.2111	0.0042	0.0085	0.0043	0.1702

	Roll Measure, Bid-Ask Spread				Effective Bid-Ask Spread				Effective Tick, Holden (2009)			
Year	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
-1	1.5646	1.5690	0.0044	0.9562	0.8244	0.9575	0.1332	0.0977	1.3589	1.3002	-0.0587	0.3370
0	1.4782	1.5611	0.0830	0.5297	0.8332	0.9745	0.1413	0.0680	1.2413	1.2234	-0.0178	0.7414
1	1.5104	1.4802	-0.0302	0.7060	0.8474	0.8999	0.0525	0.4614	1.3091	1.2173	-0.0918	0.0612
2	1.3729	1.3531	-0.0199	0.8749	0.8466	0.8858	0.0392	0.4844	1.4761	1.2995	-0.1766	0.1007
3	1.3061	1.4598	0.1538	0.2534	0.7940	0.9175	0.1234	0.0197	1.5436	1.3209	-0.2227	0.0639
4	1.2090	1.2960	0.0871	0.1441	0.7663	0.8933	0.1270	0.0205	1.3188	1.1475	-0.1713	0.1221
5	1.3345	1.3696	0.0351	0.7737	0.7794	0.8825	0.1031	0.2214	1.2328	1.1372	-0.0957	0.4765

Panel F. Liquidity of Convertible Debt Issuers with Low-Prestige Underwriters

	Turnover				Zero Return Frequency				Amihud Measure, Price Impact			
Year	**Issuer**	**Match**	**I-M**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
-1	0.1617	0.1046	0.0571	0.0006	0.1038	0.1068	0.0029	0.6616	0.0521	0.0552	0.0031	0.7885
0	0.1933	0.1165	0.0768	0.0004	0.0947	0.1060	0.0113	0.1564	0.0362	0.0471	0.0109	0.1089
1	0.2075	0.1054	0.1021	0.0031	0.1062	0.1058	-0.0004	0.9625	0.0374	0.0404	0.0030	0.6663
2	0.1931	0.1178	0.0753	0.0004	0.1183	0.1163	-0.0019	0.8089	0.0438	0.0424	-0.0014	0.8998
3	0.1681	0.1167	0.0515	0.0324	0.1110	0.1149	0.0039	0.6474	0.0515	0.1126	0.0611	0.1084
4	0.1849	0.1277	0.0572	0.2249	0.1189	0.1097	-0.0092	0.3300	0.0700	0.0977	0.0277	0.5707
5	0.1654	0.1221	0.0433	0.3977	0.1110	0.1106	-0.0004	0.9479	0.1355	0.1228	-0.0127	0.8974

	Roll Measure, Bid-Ask Spread				Effective Bid-Ask Spread				Effective Tick, Holden (2009)			
Year	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**	**Issuer**	**Match**	**M-I**	**p-value**
-1	1.7816	1.9026	0.1211	0.5133	1.0439	1.1223	0.0784	0.4329	2.0977	1.8145	-0.2832	0.1377
0	1.5742	1.6831	0.1089	0.4307	0.9747	1.1314	0.1567	0.1189	1.8678	1.7359	-0.1319	0.2877
1	1.6053	1.6711	0.0658	0.6743	0.9370	1.0824	0.1454	0.0483	2.1120	1.7579	-0.3541	0.1265
2	1.7089	1.6394	-0.0695	0.4862	0.8936	0.9984	0.1048	0.1611	2.3992	1.9842	-0.4150	0.1283
3	1.5236	1.4192	-0.1044	0.3755	0.8713	0.9823	0.1110	0.1515	2.0846	1.7279	-0.3567	0.0371
4	1.7253	1.5023	-0.2230	0.1336	0.8493	0.9123	0.0630	0.4159	2.1705	1.6535	-0.5169	0.0473
5	1.5337	1.4058	-0.1279	0.2899	0.7952	0.8731	0.0779	0.3671	2.0246	1.5605	-0.4641	0.0005

Table 8A. Additional Liquidity Drivers: Venture Capital, Underpricing, and Underwriters

The table presents the results of panel regressions of liquidity measures on the IPO dummy (1 in the three years after the IPO, 0 otherwise) and its interaction with either 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 underpriced 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). The dummy for SEOs and convertible debt issuers are also interacted with the Rank dummy (for convertible debt issuers, Rank is redefined to be 1 only if the underwriter's rank is 9). All liquidity measures are defined in the header of Table 2, all controls are defined in the Data Appendix. The t-statistics use standard errors clustered by firm-year-month. The sample period is from January 1986 to December 2017.

Panel A. Size and MB as Controls

A1. Role of Venture Capitalists

	Turn	Roll	Spread	EffTick	Amihud	Zero
IPO	-0.027	-0.367	0.535	-0.461	-3.467	-1.451
tstat	*-0.11*	*-3.74*	*11.3*	*-5.53*	*-6.81*	*-4.06*
VC	4.037	-0.319	0.066	0.235	0.737	-4.145
tstat	*10.0*	*-2.96*	*1.11*	*2.80*	*1.47*	*-10.3*

A2. Role of Underpricing

	Turn	Roll	Spread	EffTick	Amihud	Zero
IPO	0.340	-0.442	0.582	-0.555	-3.753	-2.272
tstat	*1.40*	*-4.66*	*11.9*	*-6.95*	*-7.49*	*-6.24*
Under	3.426	-0.175	-0.017	0.463	1.426	-2.462
tstat	*8.66*	*-1.71*	*-0.27*	*5.44*	*2.82*	*-5.61*

Panel B. Full Set of Controls

B1. Role of Venture Capitalists

	Turn	Roll	Spread	EffTick	Amihud	Zero
IPO	-0.118	-0.416	0.499	0.105	-4.046	0.651
tstat	*-0.49*	*-5.09*	*9.79*	*1.15*	*-11.1*	*1.78*
VC	1.756	-0.387	0.091	0.081	0.641	-3.660
tstat	*4.51*	*-2.97*	*1.33*	*0.79*	*1.41*	*-7.90*

B2. Role of Underpricing

	Turn	Roll	Spread	EffTick	Amihud	Zero
IPO	-0.290	-0.720	0.530	-0.064	-4.547	-0.031
tstat	*-1.27*	*-7.95*	*9.90*	*-0.77*	*-11.4*	*-0.08*
Under	2.360	0.373	0.033	0.456	2.220	-2.231
tstat	*6.02*	*2.88*	*0.46*	*4.82*	*4.67*	*-4.73*

A3. Role of High-Prestige Underwriters

	Turn	Roll	Spread	EffTick	Amihud	Zero
IPO	0.871	-0.846	0.721	-0.612	-5.901	-2.904
tstat	*3.21*	*-6.37*	*10.5*	*-4.88*	*-10.9*	*-5.49*
Rank	0.679	0.270	-0.172	0.391	3.870	-1.049
tstat	*1.99*	*2.14*	*-2.29*	*3.20*	*6.28*	*-2.00*

	Turn	Roll	Spread	EffTick	Amihud	Zero
SEO	7.429	-1.522	0.059	-0.742	-4.193	-8.025
tstat	*12.3*	*-15.5*	*1.40*	*-9.72*	*-8.46*	*-21.3*
Rank	-1.572	1.586	0.124	1.187	4.564	6.184
tstat	*-2.55*	*15.2*	*3.01*	*13.9*	*9.01*	*15.8*

	Turn	Roll	Spread	EffTick	Amihud	Zero
Conv	5.124	0.339	-0.045	-0.200	-1.625	2.274
tstat	*3.96*	*1.70*	*-0.66*	*-1.58*	*-2.92*	*4.37*
Rank	0.055	1.177	0.166	1.244	4.851	2.261
tstat	*0.03*	*4.71*	*2.06*	*7.37*	*6.59*	*3.21*

B3. Role of High-Prestige Underwriters

	Turn	Roll	Spread	EffTick	Amihud	Zero
IPO	0.517	-0.488	0.680	0.199	-5.287	0.641
tstat	*1.96*	*-4.10*	*9.08*	*1.44*	*-9.77*	*1.20*
Rank	0.112	-0.147	-0.237	-0.098	2.520	-2.437
tstat	*0.32*	*-1.13*	*-2.94*	*-0.72*	*5.01*	*-4.41*

	Turn	Roll	Spread	EffTick	Amihud	Zero
SEO	5.661	-1.732	-0.279	-0.587	-5.327	-4.530
tstat	*9.51*	*-12.90*	*-6.73*	*-7.25*	*-8.73*	*-13.41*
Rank	-0.170	1.357	0.357	0.828	4.956	2.566
tstat	*-0.27*	*10.28*	*8.03*	*9.69*	*8.10*	*7.41*

	Turn	Roll	Spread	EffTick	Amihud	Zero
Conv	6.432	-0.152	-0.200	-0.183	-2.276	2.138
tstat	*4.12*	*-0.84*	*-3.09*	*-1.90*	*-4.31*	*4.72*
Rank	-0.088	0.316	0.241	0.676	2.530	0.319
tstat	*-0.05*	*1.37*	*3.00*	*5.31*	*3.81*	*0.54*

Table 9A. Liquidity of Stock and Debt Issuers: The Role of Market Liquidity and Price Pressure

The table 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 and 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 market beta and age (for SEOs and convertible debt issuers).

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

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 the five liquidity measures that are defined in the header of Table 1A.

Panel A adds to the regression above the dummy for good market liquidity (MktLiq, 1 if market-wide average Amihud ratio is outside of its top quartile in 1986-2017 sample, 0 otherwise) and the product of the MktLiq dummy with the issuer dummy. The slopes on the controls and MktLiq are not reported for brevity.

Panel B replaces MktLiq dummy with Press dummy, which equals one if in the quarter immediately preceding the issue the issuing firm is in the top decile in terms of price pressure coming from mutual fund purchases, and zero otherwise.

Detailed definitions of the controls are in the Data Appendix. The t-statistics use standard errors clustered by firm-year-month. In Panel A, the sample period for the regressions is from January 1986 to December 2017. In Panel B, the sample is from January 1999 to December 2017 based on availability of mutual funds flows data.

Panel C. Full Set of Controls and Market Liquidity

Panel C1. Post-Issue Liquidity of IPOs

Liq=	**Turn**	**EffTick**	**Roll**	**Spread**	**Amihud**	**Zero**
IPO	1.832	1.140	0.850	0.616	0.994	3.498
***t*-stat.**	*8.46*	*9.30*	*11.5*	*9.90*	*2.64*	*8.97*
IPO·LiqMkt	-4.224	-1.081	-0.644	-0.500	-1.543	-2.621
***t*-stat.**	*-10.2*	*-8.42*	*-8.18*	*-7.93*	*-4.00*	*-5.81*

Panel C2. Post-Issue Liquidity of SEOs

Liq=	**Turn**	**EffTick**	**Roll**	**Spread**	**Amihud**	**Zero**
SEO	0.889	-0.041	0.081	0.022	-0.442	-1.249
***t*-stat.**	*5.82*	*-0.52*	*2.07*	*0.69*	*-4.29*	*-5.56*
SEO·LiqMkt	1.411	-0.406	-0.229	-0.042	-0.120	0.563
***t*-stat.**	*4.03*	*-4.82*	*-5.05*	*-1.28*	*-0.94*	*2.21*

Panel C3. Post-Issue Liquidity of Convertible Debt Issuers

Liq=	**Turn**	**EffTick**	**Roll**	**Spread**	**Amihud**	**Zero**
Conv	0.417	-0.286	-0.073	-0.147	-0.623	-0.655
***t*-stat.**	*1.35*	*-2.74*	*-1.32*	*-5.13*	*-6.41*	*-1.92*
Conv·LiqMkt	5.541	0.332	0.078	0.213	0.561	1.885
***t*-stat.**	*4.25*	*2.59*	*1.06*	*5.19*	*4.51*	*4.38*

Panel D. Price Pressure and Opportunistic Issuance

Panel D1. Post-Issue Liquidity of SEOs

	Turn	**EffTick**	**Roll**	**Spread**	**Amihud**	**Zero**
SEO	5.074	-0.303	-0.034	0.052	-0.246	-0.633
***t*-stat.**	*9.59*	*-7.26*	*-1.34*	*4.48*	*-1.46*	*-7.04*
SEO·Press	-3.906	0.116	0.040	-0.038	0.125	0.293
***t*-stat.**	*-4.53*	*2.73*	*0.92*	*-1.98*	*0.77*	*2.85*

Panel D2. Post-Issue Liquidity of Convertible Debt Issuers

	Turn	**EffTick**	**Roll**	**Spread**	**Amihud**	**Zero**
Conv	12.27	-0.147	0.026	0.092	-0.120	-0.304
***t*-stat.**	*5.97*	*-2.24*	*0.58*	*4.27*	*-2.29*	*-1.88*
Conv·Press	2.913	0.179	0.166	0.099	0.330	0.275
***t*-stat.**	*0.90*	*2.12*	*1.99*	*1.82*	*4.03*	*1.29*

Table 10A. Related Puzzles and Liquidity

Panel A reports median liquidity of small growth firms (the intersection of bottom (second smallest) size quintile and top market-to-book quintile, denoted SG1 (SG2)) and compares it with the average median liquidity across all 25 size and market-to-book portfolios. Panel B reports median liquidity across three groups on cumulative issuance (top 30%, middle 40%, bottom 30%). The liquidity measures are defined in the header of Table 1A. Cumulative issuance is the log market value growth minus the cumulative log return in the past five years. The sorts on cumulative issuance use NYSE (exchcd=1) breakpoints. P-values use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2017.

Panel A. Liquidity of Small Growth Firms

	SG1	**SG2**	**Avg**	**Avg-SG1**	**p-value**	**Avg-SG2**	**p-value**
Turn	0.039	0.109	0.109	-0.071	0.000	0.000	0.944
Zero	0.214	0.121	0.094	0.119	0.000	0.027	0.023
Amihud	3.441	0.048	0.340	3.102	0.009	-0.291	0.013
Roll	3.229	1.572	1.593	1.635	0.000	-0.021	0.766
Spread	0.069	0.021	0.021	0.048	0.000	0.000	0.517
EffTick	1.881	0.870	0.945	0.937	0.001	-0.074	0.279

Panel B. Liquidity and Cumulative Issuance

	Low	**Middle**	**High**	**H-L**	**p-value**
Turn	0.069	0.068	0.093	0.024	0.002
Zero	0.104	0.119	0.128	0.024	0.016
Amihud	0.056	0.203	0.267	0.211	0.104
Roll	1.230	1.596	2.025	0.795	0.000
Spread	0.621	0.871	1.275	0.654	0.000
EffTick	1.297	2.045	3.304	2.007	0.003

Table 11A. Small Growth Puzzle and Cumulative Issuance Puzzle: Volatility Risk and Liquidity Explanations

The table reports the results of several asset-pricing models to returns to small growth firms and the low-minus-high cumulative issuance portfolio. The models are fitted to monthly returns and include the CAPM, the Fama-French model (FF), the CAPM augmented with FVIX (ICAPM), and the CAPM augmented with liquidity factor, LMH (LCAPM).

$$\text{CAPM}: \quad Ret_t^X = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) \tag{2}$$

$$\text{FF}: \quad Ret_t^X = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t \tag{3}$$

$$\text{ICAPM}: \quad Ret_t^X = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{FVIX} \cdot FVIX_t \tag{4}$$

$$\text{LCAPM}: \quad Ret_t^X = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{LMH} \cdot LMH_t \tag{5}$$

$$\text{ICAPM3}: \quad Ret_t^X = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{FVIX} \cdot FVIX_t + \beta_{LMH} \cdot LMH_t \tag{6}$$

$$Ret_t^X \in \{SG1_t - RF_t;\ SG2_t - RF_t;\ CumIss_t\} \tag{7}$$

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. 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 heteroscedasticity. The sample period is from January 1986 to December 2017.

A. Smallest Growth Firms

	CAPM	**FF**	**ICAPM**	**LCAPM**	**ICAPM3**
$\boldsymbol{\alpha}$	-0.788	-0.631	-0.065	-0.498	-0.087
t-stat	*-3.15*	*-4.32*	*-0.18*	*-1.90*	*-0.25*
$\boldsymbol{\beta_{MKT}}$	1.354	1.107	3.447	0.979	2.548
t-stat	*24.2*	*28.2*	*4.78*	*12.0*	*3.73*
$\boldsymbol{\beta_{SMB}}$		1.328			
t-stat		*19.7*			
$\boldsymbol{\beta_{HML}}$		-0.494			
t-stat		*-5.90*			
$\boldsymbol{\beta_{FVIX}}$			1.580		1.095
t-stat			*3.03*		*2.26*
$\boldsymbol{\beta_{LMH}}$				-0.602	-0.412
t-stat				*-4.50*	*-4.15*

B. Second Smallest Growth Firms

	CAPM	FF	ICAPM	LCAPM	ICAPM3
α	-0.342	-0.189	0.162	-0.133	0.145
t-stat	*-1.97*	*-2.34*	*0.67*	*-0.76*	*0.64*
β_{MKT}	1.336	1.132	2.778	1.066	2.097
t-stat	*32.5*	*44.4*	*5.15*	*16.5*	*4.21*
β_{SMB}		1.024			
t-stat		*28.8*			
β_{HML}		-0.486			
t-stat		*-11.6*			
β_{FVIX}			1.088		0.721
t-stat			*2.77*		*2.00*
β_{LMH}				-0.435	-0.312
t-stat				*-4.51*	*-4.68*

C. Cumulative Issuance Puzzle

	CAPM	FF	ICAPM	LCAPM	ICAPM3
α	-0.740	-0.610	-0.341	-0.512	-0.363
t-stat	*-4.27*	*-4.99*	*-1.62*	*-3.09*	*-1.92*
β_{MKT}	0.397	0.264	1.548	0.101	0.656
t-stat	*7.12*	*6.31*	*3.89*	*1.86*	*1.82*
β_{SMB}		0.568			
t-stat		*9.17*			
β_{HML}		-0.413			
t-stat		*-5.20*			
β_{FVIX}			0.869		0.387
t-stat			*3.12*		*1.60*
β_{LMH}				-0.475	-0.409
t-stat				*-6.24*	*-5.68*

Table 12A. Cumulative Issuance Puzzle in the Cross-Section

The table presents the results of estimating various asset-pricing models for the low-minus-high cumulative issuance portfolio (CumIss) 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).

$$\begin{aligned} \text{CAPM}: \quad & Ret_t - RF_t && = \alpha_{CAPM} + \beta_{MKT} \cdot (MKT_t - RF_t) && (8) \\ \text{ICAPM}: \quad & Ret_t - RF_t && = \alpha_{ICAPM} + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{FVIX} \cdot FVIX_t && (9) \\ \text{LCAPM}: \quad & Ret_t - RF_t && = \alpha_{LCAPM} + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{LMH} \cdot LMH_t && (10) \end{aligned}$$

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 CumIss is long in the top 30% issuance stocks and short in the bottom 30% issuance stocks. Cumulative issuance is the log market value growth minus the cumulative log return in the past five years. The size and market-to-book groups are the top 30%, the middle 40%, and the bottom 30%. The size and market-to-book sorts use NYSE (exchcd=1) breakpoints. 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 is from January 1986 to December 2017.

Panel A. Size Sorts

	Small	**Med**	**Big**	**S-B**
$\boldsymbol{\alpha_{CAPM}}$	-0.969	-0.688	-0.567	-0.402
t-stat	*-4.08*	*-4.63*	*-4.23*	*-2.00*
$\boldsymbol{\alpha_{ICAPM}}$	-0.532	-0.338	-0.403	-0.129
t-stat	*-1.89*	*-1.79*	*-2.75*	*-0.51*
$\boldsymbol{\beta_{FVIX}}$	0.936	0.736	0.357	0.580
t-stat	*2.75*	*2.38*	*2.98*	*2.07*
$\boldsymbol{\alpha_{LCAPM}}$	-0.519	-0.362	-0.364	-0.155
t-stat	*-2.43*	*-2.96*	*-3.28*	*-0.69*
$\boldsymbol{\beta_{LMH}}$	-0.758	-0.549	-0.341	-0.417
t-stat	*-6.35*	*-10.53*	*-8.23*	*-3.19*

Panel B. Market-to-Book Sorts

	Value	**Neut**	**Growth**	**G-V**
$\boldsymbol{\alpha_{CAPM}}$	-0.120	-0.222	-0.747	-0.627
t-stat	*-0.67*	*-1.39*	*-3.07*	*-3.70*
$\boldsymbol{\alpha_{ICAPM}}$	0.141	0.095	-0.063	-0.203
t-stat	*0.71*	*0.47*	*-0.19*	*-0.85*
$\boldsymbol{\beta_{FVIX}}$	0.567	0.699	1.491	0.924
t-stat	*2.55*	*2.99*	*3.15*	*2.87*
$\boldsymbol{\alpha_{LCAPM}}$	0.039	-0.042	-0.448	-0.487
t-stat	*0.22*	*-0.27*	*-1.79*	*-2.72*
$\boldsymbol{\beta_{LMH}}$	-0.331	-0.375	-0.623	-0.291
t-stat	*-4.31*	*-5.67*	*-5.03*	*-3.50*

Table 13A. Frequent Issuers Puzzle: Volatility Risk and Liquidity Explanations

Panel A reports median turnover and trading costs measures for frequent issuers and for all Compustat firms, as well as the difference between the two. FI (LFI) is the portfolio of firms that have performed at least three (large) issues of debt or equity in the past three years that exceed, in term of proceeds, 5% (10%) of total assets and 3% of market value of equity. The trading costs measures are defined in the header of Table 1A.

Panel B and C report the results of several asset-pricing models to returns to small growth firms and the low-minus-high cumulative issuance portfolio. The models are fitted to monthly returns and include the CAPM, the Fama-French model (FF), the CAPM augmented with FVIX (ICAPM), and the CAPM augmented with liquidity factor, LMH (LCAPM).

$$\text{CAPM}: \quad FI_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) \tag{11}$$

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

$$\text{ICAPM}: \quad FI_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{FVIX} \cdot FVIX_t \tag{13}$$

$$\text{LCAPM}: \quad FI_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{LMH} \cdot LMH_t \tag{14}$$

$$\tag{15}$$

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 heteroscedasticity. The sample period is from January 1986 to December 2017.

Panel A. Liquidity of Frequent Issuers

	FI	**LFI**	**All**	**All-FI**	**p-value**	**All-LFI**	**p-value**
Turn	0.114	0.116	0.076	0.037	0.000	0.039	0.000
Zero	0.130	0.133	0.129	0.001	0.786	0.003	0.512
Amihud	0.345	0.372	0.284	0.061	0.126	0.088	0.068
Roll	2.364	2.537	1.701	0.663	0.000	0.836	0.000
Spread	1.533	1.710	0.994	0.538	0.000	0.715	0.000
EffTick	4.093	4.515	2.581	1.511	0.000	1.933	0.000

Panel B. Frequent Issuers

	Panel B1. Value-Weighted				Panel B2. Equal-Weighted			
	CAPM	**FF**	**ICAPM**	**LCAPM**	**CAPM**	**FF**	**ICAPM**	**LCAPM**
$\boldsymbol{\alpha}$	-0.350	-0.374	-0.094	-0.144	-0.664	-0.681	-0.210	-0.333
t-stat	*-2.13*	*-2.34*	*-0.53*	*-1.00*	*-2.50*	*-3.51*	*-0.73*	*-1.42*
$\boldsymbol{\beta_{MKT}}$	1.326	1.275	2.072	1.044	1.261	1.120	2.581	0.808
t-stat	*29.4*	*30.6*	*11.8*	*30.2*	*24.4*	*24.8*	*7.79*	*11.8*
$\boldsymbol{\beta_{SMB}}$		0.429				1.048		
t-stat		*6.08*				*10.5*		
$\boldsymbol{\beta_{HML}}$		0.049				-0.001		
t-stat		*0.80*				*-0.01*		
$\boldsymbol{\beta_{FVIX}}$			0.563				0.996	
t-stat			*4.41*				*4.10*	
$\boldsymbol{\beta_{LMH}}$				-0.451				-0.728
t-stat				*-8.25*				*-9.34*

Panel C. Large Frequent Issuers

	Panel C1. Value-Weighted				Panel C2. Equal-Weighted			
	CAPM	**FF**	**ICAPM**	**LCAPM**	**CAPM**	**FF**	**ICAPM**	**LCAPM**
$\boldsymbol{\alpha}$	-1.015	-0.943	-0.636	-0.789	-1.019	-0.998	-0.530	-0.669
t-stat	*-4.25*	*-4.31*	*-2.54*	*-3.50*	*-3.53*	*-4.57*	*-1.69*	*-2.50*
$\boldsymbol{\beta_{MKT}}$	1.449	1.342	2.533	1.139	1.322	1.161	2.751	0.844
t-stat	*28.8*	*27.7*	*10.4*	*24.2*	*22.7*	*21.6*	*6.46*	*11.0*
$\boldsymbol{\beta_{SMB}}$		0.553				1.080		
t-stat		*5.32*				*10.7*		
$\boldsymbol{\beta_{HML}}$		-0.237				-0.111		
t-stat		*-2.69*				*-0.82*		
$\boldsymbol{\beta_{FVIX}}$			0.818				1.078	
t-stat			*4.82*				*3.54*	
$\boldsymbol{\beta_{LMH}}$				-0.498				-0.768
t-stat				*-9.45*				*-7.82*

Table 14A. Frequent Issuers Puzzle in the Cross-Section

The table presents the results of estimating, in different size groups, various asset-pricing models for 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. 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).

$$\text{CAPM}: \quad Ret_t - RF_t = \alpha_{CAPM} + \beta_{MKT} \cdot (MKT_t - RF_t) \tag{16}$$
$$\text{ICAPM}: \quad Ret_t - RF_t = \alpha_{ICAPM} + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{FVIX} \cdot FVIX_t \tag{17}$$
$$\text{LCAPM}: \quad Ret_t - RF_t = \alpha_{LCAPM} + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{LMH} \cdot LMH_t \tag{18}$$

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 size groups are the top 30%, the middle 40%, and the bottom 30% in terms of market cap among all frequent issuers. 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

	Small	Med	Big	S-B
$\boldsymbol{\alpha_{CAPM}}$	-0.884	-0.633	-0.122	-0.762
t-stat	*-3.62*	*-2.82*	*-0.66*	*-2.80*
$\boldsymbol{\alpha_{ICAPM}}$	-0.401	-0.375	0.101	-0.502
t-stat	*-1.54*	*-1.58*	*0.51*	*-1.75*
$\boldsymbol{\beta_{FVIX}}$	1.052	0.557	0.503	0.549
t-stat	*4.96*	*3.19*	*3.68*	*2.69*
$\boldsymbol{\alpha_{LCAPM}}$	-0.566	-0.362	0.076	-0.643
t-stat	*-2.48*	*-1.83*	*0.43*	*-2.20*
$\boldsymbol{\beta_{LMH}}$	-0.661	-0.562	-0.412	-0.249
t-stat	*-7.82*	*-8.04*	*-6.37*	*-2.03*

Panel B. Equal-Weighted

	Small	Med	Big	S-B
$\boldsymbol{\alpha_{CAPM}}$	-0.764	-0.579	-0.231	-0.533
t-stat	*-2.41*	*-2.55*	*-1.17*	*-1.71*
$\boldsymbol{\alpha_{ICAPM}}$	-0.228	-0.274	0.004	-0.232
t-stat	*-0.66*	*-1.10*	*0.02*	*-0.65*
$\boldsymbol{\beta_{FVIX}}$	1.182	0.655	0.527	0.656
t-stat	*3.75*	*4.00*	*3.22*	*2.18*
$\boldsymbol{\alpha_{LCAPM}}$	-0.373	-0.291	-0.003	-0.370
t-stat	*-1.27*	*-1.43*	*-0.02*	*-1.10*
$\boldsymbol{\beta_{LMH}}$	-0.813	-0.599	-0.473	-0.340
t-stat	*-7.51*	*-8.46*	*-7.28*	*-2.31*

Table 15A. Turnover and Liquidity Distribution

Panel A (B) presents the distribution of turnover and trading costs measures in the pre-decimalization, 1986-2001 (post-decimalization, 2002-2017) sample. The columns report the 10th (p10), 25th (p25), etc. percentage points: the percentage points are calculated for all firms in the IPO (SEO, convertible debt issuers portfolio) separately in each month, and then the tables report the average of those monthly percentage points across all months in the subsample. The new issues portfolios include firms that performed an IPO (Panels A1 and B1), SEO (Panel A2 and B2) or issued convertible debt (Panel A3 and B3) 2 to 37 months ago. The trading costs measures are defined in the header of Table 1 in the paper. Panels A4 and B4 look at the percentage points of the trading costs measures for all CRSP firms.

Panel A. Liquidity Percentiles in 1986-2001

A1. Turnover and Liquidity of IPOs

	p10	p25	p50	p75	p90
Turn	0.014	0.025	0.048	0.091	0.155
EffTick	1.846	2.874	5.227	9.875	18.187
Roll	0.963	1.688	2.906	5.047	8.573
Spread	0.596	1.046	1.700	2.880	5.914
Amihud	0.016	0.111	0.688	3.817	14.744
Zero	0.098	0.148	0.209	0.284	0.411

A2. Turnover and Liquidity of SEOs

	p10	p25	p50	p75	p90
Turn	0.020	0.036	0.066	0.113	0.174
EffTick	1.135	1.715	2.886	5.412	10.568
Roll	0.643	1.100	1.840	3.104	5.100
Spread	0.424	0.621	1.081	1.776	2.818
Amihud	0.002	0.009	0.070	0.521	2.880
Zero	0.067	0.105	0.162	0.224	0.292

Panel B. Liquidity Percentiles in 2002-2017

B1. Turnover and Liquidity of IPOs

	p10	p25	p50	p75	p90
Turn	0.051	0.091	0.153	0.260	0.417
EffTick	0.248	0.401	0.768	1.656	3.531
Roll	0.582	0.992	1.577	2.440	3.678
Spread	0.615	0.806	1.080	1.438	1.871
Amihud	0.001	0.003	0.014	0.108	1.245
Zero	0.004	0.010	0.021	0.045	0.080

B2. Turnover and Liquidity of SEOs

	p10	p25	p50	p75	p90
Turn	0.057	0.105	0.179	0.294	0.468
EffTick	0.170	0.280	0.566	1.493	3.463
Roll	0.512	0.850	1.402	2.191	3.387
Spread	0.526	0.682	0.964	1.370	1.870
Amihud	0.000	0.001	0.004	0.033	0.267
Zero	0.003	0.008	0.018	0.038	0.070

A3. Liquidity of Conv. Debt Issuers

	p10	p25	p50	p75	p90
Turn	0.026	0.048	0.084	0.132	0.207
EffTick	0.959	1.431	2.472	4.553	9.680
Roll	0.614	0.984	1.534	2.507	4.574
Spread	0.385	0.542	0.820	1.331	2.296
Amihud	0.001	0.005	0.033	0.238	1.669
Zero	0.058	0.093	0.147	0.214	0.285

B3. Liquidity of Conv. Debt Issuers

	p10	p25	p50	p75	p90
Turn	0.107	0.156	0.233	0.353	0.590
EffTick	0.130	0.200	0.389	0.829	2.068
Roll	0.436	0.700	1.133	1.803	2.796
Spread	0.476	0.581	0.767	1.076	1.471
Amihud	0.000	0.000	0.001	0.003	0.020
Zero	0.002	0.006	0.012	0.026	0.050

A4. Turnover and Liquidity - Full Sample

	p10	p25	p50	p75	p90
Turn	0.008	0.017	0.038	0.072	0.121
EffTick	1.381	2.396	4.529	9.574	19.470
Roll	0.634	1.132	2.171	4.146	7.257
Spread	0.330	0.582	1.269	3.032	8.627
Amihud	0.006	0.052	0.546	3.950	17.661
Zero	0.092	0.156	0.236	0.351	0.531

B4. Turnover and Liquidity - Full Sample

	p10	p25	p50	p75	p90
Turn	0.022	0.052	0.115	0.210	0.350
EffTick	0.170	0.299	0.633	1.627	3.987
Roll	0.387	0.688	1.231	2.161	3.685
Spread	0.203	0.397	0.720	1.164	1.781
Amihud	0.000	0.002	0.022	0.286	3.225
Zero	0.002	0.009	0.023	0.054	0.096

Table 16A. Descriptive Statistics of Asset-Pricing Factors

The table presents descriptive statistics of the five Fama-French (2015) factors, the momentum factor, and FVIX factor. SMB is the difference in the returns of small and large portfolios, HML is the difference in the returns of high and low book-to-market portfolios, RMW is the difference in the returns of robust and weak (high and low) operating profitability portfolios, and CMA is the difference in the returns of conservative and aggressive (low and high) investment portfolios. MOM is the difference between returns of winner and loser portfolios (based on sorts on cumulative returns from month t-2 to month t-12). All factor returns are from the web site of Kenneth French, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/. FVIX is the factor-mimicking portfolio that tracks daily changes in VIX.

	Mean	**StDev**	**Sharpe**	$\boldsymbol{\alpha}_{CAPM}$	**Appraisal**	**Skew**	**Kurt**
MKT	0.682	4.385	0.155			-0.930	5.902
SMB	0.089	3.003	0.029	-0.002	-0.001	0.477	8.135
HML	0.216	2.917	0.074	0.311	0.109	0.160	5.597
MOM	0.519	4.585	0.113	0.649	0.144	-1.548	14.762
CMA	0.263	2.029	0.129	0.380	0.202	0.508	5.212
RMW	0.351	2.567	0.137	0.496	0.207	-0.463	15.188
FVIX	-1.366	5.978	-0.229	-0.463	-0.337	1.003	6.203

Table 17A. New Issues in the Five-Factor Fama-French Model

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 three-factor and five-factor Fama-French models (FF3 and FF5), and FF3 augmented with either CMA or RMW factors (FF3+CMA and FF3+RMW).

$$\text{FF3}: \quad Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t \tag{19}$$

$$\text{FF3} + \text{CMA}: \quad Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t + \beta_{CMA} \cdot CMA_t \tag{20}$$

$$\text{FF3} + \text{RMW}: \quad Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t + \beta_{RMW} \cdot RMW_t \tag{21}$$

$$\text{FF5}: \quad Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t + \beta_{CMA} \cdot CMA_t + \beta_{RMW} \cdot RMW_t \tag{22}$$

The new issues portfolios include firms that performed an IPO (Panels A1 and B1), SEO (Panels A2 and B2), or issued convertible debt (Panels A3 and B3) 2 to 37 months ago. 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 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 uses all months in the sample, and Panel B excludes January 2001.

Panel A. All Observations

	Panel A1. IPOs				**Panel A2. SEOs**				**Panel A3. Convertible Debt Issuers**			
	FF3	**+CMA**	**+RMW**	**FF5**	**FF3**	**+CMA**	**+RMW**	**FF5**	**FF3**	**+CMA**	**+RMW**	**FF5**
$\boldsymbol{\alpha}$	-0.340	-0.213	-0.071	0.104	-0.419	-0.340	-0.292	-0.187	-0.683	-0.644	-0.560	-0.502
t-stat	*-2.22*	*-1.32*	*-0.32*	*0.49*	*-4.02*	*-2.99*	*-2.11*	*-1.37*	*-4.98*	*-4.63*	*-3.41*	*-3.09*
$\boldsymbol{\beta_{MKT}}$	1.183	1.122	1.095	1.013	1.214	1.176	1.172	1.123	1.328	1.309	1.287	1.260
t-stat	*21.6*	*16.9*	*17.4*	*17.6*	*29.1*	*26.1*	*25.7*	*29.7*	*27.4*	*26.0*	*28.1*	*32.1*
$\boldsymbol{\beta_{SMB}}$	1.058	1.087	0.859	0.878	0.845	0.863	0.751	0.762	0.652	0.660	0.561	0.567
t-stat	*9.31*	*10.9*	*7.41*	*8.25*	*9.45*	*11.3*	*9.02*	*10.0*	*8.89*	*9.84*	*7.35*	*7.73*
$\boldsymbol{\beta_{HML}}$	-0.489	-0.275	-0.360	-0.089	-0.085	0.048	-0.023	0.139	0.250	0.315	0.309	0.399
t-stat	*-3.52*	*-2.14*	*-3.64*	*-0.72*	*-0.95*	*0.47*	*-0.32*	*1.42*	*3.25*	*3.05*	*4.37*	*4.10*
$\boldsymbol{\beta_{CMA}}$		-0.509		-0.620		-0.317		-0.370		-0.155	-0.285	-0.205
t-stat		*-1.60*		*-2.45*		*-1.76*		*-2.49*		*-0.90*	*-2.09*	*-1.42*
$\boldsymbol{\beta_{RMW}}$			-0.623	-0.672			-0.295	-0.325				-0.301
t-stat			*-3.05*	*-3.73*			*-2.14*	*-2.63*				*-2.33*

Panel B. January 2001 Excluded

	Panel B1. IPOs				Panel B2. SEOs				Panel B3. Convertible Debt Issuers			
	FF3	**+CMA**	**+RMW**	**FF5**	**FF3**	**+CMA**	**+RMW**	**FF5**	**FF3**	**+CMA**	**+RMW**	**FF5**
$\boldsymbol{\alpha}$	-0.427	-0.339	-0.171	-0.036	-0.462	-0.400	-0.341	-0.253	-0.711	-0.685	-0.592	-0.546
t-stat	*-2.56*	*-2.25*	*-0.83*	*-0.20*	*-4.35*	*-3.74*	*-2.62*	*-2.08*	*-5.24*	*-5.06*	*-3.71*	*-3.50*
$\boldsymbol{\beta_{MKT}}$	1.185	1.144	1.102	1.042	1.215	1.186	1.176	1.137	1.328	1.316	1.290	1.269
t-stat	*22.0*	*18.2*	*19.0*	*21.3*	*29.5*	*26.6*	*26.8*	*31.1*	*27.5*	*25.8*	*28.6*	*31.6*
$\boldsymbol{\beta_{SMB}}$	1.012	1.033	0.826	0.843	0.823	0.837	0.735	0.745	0.637	0.643	0.550	0.556
t-stat	*9.75*	*11.3*	*7.37*	*8.20*	*9.75*	*11.4*	*9.04*	*9.99*	*9.05*	*9.77*	*7.34*	*7.67*
$\boldsymbol{\beta_{HML}}$	-0.446	-0.306	-0.325	-0.130	-0.064	0.034	-0.007	0.119	0.264	0.305	0.320	0.386
t-stat	*-4.16*	*-2.42*	*-4.11*	*-1.18*	*-0.82*	*0.34*	*-0.10*	*1.29*	*3.66*	*2.99*	*4.61*	*4.08*
$\boldsymbol{\beta_{CMA}}$		-0.338		-0.452		-0.235		-0.290		-0.100	-0.274	-0.152
t-stat		*-1.42*		*-2.61*		*-1.55*		*-2.38*		*-0.60*	*-2.07*	*-1.08*
$\boldsymbol{\beta_{RMW}}$			-0.586	-0.625			-0.277	-0.302				-0.287
t-stat			*-3.21*	*-3.83*			*-2.15*	*-2.58*				*-2.26*

Table 18A. Overlap between FVIX and the New Fama-French Factors, RMW and CMA

Panels A and C present the estimates of four factor models fitted to returns to RMW and CMA factors, respectively. The models include the CAPM and the three-factor Fama-French model (FF3), as well as their versions augmented with FVIX (in the columns labeled "+FVIX"). Panel B fits to FVIX returns the CAPM and the three-factor Fama-French model (FF3), as well as their versions augmented with RMW (in the columns labeled "+RMW"), and also fits to FVIX returns the five-factor Fama-French model (FF5). Panel D does the same thing as Panel B replacing RMW with CMA. 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 heteroskedasticity. The sample period is from January 1986 to December 2017.

	Panel A. RMW on FVIX				**Panel B. FVIX on RMW**				
	CAPM	**+FVIX**	**FF3**	**+FVIX**	**CAPM**	**+RMW**	**FF**	**+RMW**	**FF5**
$\boldsymbol{\alpha}$	0.496	0.116	0.431	0.176	-0.463	-0.325	-0.439	-0.347	-0.305
t-stat	*3.55*	*0.70*	*3.28*	*1.42*	*-4.73*	*-3.87*	*-4.00*	*-3.72*	*-3.73*
$\boldsymbol{\beta_{MKT}}$	-0.213	-1.319	-0.141	-0.947	-1.325	-1.384	-1.358	-1.388	-1.407
t-stat	*-4.23*	*-3.68*	*-2.94*	*-5.02*	*-37.0*	*-44.7*	*-35.2*	*-41.7*	*-50.7*
$\boldsymbol{\beta_{SMB}}$			-0.320	-0.218			0.170	0.103	0.107
t-stat			*-3.12*	*-2.63*			*4.94*	*4.43*	*4.56*
$\boldsymbol{\beta_{HML}}$			0.208	0.166			-0.073	-0.028	0.034
t-stat			*2.10*	*2.04*			*-1.41*	*-0.65*	*0.59*
$\boldsymbol{\beta_{FVIX}}$		-0.835		-0.593					-0.142
t-stat		*-3.23*		*-4.37*					*-2.31*
						-0.275		-0.212	-0.224
						-7.00		*-5.52*	*-6.15*

	Panel C. CMA on FVIX				**Panel D. FVIX on CMA**				
	CAPM	**+FVIX**	**FF3**	**+FVIX**	**CAPM**	**+CMA**	**FF**	**+CMA**	**FF5**
$\boldsymbol{\alpha}$	0.380	0.281	0.249	0.196	-0.463	-0.415	-0.439	-0.413	-0.305
t-stat	*3.17*	*2.63*	*3.07*	*2.19*	*-4.73*	*-4.32*	*-4.00*	*-4.23*	*-3.73*
$\boldsymbol{\beta_{MKT}}$	-0.173	-0.477	-0.121	-0.309	-1.325	-1.346	-1.358	-1.371	-1.407
t-stat	*-4.06*	*-2.92*	*-3.82*	*-2.89*	*-37.0*	*-39.7*	*-35.2*	*-42.8*	*-50.7*
$\boldsymbol{\beta_{SMB}}$			0.056	0.080			0.170	0.176	0.107
t-stat			*1.21*	*1.74*			*4.94*	*4.71*	*4.56*
$\boldsymbol{\beta_{HML}}$			0.421	0.411			-0.073	-0.029	0.034
t-stat			*8.53*	*8.88*			*-1.41*	*-0.42*	*0.59*
$\boldsymbol{\beta_{FVIX}}$		-0.230		-0.138		-0.122		-0.103	-0.142
t-stat		*-2.12*		*-1.70*		*-2.47*		*-1.45*	*-2.31*
									-0.224
									-6.15

Table 19A. New Issues Puzzle in 2002-2017

The table reports the results of fitting several time-series asset-pricing models to value-weighted 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). The new issues portfolios include firms that performed an IPO (Panel A and D), SEO (Panel B and E) or issued convertible debt (Panel C and F) 2 to 37 months ago. In Panels A-C (D-F), returns to the new issues portfolios are value-weighted (equal-weighted). FVIX is the factor-mimicking portfolio that tracks the daily changes in VIX. LMH is the portfolio that buys firms in the top 20% and shorts firms in the bottom 20% in terms of turnover. The t-statistics use the Newey-West (1987) correction for autocorrelation and heteroscedasticity. The sample period for the asset-pricing models is from January 2002 to December 2017 (new issues are from December 1998 to November 2017).

Value-Weighted Returns

	Panel A. IPOs				**Panel B. SEOs**				**Panel C. Convertible Debt**			
	CAPM	**FF**	**ICAPM**	**LCAPM**	**CAPM**	**FF**	**ICAPM**	**LCAPM**	**CAPM**	**FF**	**ICAPM**	**LCAPM**
$\boldsymbol{\alpha}$	-0.152	-0.219	0.237	0.035	-0.445	-0.462	-0.157	-0.298	-0.767	-0.758	-0.481	-0.674
t-stat	*-0.69*	*-1.20*	*1.05*	*0.19*	*-2.75*	*-2.97*	*-1.17*	*-2.16*	*-3.12*	*-3.61*	*-2.50*	*-2.75*
$\boldsymbol{\beta_{MKT}}$	1.193	1.124	2.122	0.879	1.341	1.293	2.030	1.094	1.437	1.402	2.120	1.281
t-stat	*19.3*	*18.0*	*5.27*	*12.7*	*19.9*	*20.5*	*23.6*	*16.6*	*12.7*	*14.8*	*8.97*	*9.60*
$\boldsymbol{\beta_{SMB}}$		0.673				0.127				-0.149		
t-stat		*7.36*				*1.94*				*-1.26*		
$\boldsymbol{\beta_{HML}}$		-0.546				0.172				0.517		
t-stat		*-5.46*				*1.48*				*3.53*		
$\boldsymbol{\beta_{FVIX}}$			0.724				0.537				0.533	
t-stat			*2.44*				*7.26*				*2.88*	
$\boldsymbol{\beta_{LMH}}$				-0.422				-0.332				-0.209
t-stat				*-7.71*				*-9.33*				*-3.39*

Equal-Weighted Returns

	Panel D. IPOs				Panel E. SEOs				Panel F. Convertible Debt			
	CAPM	**FF**	**ICAPM**	**LCAPM**	**CAPM**	**FF**	**ICAPM**	**LCAPM**	**CAPM**	**FF**	**ICAPM**	**LCAPM**
$\boldsymbol{\alpha}$	-0.031	-0.137	0.398	0.174	-0.305	-0.406	0.027	-0.081	-0.450	-0.518	-0.129	-0.215
t-stat	*-0.10*	*-0.61*	*1.36*	*0.59*	*-1.43*	*-2.52*	*0.13*	*-0.45*	*-1.95*	*-2.52*	*-0.50*	*-1.07*
$\boldsymbol{\beta_{MKT}}$	1.396	1.255	2.421	1.051	1.450	1.280	2.244	1.074	1.568	1.421	2.336	1.173
t-stat	*19.8*	*15.7*	*4.53*	*12.5*	*28.7*	*21.6*	*5.92*	*18.7*	*21.5*	*20.4*	*7.36*	*14.3*
$\boldsymbol{\beta_{SMB}}$		1.014				0.923				0.572		
t-stat		*8.24*				*10.42*				*6.08*		
$\boldsymbol{\beta_{HML}}$		-0.527				-0.154				0.237		
t-stat		*-4.79*				*-1.52*				*1.99*		
$\boldsymbol{\beta_{FVIX}}$			0.798				0.618				0.598	
t-stat			*2.15*				*2.29*				*2.46*	
$\boldsymbol{\beta_{LMH}}$				-0.464				-0.506				-0.531
t-stat				*-6.14*				*-7.31*				*-6.23*