

The time-varying liquidity risk of value and growth stocks^{*}

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ABSTRACT

We study the liquidity exposures of value and growth stocks over business cycles. In worst times, value stocks have higher liquidity betas than in best times, while the opposite holds for growth stocks. Small value stocks have higher liquidity exposures than small growth stocks in worst times. Small growth stocks have higher liquidity exposures than small value stocks in best times. Our results are consistent with a flight-to-quality explanation for the countercyclical nature of the value premium. Exposure to time-varying liquidity risk captures 35% of the small-stock value premium and 100% of the large-stock value premium.

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I. Introduction

This paper provides new evidence for a risk-based explanation of the value premium. We focus on the time-varying liquidity risk of value and growth stocks, in addition to their market risk. This choice is motivated by the observation that investors tend to switch from riskier assets to safer ones in bad times.¹ We hypothesize that this flight-to-quality may affect value and growth stocks differently. Namely, since value stocks are riskier than growth stocks in bad times², investors seeking safer assets may want to liquidate value stocks more aggressively than growth stocks. This increase in selling pressure could make value stocks more sensitive to liquidity risk than growth stocks in recessions. Since bad times are characterized by liquidity dry-ups and a higher price of liquidity risk³, time-varying liquidity exposure, combined with a higher liquidity premium in bad times, could potentially help explain the value premium.

Using the expected market risk premium to define good and bad times, our main results are consistent with this hypothesis. First, using a conditional two-factor model with the market portfolio and aggregate market liquidity, we confirm the findings of Petkova and Zhang (2005) that value (growth) stocks are riskier than growth (value) stocks in bad (good) times. Second, value stocks have higher sensitivity to liquidity risk in worst times than in best times, while the opposite holds for growth stocks. For example, for the period 1927 to 2008, the average liquidity beta of value stocks is 0.381 during best times and 0.866 during worst times, while the average liquidity beta of growth stocks is 0.324 during best times and 0.244 during worst times. The differences between the betas are highly significant. These results are quite striking: value firms' exposure to liquidity risk increases in bad

¹See, e.g., Beber, Brandt, and Kavajecz (2008), and Chalmers, Kaul and Phillips (2010).

²See, e.g., Lettau and Ludvigson (2001), and Petkova and Zhang (2005).

³See, e.g., Vayanos (2004), and Hameed, Kang and Viswanathan (2010).

times, and growth firms' exposure decreases. As a result, value-minus-growth liquidity betas tend to covary positively with the expected market risk premium. In addition, the value-minus-growth liquidity betas and the liquidity premium are higher in bad times, which is consistent with the countercyclical nature of value-minus-growth expected returns.⁴ Overall, our results suggest that exposure to time-varying liquidity risk, combined with the liquidity price of risk, can explain 35% of the small-stock value premium and 100% of the large-stock value premium.

We document a novel result for small firms, which is that small value stocks have higher liquidity exposures than small growth stocks in worst times, while small growth stocks have higher liquidity exposures than small value stocks in best times. The increase in the liquidity betas of growth stocks in best times is in line with the flight-to-quality argument. In good times, value stocks are less risky than growth stocks and risk averse investors would prefer value stocks. This finding is important since the value premium is stronger among small firms.

We provide supplemental evidence that supports the flight-to-quality hypothesis. Specifically, we analyze trade-based order imbalances and liquidity characteristics of value and growth stocks across business cycles. If investors substitute lower-risk assets for higher-risk assets, we expect selling pressure in value stocks to increase in bad times. To replace value stocks in their portfolios investors have a range of choices: they can increase their holdings of lower-risk growth stocks, purchase other lower-risk asset classes, such as bonds, or a combination of these. This suggests that the effect of these transitions on liquidity is asymmetric. One-sided selling is more pronounced in value stocks and therefore liquidity worsens more in value stocks than in growth stocks or bonds. This, in turn, suggests a

⁴Chen, Petkova, and Zhang (2008) and Gulen, Xing, and Zhang (2009) use different empirical methods to show that the expected value premium is higher in bad economic states.

significant difference in the liquidity exposures of value and growth stocks, particularly in bad times. Our empirical results are consistent with this interpretation. We show that the relative order imbalances of value-minus-growth strategies decreases as economic conditions worsen. This suggests that in bad times investors sell value stocks more aggressively than growth stocks, and this activity results in relatively greater illiquidity in value stocks.

Using the characteristic liquidity measures of the portfolios, we also show that value stocks are less liquid than growth stocks and this differential increases in bad times. This result also holds for small-value and small-growth stocks. Liu (2006) argues that investors may exhibit liquidity preference (Hicks, 1967) and prefer more liquidity per se in recessionary times. Therefore, investors' eagerness to sell value stocks in bad times is also likely to have elements of flight-to-liquidity. Longstaff (2004) defines flight-to-liquidity as a separate phenomenon from flight-to-quality and shows that market participants shift their portfolios from less liquid to more liquid bonds with identical credit risk. Our finding that the relative order imbalance of value-minus-growth strategies decreases as economic conditions worsen is consistent with both flight-to-quality and flight-to-liquidity effects in the stock market in bad times. Overall, both effects suggest a mechanism that appears to drive the countercyclical nature of the value premium. We will use the term flight-to-quality throughout the paper.

To the best of our knowledge, we are first to consider time-varying liquidity risk as a possible explanation for the existence of the value premium. We believe that this addresses an important issue, since the debate behind the sources of the value premium is still not settled.⁵ Other studies have shown that time-variation in risk is crucial in explaining the performance of value and growth stocks. Lettau and Ludvigson (2001) show that value portfolio returns are more highly correlated with consumption growth than growth portfolio

⁵DeBondt and Thaler (1987) and Lakonishok et. al. (1994), among others, suggest that overreaction-related mispricing is the primary source of the value premium.

returns in bad times.⁶ Balvers and Huang (2007) use a production-side asset-pricing model to show that value firms are most risky in bad states where the productivity risk premium is high. We differ from these studies since we focus on the time-varying liquidity exposure of value and growth stocks.

Closely related to our analysis, Petkova and Zhang (2005) find that value (growth) stocks have higher market betas than growth (value) stocks in bad (good) times when the expected market risk premium is high (low). Their findings are in line with the predictions of the rational model of Zhang (2005) who argues that it is hard for firms to scale down their unproductive capital in bad times. Since value firms have more assets in place than growth firms, they are riskier than growth firms in bad times when the price of risk is high.⁷ However, time-varying market risk, as documented in Petkova and Zhang (2005), may not fully capture the risk mentioned in Zhang (2005).

Also, as Petkova and Zhang (2005) state, while time-varying market risk goes in the right direction to explain the value premium, the observed magnitude of the value premium is too large to be explained by exposure to market risk alone. This suggests that we need further investigation into other potential sources of the value premium, and we document that liquidity risk plays an important role in this regard.

A large body of asset pricing research shows that liquidity is an important source of priced risk.⁸ Relatively fewer are the studies that try to explain the value premium using liquidity risk. Liu (2006), for example, constructs a two-factor model with the market return and a liquidity factor, and shows that the unconditional alphas of book-to-market-sorted

⁶Yogo (2006) and Parker and Julliard (2005) also use consumption variables to explain the value premium.

⁷Cooper (2006) derives a similar conclusion that value stocks are riskier than growth stocks, arguing that excess installed capital capacity makes value firms more sensitive to aggregate conditions and increases their systematic risk.

⁸Pastor and Stambaugh (2003), for example, show that sensitivity to market liquidity is priced. Acharya and Pederson (2005) incorporate liquidity risk into the CAPM and show that the CAPM applies to returns net of illiquidity costs.

portfolios relative to the model are zero. He shows that, unconditionally, value stocks have higher liquidity exposures than growth stocks. We differ from Liu (2006) in several important ways. First, we analyze portfolios double-sorted by size and book-to-market, since the value premium is negatively correlated with size. Second, we show that value stocks do not always have higher liquidity exposures than growth stocks. Several of our results indicate that in best economic times value stocks have lower liquidity betas than growth stocks. Third, we show that the spread in liquidity betas between good and bad times is much higher for value stocks than growth stocks, indicating that the time-varying liquidity betas of value stocks might contribute more to the explanation of the value premium. Finally, using a cross-sectional analysis, we estimate the premium for time-varying liquidity risk and show that it adds significant explanatory power over and above the unconditional liquidity risk premium.

Watanabe and Watanabe (2008) also study time-varying liquidity risk that arises because investors are asymmetrically informed about each others preferences. They show that time-varying liquidity betas are significantly priced in the cross-section of stock returns. Our analysis differs from theirs in that we specifically examine time-varying liquidity risk in the context of the value premium and we suggest a distinct mechanism that drives this time-variation. Namely, fluctuation in liquidity risk for value and growth portfolios might arise due to the tendency of investors to switch to safer stocks in bad times. Growth stocks are less risky in bad times and so investors may increase portfolio weights in these stocks in bad times. Because of this increase in demand from investors in bad times, growth stocks could become less sensitive to aggregate liquidity in bad times. The opposite holds for value stocks. In addition, unlike Watanabe and Watanabe (2008) who use high and low liquidity beta states, we define states of the world by business cycle variables. In Watanabe and

Watanabe (2008), liquidity in high beta states could be both high and low and therefore, their high beta states do not necessarily coincide with recessions and liquidity dry-ups.

In a recent paper, Naes, Skjeltorp, and Odegaard (2010) show that the liquidity of small firms is a leading indicator of aggregate economic conditions. They interpret this result as being consistent with a flight-to-quality effect: since small firms are relatively more sensitive to economic downturns than large firms, investors tend to move out of small stocks in recessions. Therefore, Naes, Skjeltorp, and Odegaard (2010) show that variation in liquidity over time is related to a flight-to-quality during economic downturns. In our paper we focus instead on the cross-sectional implications of flight-to-quality. We show that differences in exposure to liquidity risk drive differences in expected returns between value and growth stocks.

The rest of the paper is organized as follows. Section II describes the research design and the data we use. Section III presents evidence on the time-varying liquidity risk of value and growth stocks. Section IV examines the liquidity characteristics of value and growth stocks, and Section V provides further evidence for the flight-to-quality argument. In Section VI we examine whether time-varying liquidity risk can capture the magnitude of the value premium. Section VII concludes.

II. Data and Research Design

A. Research Design

We assume that liquidity risk is an important determinant of the returns of value and growth stocks. Therefore, we specify the following return-generating process for their excess returns:

$$R_{it+1} = \alpha_i + \beta_{Mit+1}R_{Mt+1} + \beta_{Lit+1}LIQ_{t+1} + \varepsilon_{it+1}, \quad (1)$$

where R_{it+1} is the excess return of asset i at time $t + 1$, R_{Mt+1} is the excess market return, LIQ_{t+1} is the return on a portfolio that tracks liquidity risk, β_{Mit+1} is the time-varying market beta, and β_{Lit+1} is the time-varying liquidity beta. A detailed description of the construction of LIQ is provided in the data section. The inclusion of liquidity as a source of priced risk, in addition to the market return, is motivated by recent literature, both empirical and theoretical, that shows that liquidity is an important source of priced risk (see e.g., Pastor and Stambaugh, 2003; Acharya and Pederson, 2005; Liu, 2005).

Equation (1) above conveys the idea that the market and liquidity risk of an asset change over time. We model the time-variation in risk exposures using two different methods. The first method computes rolling market and liquidity betas by running regression (1) for each asset separately, using a 60-month rolling window.⁹ The second method computes fitted market and liquidity betas by assuming that they vary with a set of conditioning variables. The conditioning variables are chosen for their ability to capture fluctuations in business conditions. More specifically, we assume that the following time-varying process describes the fluctuation in risk exposures:

$$\beta_{Mit+1} = b_{0i} + b_{1it}DIV_t + b_{2it}TERM_t + b_{3it}DEF_t + b_{4it}TB_t, \quad (2)$$

and

$$\beta_{Lit+1} = c_{0i} + c_{1it}DIV_t + c_{2it}TERM_t + c_{3it}DEF_t + c_{4it}TB_t, \quad (3)$$

where the conditioning variables are the dividend yield (DIV), term spread (TERM), default spread (DEF), and short-term Treasury bill rate (TB).¹⁰ Substituting equations (2) and (3)

⁹We also use 24-, 36-, and 48-month rolling windows and find similar results. They are available upon request.

¹⁰The motivation behind using these variables comes from the time series predictability literature. Keim and Stambaugh (1986) and Fama and French (1989) use the default spread and the dividend yield to predict returns. Campbell (1987) and Schwert (1989) use nominal interest rates to predict the conditional moments of the market return. The method of making beta a linear function of predictive variables was pioneered by

in equation (1) leads to:

$$R_{it+1} = \alpha_i + (b_{0i} + b_{1it}DIV_t + b_{2it}TERM_t + b_{3it}DEF_t + b_{4it}TB_t)R_{Mt+1} \\ + (c_{0i} + c_{1it}DIV_t + c_{2it}TERM_t + c_{3it}DEF_t + c_{4it}TB_t)LIQ_{t+1} + \varepsilon_{it+1}. \quad (4)$$

We use the estimated coefficients from (4) to compute the time series of fitted betas in (2) and (3).¹¹

We use the same conditioning variables to calculate fitted illiquidity betas. These variables define investment opportunities and are predictors of market conditions. Since Pastor and Stambaugh (2003) document that aggregate liquidity follows market conditions very closely and our main focus is on the behavior of liquidity betas over the business cycle, using these variables to estimate the conditional liquidity betas seems reasonable. To the best of our knowledge, we are first to use the set of these four predictive variables to study time variation in liquidity betas.¹²

Once the time series of rolling and fitted betas are estimated, we use a sorting procedure to study their variation over different stages of the business cycle. We define the various states of the business cycle in two different ways. First we use the expected market risk premium as in Petkova and Zhang (2005). The expected market risk premium is estimated by regressing the realized market excess return at time $t+1$ on conditioning variables known at time t :

$$R_{Mt+1} = \gamma_0 + \gamma_1DIV_t + \gamma_2TERM_t + \gamma_3DEF_t + \gamma_4TB_t + u_{t+1}. \quad (5)$$

Ferson, Kandel, and Stambaugh (1987), Harvey (1989), and Shanken (1990).

¹¹Following Ferson, Sarkissian and Simin (2008), we additionally use time-varying alphas in our analysis. The results are qualitatively similar. They are available upon request.

¹²We also use short-window regressions, as in Lewellen and Nagel (2006), as an additional robustness test. Specifically, for each quarter after 1963, we regress daily HML and HMLs returns on daily market and LIQ returns to estimate market and liquidity betas for that quarter. The advantage of this approach is that it does not impose any structure on the time-variation in betas. The results from the short-window regressions are qualitatively similar to our main results in Section III and they are available upon request.

The expected market risk premium is the fitted value from the regression above:

$$\hat{\gamma}_t = \hat{\gamma}_0 + \hat{\gamma}_1 DIV_t + \hat{\gamma}_2 TERM_t + \hat{\gamma}_3 DEF_t + \hat{\gamma}_4 TB_t. \quad (6)$$

Having computed the expected market risk premium, we designate state "best" as the lowest 10% observations of the expected market risk premium; state "good" represents the remaining months with the premium below its average; state "bad" represents the months with the premium above its average but other than the 10% highest; and state "worst" represents the months with the 10% highest observations of the expected market risk premium. The classification based on the expected market risk premium is motivated by Campbell and Cochrane (1999) and Constantinides and Duffie (1996) who predict that this premium is countercyclical.

Our second measure of business cycle states is the NBER recession dummy. We use this measure to test the robustness of our results to different classifications of good and bad economic states.¹³

B. Data

We define the four conditioning variables similarly as Petkova and Zhang (2005) do. To obtain dividend yield (DIV), we sum dividends accruing to the CRSP value-weighted market portfolio over the previous 12 months and divide by the level of the market index at the end of this period. The yield spread between Moody's Baa and Aaa corporate bonds is the default premium, DEF, and TERM is the yield spread between the ten-year and the one-year Treasury bond.¹⁴ Finally, the short-term interest rate, TB, is the one-month Treasury bill rate from CRSP.

¹³Fama and French (1989), among others, use NBER dates to determine business cycles.

¹⁴Bond yields are from the monthly database of the Federal Reserve Bank of St. Louis.

We use HML and HMLs as our value-minus-growth strategies. HML is the value portfolio (High) minus the growth portfolio (Low) in a two-by-three sort on size and book-to-market. HMLs is the small-stock value premium, calculated as the small-value (Hs) minus small-growth (Ls) portfolio in a five-by-five sort on size and book-to-market. Since the value premium is stronger in the smallest quintile, HMLs is economically interesting. Monthly portfolio data from January 1927 to December 2008 come from Ken French’s website.

We follow Amihud (2002) to estimate a liquidity measure for each stock from daily CRSP data. The literature proposes many different high frequency measures of (il)liquidity.¹⁵ However, these measures are not available for periods long enough for meaningful asset pricing tests. Hence, as in Watanabe and Watanabe (2008) and Acharya and Pederson (2005), we use Amihud’s measure in order to obtain a liquidity factor that goes back to 1927. The Amihud measure of stock i in month t is calculated as follows:

$$A_{it} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \frac{|r_{i,d,t}|}{dvol_{i,d,t}}, \quad (7)$$

where $r_{i,d,t}$ and $dvol_{i,d,t}$ are the return and dollar volume, respectively, of stock i on day d in month t , and $D_{i,t}$ is the number of daily observations during that month.

Intuitively, this measure captures the price impact of trading volume. The higher A_{it} is, the more illiquid the stock is and the more its price responds to low volume. Amihud (2002) shows that expected returns are increasing in this ratio and the ratio has a strong positive correlation with both the price impact and the fixed cost component estimates of Brennan and Subrahmanyam (1996). Moreover, Hasbrouck (2002) finds that among the liquidity measures constructed from daily data, Amihud’s is the best proxy for the high-frequency dynamic price impact measures of liquidity.

¹⁵See Korajczyk and Sadka (2008) for a review.

We compute the monthly Amihud measures of NYSE/AMEX stocks (share codes 10 and 11) that have at least 15 days of volume and return data in a month and a beginning of the month price between \$5 and \$1000. Following Pastor and Stambaugh (2003), we do not consider NASDAQ stocks in creating the liquidity factor, because due to interdealer activities their reported volumes are not comparable to volumes reported by the NYSE. Our sample consists of stocks ranging in number from 1324 to 2200 each month, and it covers the period from January 1927 to December 2008.

We construct a liquidity mimicking portfolio, LIQ , using the monthly series of individual Amihud measures. Mimicking portfolios have been used in a number of studies of economic factors. Breeden (1979) argues that state variables in Merton's (1973)'s ICAPM can be replaced by mimicking portfolios. Chen et. al. (1986) and Breeden et. al (1989) use these portfolios for several macroeconomic factors, while Fama and French (1992, 1993) try to capture book-to-market and size effects by using mimicking portfolios. Recently, Balduzzi and Robotti (2008) compare linear factor models using non-traded factors and mimicking portfolios. They show that mimicking portfolios allow to translate the characteristics-based explanation of the cross section of stock returns into a risk-based explanation and conclude that formulating linear models with mimicking portfolios is preferred.

The construction of our liquidity factor is very similar to the construction of SMB and HML by Fama and French (1993). Specifically, at the beginning of each month from January 1927 to December 2008, we sort all common NYSE/AMEX stocks in ascending order based on their Amihud ratio. Based on this sort, we form two portfolios: 1) High illiquidity portfolio which contains the highest 30% of stocks based on NYSE liquidity breakpoints, and 2) Low illiquidity portfolio which contains the lowest 30% of stocks based on NYSE liquidity breakpoints. Stocks are held in each portfolio for a month after portfolio formation

and the liquidity factor is computed as the monthly return from investing 1 dollar in the equally-weighted high illiquidity portfolio and shorting 1 dollar of the equally-weighted low illiquidity portfolio.¹⁶

Figure 1 plots the liquidity factor for the whole sample period together with the NBER recession dummy. The realized values of LIQ range from -12.7% to 39%. The mean value is 0.25%. It varies over time with a standard deviation of 3.6% and it spikes occasionally, often around major economic crises such as the Great Depression, the debacle of Penn Central company in June 1970, the oil crisis of November 1973, the 1975 economic downturn, and the Asian financial crisis of 1997. Moreover, untabulated results show that the average value of LIQ monotonically increases from -0.9% to 1.6% as business cycle states, based on the expected risk premium, change from "best" to "worst" and the difference between worst and best is significant at the 1% level.

III. Time-varying Liquidity Risk of Value-minus-Growth Strategies

In this section we document the time-varying liquidity and market risk of value-minus-growth strategies. We show that results hold for both rolling and fitted betas. We define states of the world by sorting on the expected market risk premium and the NBER recession dummy. We examine three sample periods: January 1927-December 2008, January 1935-December 2008, and January 1963-December 2008. We examine the second sample period since it excludes the Great Depression, which may be an influential observation and drive the results. For the third sample period, the literature has documented a stronger value

¹⁶We use equally-weighted portfolios since otherwise the liquidity factor will be dominated by large stocks which are more liquid. Among many others, Pastor and Stambaugh (2003) and Watanabe and Watanabe (2008) also construct their market-wide liquidity factors as equally-weighted for the same reason.

premium.

A. Full Sample: January 1927-December 2008

We calculate the average fitted and rolling betas of value (High), growth (Low), value-minus-growth (HML), and value-minus-growth among small firms (HMLs) portfolios separately in each state of the world. We investigate how the liquidity and market betas of these portfolios vary across different states of the world and whether the differences between value and growth are significant.

Table 1 reports the full sample results for market and liquidity fitted betas. Panel A documents average conditional betas using the expected market risk premium as a measure of economic states, while panel B uses the NBER recession dummy.

Average Liquidity Betas

We find that HML displays a countercyclical pattern of risk for liquidity betas. In Panel A of Table 1, the average fitted liquidity beta of HML is 0.626 in the worst state and monotonically decreases to 0.057 in the best state. The difference between worst and best is 0.569 with a t-statistic of 32.6.¹⁷

We observe a similar pattern for the small-stock value strategy (HMLs). The average fitted liquidity beta of HMLs is 0.298 in the worst state and it decreases to -0.023 in the best state. The difference between worst and best is 0.321 with t-statistic of 9.3. Interestingly, the average fitted liquidity beta of HMLs changes its sign when we shift from the worst state to the best state. This change in sign indicates that the small value portfolio (Hs) beta is lower than the small growth portfolio (Ls) beta in best times and vice versa in worst times. Therefore, among small stocks, value firms do not always have higher liquidity betas than

¹⁷The t-statistic of the average beta in each state is computed as the ratio of the average beta in that state and the standard error of the time series of betas in that state.

growth firms. So the countercyclical pattern in liquidity betas is stronger for HMLs than HML, and it is in HMLs that we observe a higher value premium. The results are similar when we use rolling betas in Panel A of Table 1.

The average liquidity betas of the value and growth portfolios individually exhibit interesting patterns for both fitted and rolling betas. In Panel A of Table 1, the average fitted liquidity beta of the value portfolio (High) is 0.869 in the worst state and it decreases to 0.381 in the best state. The difference between the betas in the two states is highly significant. We find an opposite pattern in the average fitted liquidity betas of the growth portfolio (Low). While its average beta is 0.243 in worst times, it increase to 0.324 in best times. Again the difference is highly significant. These results are striking because value firms' exposure to liquidity risk increases in bad times and growth firms' exposure decreases at the same time. This could conceivably explain the countercyclical behavior of expected value-minus-growth returns. We observe similar patterns when we use rolling betas in Panel A of Table 1. Finally, it is interesting to note that most of the variation in liquidity betas is within portfolio High and value firms seem more sensitive to liquidity risk than growth firms.

To show that our results are robust to the definition of the state of the world, we sort the liquidity betas of value and growth stocks based on the NBER recession dummy. The average rolling and fitted liquidity betas in Panel B exhibit similar patterns to the ones reported before. There is only one exception. The pattern in the rolling betas of HMLs is somewhat weaker compared to the pattern for fitted betas. Overall, the results indicate that the observed liquidity beta patterns are robust to an alternative definition of the states of the world.¹⁸

¹⁸In addition to the expected market risk premium and NBER, we also define states of the world using the expected liquidity premium. We calculate the expected liquidity premium using the same conditioning variables since they are good proxies for capturing variation in the business cycle and the liquidity premium

Average Market Betas

Table 1 reports the average market betas of value and growth portfolios as well. Our findings are largely similar to the findings of Petkova and Zhang (2005). When we define states of the world according to the expected market risk premium, HML displays a countercyclical pattern of market risk. The average HML market betas, both fitted and rolling, are positive in the worst state and negative in the best state. Value (growth) firms are more exposed to market risk in bad (good) times than growth (value) firms. For example, the average fitted market beta of HML is 0.204 in the worst state and it monotonically decreases to -0.269 in the best state. The difference between worst and best is 0.473 with a t-statistic of 28.4. However, we generally find the opposite pattern for the market betas of HMLs, which is consistent with the results reported by Petkova and Zhang (2005).

We obtain slightly different results when we sort market betas with respect to the NBER recession dummy (Panel B of Table 1). For both rolling and fitted betas, while the difference between the market betas of HML across bad and good times is still significantly positive, the betas are negative in both states. This suggests that, in contrast to the liquidity betas, the market betas of value and growth stocks are in fact sensitive to the definition of good and bad times.

Overall we find that the liquidity betas of both HML and HMLs exhibit a countercyclical pattern. This suggests that liquidity risk goes in the right direction to explain the value premium for the period from January 1927 to December 2008. Moreover, the patterns in average market betas and average liquidity betas of value and growth stocks across different states of the world are consistent with a flight-to-quality hypothesis. The countercyclical

changes over the business cycle. We argue that if a security has a high liquidity beta in states when the liquidity premium is high then this security is not a good hedge against liquidity dry-ups and so should have a higher expected return. The results are qualitatively similar to using NBER or the expected market risk premium as sorting variables.

(procyclical) pattern in the market betas of value (growth) stocks provides supporting evidence for a shift in the riskiness of these stocks across the business cycle, consistent with the costly reversibility of investment argument in Zhang (2005).¹⁹

As the riskiness of value and growth stocks changes, investors respond to the shift in risk exposures. Growth stocks might be viewed as safer assets in bad times. Therefore, the tendency of investors to sell riskier assets in bad times will deteriorate liquidity more in value stocks than in growth stocks. Our results are consistent with this argument and are even stronger in the case of small stocks. This makes sense because liquidity is correlated with firm size, which should amplify the flight-to-quality effect among small stocks. We provide additional evidence in support of the flight-to-quality hypothesis in sections IV and V.

B. The Post-Depression Sample: January 1935-December 2008

The Great Depression was characterized by extreme conditions so if liquidity shocks occurring during that time period drive the observed liquidity betas, our earlier results should not hold in the post-Depression sample. Therefore, to study the sensitivity of our results with respect to the Depression period, we exclude the Great Depression from the sample.

Table 2 presents the results. As before, Panels A and B document the average market and liquidity betas of value and growth portfolios using the expected market risk premium and the NBER recession dummy, respectively, as measures of the business cycle.

¹⁹The model of Zhang (2005) is based on costly reversibility of investment. However, market beta may not capture this risk completely. While the evidence in Petkova and Zhang (2005) supports the predictions in Zhang (2005) as the market betas exhibit a countercyclical pattern, they do not argue that market beta captures all the risk associated with costly investment reversibility. It should be noted that costly reversibility might be captured by another source of risk that we do not control for in our two-factor model.

Average Liquidity Betas

Panel A of Table 2 reports the average fitted and rolling liquidity betas across different states of the world. Similar to the full sample, both HML and HMLs display a countercyclical pattern of liquidity risk. The HML betas are comparable to the full sample betas with only a slight drop in their variation across states. For both fitted and rolling betas, the difference between worst and best time liquidity betas decreases relative to the full sample. In particular, the difference between worst and best fitted betas decreases from 0.565 to 0.499, and the difference between worst and best rolling betas decreases from 0.419 to 0.315.

The results for HMLs betas are somewhat weaker compared to the ones for the full sample period. In particular, the rolling betas of HMLs are negative across all states of the business cycle and the difference between good and bad times is not statistically significant.

Panel B of Table 2 reports results using the NBER recession dummy. The HML liquidity betas exhibit very similar patterns compared to the full sample. Again, the results for HMLs are somewhat weaker.

The average liquidity betas of the separate value and growth portfolios exhibit opposite patterns, as in the full sample. Both the average fitted and rolling liquidity betas of the value portfolio (High) decrease from worst to best times. The opposite is valid for the growth portfolio (Low). The differences between worst and best times are significant for both rolling and fitted betas of value and growth portfolios. Most of the variation in liquidity betas comes from the value portfolio and the results are robust to the definition of the states of the world. Overall, the results indicate that the Great Depression is not the primary cause of our main results.

Average Market Betas

The post-Depression market betas of HML resemble the ones in the full sample. When we use the market risk premium to define different states of the world (Panel A of Table 2), the difference in the market betas of HMLs between good and bad states is still positive but the betas are negative across all states. The results are similar to Petkova and Zhang (2005). Also, once good and bad times are determined using the NBER variable (Panel B of Table 2), there is no longer a countercyclical pattern in the market betas of HML and HMLs.

C. The post-Compustat Sample: January 1963-December 2008

We also investigate the role of time-varying liquidity risk in explaining the value premium in the post-Compustat sample. This sample period has received a lot of attention in the value premium literature (see e.g., Fama and French, 1992, 1993; Lakonishok et al., 1994).

Average Liquidity Betas

In Table 3, Panel A, we present results for states of the world defined by the expected market risk premium. The average fitted HML liquidity beta is 0.169 in worst times and it decreases to -0.137 in best times. Both are significant and the difference between them is 0.306 with a t-statistic of 8.8. The pattern in the HML rolling betas is similar to the one for the fitted betas. On the other hand, results for HMLs are stronger compared to the full sample and the post-Depression sample. Even though there are fewer recessions in the post-Compustat sample, the pattern in HMLs liquidity betas is more pronounced in this sub-sample in which the HMLs liquidity betas also exhibit a countercyclical pattern. The average fitted liquidity beta is 0.104 in worst times and becomes negative in best times at -0.495. The difference is 0.599 and it is almost twice as big as the difference in the full

sample period (0.321).²⁰ Similar to the full sample period, the liquidity betas of portfolio High increase in bad times and decrease in good times. The opposite pattern holds for portfolio Low. The increase in the liquidity betas of growth stocks in best times is in line with our previous arguments. In good times, value stocks are less risky than growth stocks and risk averse investors would prefer value stocks. However, since investors are in general less risk averse in good times, the difference between the liquidity exposures of value and growth stocks are not as high as in bad times.

The results for rolling betas are qualitatively identical to the ones for fitted betas. One exception is the difference between the average rolling betas of the value portfolio in good and bad states which is not significant.

Panel B of Table 3 reports results using NBER recession dates. The results are very similar to the ones reported above. In summary, the results for the liquidity betas of value and growth are robust across different sample periods. The liquidity betas of HML and HMLs exhibit a countercyclical pattern and move in the right direction to explain the value premium. The value portfolio liquidity betas increase as economic conditions worsen, while the growth portfolio liquidity betas decrease. In other words, value stocks are more sensitive to liquidity risk in recessions and growth stocks are less sensitive to liquidity risk in recessions. The patterns in all four portfolios, HML, HMLs, High, and Low, are robust to the definition of good/bad times.

²⁰A possible reason for the stronger results in the post-Compustat period might be the inclusion of Nasdaq firms which are relatively smaller and potentially more illiquid. Since we exclude Nasdaq firms when we calculate the liquidity factor, but include them in our value and growth portfolios as we obtain them from Kenneth French's web site, in the post-Compustat period their weights should be higher as the sample period is smaller. However, the results are qualitatively similar, although not as strong, when we calculate HML returns by excluding Nasdaq firms. So the potential effect of Nasdaq firms is important but it does not drive our results. These results are available upon request.

Average Market Betas

Post-Compustat average market betas are presented in Table 3 as well. On average, the market betas seem to lose their countercyclical behavior and are mostly negative for both the rolling and fitted methods across all states. The difference in market betas between worst and best times is not significant in most of the cases. Our results resemble findings in Petkova and Zhang (2005) who fail to uncover any significant countercyclical behavior in market risk during this period. They argue that the reason is the low number of recessions in the post-Compustat sample. However, the results for liquidity betas are robust to the sample period used. Since it is possible that costly reversibility of investment might not be completely captured by market risk, our flight-to-quality interpretation of the business cycle pattern in liquidity betas should not be affected by weaker results for the market betas. Value stocks are still riskier in recessions (as argued by Zhang, 2005), but we might not be able to clearly show this in the post-Compustat sample due to the low number of months classified as recessionary.

Overall, the results in this section are in line with the flight-to-quality behavior of investors in bad times. If investors seek lower-risk assets in bad times, we expect selling pressure in value stocks to increase in those times. While all traders leave value stocks, some of them might turn to growth stocks or other safer securities. Therefore, one-sided selling would be more pronounced in value stocks and this, in turn, would lead to a significant difference in the liquidity exposures of value and growth stocks, particularly in bad times.

D. Robustness Tests

In this section we examine alternative ways of measuring aggregate liquidity. First, we perform a double sort on book-to-market and liquidity to derive an aggregate liquidity

factor. Second, we use three other measures of aggregate liquidity to test the robustness of our previous results.

Controlling for the Correlation between Book-to-Market and Liquidity

Since value firms tend to be less liquid than growth firms, the high (low) illiquidity portfolio we used before might be dominated by value (growth) firms. As a result, in constructing our *LIQ* factor, a sort on liquidity might act as a sort on book-to-market. To address this potential concern, we derive a new liquidity factor, *LIQ1*, using a double sort on Amihud liquidity and book-to-market. High (Low) illiquidity portfolios are constructed by equally-weighting high (low) illiquidity stocks (i.e., stocks that are in the top (bottom) 30% according to Amihud’s measure) across different book-to-market groups. This procedure prevents any book-to-market group from dominating the High or Low illiquidity portfolios. Alternatively, we also construct a liquidity factor, *LIQ2*, by using stocks in the middle book-to-market group only.

Table 4 reports the post-Compustat sample results for fitted liquidity betas.²¹ Panel A documents the average conditional liquidity betas for liquidity factor *LIQ1*, while Panel B shows the average conditional liquidity betas for *LIQ2*. In both panels, different economic states are measured both by the expected market risk premium and the NBER recession dummy. Overall, the results indicate that the liquidity factor captures a source of risk different from the one related to book-to-market.²² The conditional liquidity betas show a stronger countercyclical pattern for *LIQ1* compared to the one for our main factor *LIQ*. Specifically, the average HML(s) betas are negative in best times but switch to positive in

²¹The rolling beta results are similar and they are available upon request.

²²We also check whether our liquidity factor is distinct from the SMB factor by including SMB in equation (1). The resulting liquidity betas for value and growth portfolios are not affected by the presence of SMB in the regression, and loadings on SMB are not significant in the presence of the liquidity factor. These results are available upon request.

worst times. The difference between worst and best is 0.258 for HML and 0.582 for HMLs. Both values are significant at the 5% level. Moreover, the average fitted liquidity beta of the value portfolio is 0.436 in the worst state and it decreases to 0.217 in the best state. The difference between the betas in the two states is significant. The opposite pattern is observed for the average fitted liquidity betas of the growth portfolio. The results are robust to the alternative definition of the business cycle. Panel B of Table 4 shows that the results are similar, albeit weaker, when we use liquidity factor *LIQ2*.

Other Measures of Aggregate Liquidity

Here we use three different liquidity factors, motivated from previous studies. The factors are based on Watanabe and Watanabe (2008), Pastor and Stambaugh (2003), and Liu (2006). Watanabe and Watanabe (2008) extract AR(2) innovations of the aggregate Amihud measure and Pastor and Stambaugh (2003) use a similar methodology to obtain innovations for their market-wide liquidity proxy. Both measures attempt to capture the price impact of a given trading volume. Liu (2006) uses the turnover-adjusted number of zero daily trading volumes over the prior 12-months as a proxy for liquidity and constructs a factor-mimicking portfolio based on this measure. In contrast to the other two measures, this measure emphasizes the difficulty of executing an order and therefore captures other dimensions of liquidity, in particular market depth.

Table 5 provides the market and liquidity fitted betas of HML and HMLs for the period 1927 to 2008 using the alternative liquidity factors.²³ As before, Panel A identifies the state of the economy by using the expected market risk premium, while Panel B uses the NBER recession dummy. Overall, our results are robust to the alternative definitions of liquidity. As shown in Panel A of Table 5, the average fitted liquidity betas of HML are monotonically

²³Results for the post-Depression and the post-Compustat samples are similar and available upon request.

decreasing from worst to best times, for all measures of aggregate liquidity. For two of the liquidity measures, the liquidity betas of HML change sign from worst to best times indicating that growth stocks are more exposed to liquidity risk than value stocks in good times and vice versa in bad times. The difference between the worst-state and best-state liquidity betas of HML is significant for all three liquidity measures with values of 0.136, 0.453, and 0.318, respectively.

The patterns in the liquidity betas of the small-stock value strategy HMLs are even stronger than the ones for HML. For all three liquidity measures, the fitted liquidity betas of HMLs are negative in best times and positive in worst times. The difference between the liquidity betas of HMLs across worst and best states is much higher than the one for HML, showing a much stronger variation in liquidity risk exposure for small stocks. For example, the difference between HMLs liquidity betas in worst and best times is 1.659 based on Liu's (2005) measure, which is five times greater than the difference between the liquidity betas of HML. In Panel B of Table 5, we further check the sensitivity of our results to the definition of economic states by using the NBER recession dummy. Here, Pastor and Stambaugh liquidity betas exhibit the opposite pattern, but the liquidity measures of Watanabe and Watanabe (2008) and Liu (2006) yield a countercyclical pattern in the liquidity betas of HML and HMLs. Moreover, as in Panel A, the variation in betas across states is greater for small stocks. Overall, our results are fairly robust to the way we measure liquidity.

IV. Liquidity Characteristics of Value-minus-Growth Strategies

In this section we focus on liquidity as a portfolio characteristic rather than a measure of risk. If investors are more eager to sell value stocks than growth stocks in bad times then the

liquidity of value stocks relative to growth stocks should worsen particularly in bad times. In this section we test this predictions. We use Amihud's measure to calculate the liquidity of portfolios sorted by size and book-to-market. We use the post-Compustat sample to construct portfolios' Amihud measures as we need Compustat data to calculate the book-to-market ratio for each stock. The Compustat data is lagged 6 months relative to the liquidity measure. The size and book-to-market portfolios are constructed similar to those in Fama and French (1993). Specifically, in June of each year t , we calculate the median size for all NYSE stocks and then assign all NYSE/AMEX stocks into two size groups based on these median sizes. Independently, all NYSE/AMEX stocks are categorized into three book-to-market portfolios based on the breakpoints for NYSE stocks. The High portfolio includes the top 30% of stocks and the Low portfolio includes the bottom 30% of stocks according to their book-to-market ratios. The intersection of these groups creates six portfolios: small-high, big-low, etc. For each portfolio we calculate an equally-weighted average of the liquidity of the stocks in the portfolio and each portfolio is rebalanced at the end of June $t+1$. The Amihud liquidity of High is then calculated as the equally-weighted average of the liquidity measures of small-high and big-high, while Low's liquidity is the equally-weighted average of small-low and big-low liquidity. We calculate the average liquidity of small-value (Hs) and small-growth (Ls) by a 5-by-5 sort on size and book-to-market using the same method mentioned above. Small refers to the lowest size group in the 5-by-5 sort.

If value stocks are less liquid in bad times, then we should see a pattern in the liquidity characteristics of value and growth portfolios which is similar to the pattern in their liquidity betas, i.e, the illiquidity difference between value and growth stocks should be significantly higher in bad times than in good times.²⁴

²⁴As a general portfolio characteristic, value stocks are less liquid unconditionally than growth stocks (see Watanabe and Watanabe (2008) for further evidence).

Table 6 presents the average liquidity of value and growth portfolios. While value (High) and growth (Low) liquidity averages are presented in Panel A, Panel B presents liquidity averages of small value (Hs) and small growth (Ls) portfolios. As shown in Panel A, the average illiquidity of High is 0.563 in best times and it increases to 1.04 in worst times. The difference between worst and best is 0.478 and significant at the 1% level. On the other hand, the average illiquidity of Low is 0.199 in best times and increases up to 0.299 in worst times. The difference is again significant at the 1% level. Thus, value stocks are less liquid than growth stocks in all states of the world which is in line with their liquidity betas. Also, the difference in illiquidity between value and growth stocks increases significantly from best times to worst times. While this difference is 0.364 in best times, it increases to 0.741 in worst times. The difference in the illiquidity of value and growth stocks between worst and best times is 0.378 and significant at the 1% level. Our results remain unchanged if we use NBER dates to define states of the world.

We present the average illiquidity of Hs and Ls in Panel B of Table 6. As expected, average illiquidity increases due to the high correlation between size and illiquidity. We observe a very similar pattern in the average illiquidity of Hs and Ls compared to Panel A. Again, small value stocks are less liquid than small growth stocks and they become even more so in worst times. In best times, the difference between the illiquidity of small value and small growth stocks is 0.783. The difference increases to 1.045 in worst times indicating that Hs becomes even less liquid than Ls.

In summary, the results in table 6 suggest that value stocks are less liquid than growth stocks and this difference is more pronounced in bad times. This is in line with our findings that HML and HMLs liquidity betas increase in bad times and also with the argument that investors switch to safer assets (growth) in worsening economic conditions.

V. Order Imbalance in Value-minus-Growth Portfolios

In this section, we study the trading behavior of investors across different stages of the business cycle. If shifts in risk across business cycles affect investor preferences for risk, then one should observe a significant relation between expected economic conditions and investor trading direction. More specifically, if value stocks become riskier than growth stocks in bad times, investors might be more eager to sell value stocks than growth stocks in recessions. Therefore, we expect to observe a more pronounced one-sided selling in value stocks in bad times.

In order to test the argument made above, we investigate the relation between the monthly buy-minus-sell order imbalance (net order flow) of value-minus-growth strategies and economic conditions.²⁵ A lower net order imbalance indicates that investors sell a stock more aggressively. This, in turn, should lower liquidity because more one-sided trading increases the reward that traders expect for providing liquidity. If investors are more eager to sell value stocks than growth stocks due to shifts in risk, net order flow in value stocks should decline relative to net order flow in growth stocks. As a result, we expect a negative relation between HML net order flow and economic conditions.

We use the beginning of the month default spread (DEF) and term spread (TERM) as proxies for future economic conditions since they are well-established forward looking economic predictors.²⁶ If investors sell value stocks more aggressively than growth stocks when economic conditions turn for the worse, we expect the order imbalance of HML(s) to be negatively related to DEF and positively related to TERM. To test these predictions, we

²⁵See Chordia and Subrahmanyam (2002) and Boehmer and Wu (2008) for more details on the concept of net order flow.

²⁶Fama and French (1989), Chen(1991), and Estrella and Hardouvelis (1991), among others, show that DEF is countercyclical, while TERM is procyclical.

specify the following model for the order imbalance of a portfolio:

$$OIB_{pt} = \alpha + \beta_0 DEF_{t-1} + \beta_1 TERM_{t-1} + \beta_2 Z_t + e_t, \quad (8)$$

where OIB_{pt} is the portfolio order imbalance at time t and Z_t is a vector of control variables. The control variables include the contemporaneous and one-month lagged excess market return, the contemporaneous interest rate, the lagged portfolio return, and lagged order imbalance.²⁷

Trade and quote data that satisfy certain criteria are obtained from The Institute for the Study of Security Markets (ISSM) for the period 1988 to 1992, and from the NYSE Trade and Quote (TAQ) database for the period 1993 to 2006.²⁸ To infer the direction of a trade, we use Lee and Ready’s (1991) algorithm. Based on this algorithm, a trade executed at a price higher (lower) than the prevailing quote midpoint is classified as buyer-(seller-)initiated. If a trade occurs at the midpoint, we classify it as buyer-(seller-)initiated if the transaction price is above (below) the previous transaction price.²⁹ Following Chordia and Subrahmanyam (2002, 2004), we only consider NYSE common stocks to ensure that differences in trading protocols across venues and security types do not affect our results. Moreover, we exclude a stock for a specific year if it is not available at the beginning and end of the year in both

²⁷We add the market return and the interest rate, following Chordia and Subrahmanyam (2002), to control for current market conditions. One-month lagged values of the excess market and portfolio-own return control for any contrarian- or momentum-based relation between return and order flow. Lagged order flow controls for persistence in order imbalances.

²⁸Following Boehmer and Kelley (2009), we use trades and quotes during regular market hours only. For trades, we require that TAQ’s CORR field is equal to zero, and the COND field is either blank or equal to *, B, E, J, or K. Trades with non-positive prices or sizes are eliminated. A trade is excluded if its price is greater than 150% or less than 50% of the price of the previous trade. We include only quotes that have positive depth for which TAQ’s MODE field is equal to 1, 2, 3, 6, 10, or 12. Quotes with non-positive ask or bid prices, or where the bid price is higher than the ask price, are excluded. We require that the difference between bid and ask be less than 25% of the quote midpoint.

²⁹The algorithm produces a proxy for the imbalance between supply and demand and naturally resulting estimates are subject to measurement error. However, using TORQ database Odder-White (2000) found that the algorithm correctly classifies 85% of the transactions. Moreover, Lee and Radhakrishna (2000) report, among the trades that can be classified as buyer (seller) initiated, Lee-Ready algorithm is 93% accurate.

intraday and CRSP databases, or its month-end price exceeds \$999 during the year.

For each stock, we compute two monthly net order flow measures. The first measure is the total share difference between buyer- and seller-initiated trades in a given month, normalized by total share trading volume (OIBSHARES). The second measure is the total dollar trading volume difference between buyer- and seller-initiated trades in a given month, normalized by dollar trading volume (OIBDOLLAR). The order imbalance of HML (OIBHML) is the difference between equally-weighted average monthly order imbalances for portfolios Small-High and Big-High and portfolios Small-Low and Big-Low. A positive OIBHML implies that buyers are more aggressive in value stocks than in growth stocks, a negative OIBHML implies that sellers are more aggressive in value stocks. Moreover, a negative OIBHML when the economy moves into a recession and a positive OIBHML when it moves out of a recession would be consistent with a flight-to-quality explanation. Finally, the order imbalance of the market portfolio (OIBMRKT) is the cross-sectional average of order imbalances for all stocks.

Panel A of Table 7 presents the results using order imbalance in shares traded (OIBSHARES). The dependent variable is the order imbalance of HML (OIBHML). The coefficients of interest are the ones on default spread and term spread. Since DEF is countercyclical and TERM is procyclical, if flight-to-quality occurs we expect to find a negative coefficient on DEF and a positive one on TERM. In the regression for OIBHML the coefficient on DEF is -1.206 and the coefficient on TERM is 0.349. Both coefficients are significant at the 5% level with t-statistics of -2.2 and 2.5, respectively. The results using order imbalance in dollars (OIBDOLLAR) are in Panel B of Table 7. The results are qualitatively identical to the ones for OIBSHARES and robust to the sample period used.

Overall, when investors expect economic conditions to worsen, they tend to sell value

stocks more aggressively than growth stocks. Given the observed pattern in liquidity betas we document above, these results on net order flow are consistent with a flight-to-quality as economic conditions worsen and value stocks become riskier than growth stocks.

VI. Can Time-Varying Liquidity Risk Explain the Value Premium?

In recessions, we observe that value stocks have higher liquidity betas than growth stocks. In addition, the liquidity risk premium is higher in bad times than in good times. In this section we ask whether investors fear high liquidity exposure when business conditions turn for the worse and, as a result, value stocks earn higher average returns than growth stocks. More specifically, we examine what fraction of the value premium can be explained by the time-varying liquidity betas.

We start out by specifying the return-generating process for excess returns, which is the same as equation (4) from before:

$$\begin{aligned}
R_{it+1} = & \alpha_i + b_{0i}R_{Mt+1} + b_{1it}R_{Mt+1}DIV_t + b_{2it}R_{Mt+1}TERM_t \\
& + b_{3it}R_{Mt+1}DEF_t + b_{4it}R_{Mt+1}TB_t \\
& + c_{0i}LIQ_{t+1} + c_{1it}LIQ_{t+1}DIV_t + c_{2it}LIQ_{t+1}TERM_t \\
& + c_{3it}LIQ_{t+1}DEF_t + c_{4it}LIQ_{t+1}TB_t + \varepsilon_{it+1}.
\end{aligned} \tag{9}$$

The interaction terms involving the market return and the conditioning variables capture time-variation in the market beta. The interaction terms involving the liquidity factor and the conditioning variables capture time-variation in the liquidity beta. We are interested in whether the risk exposures from equation (9) are important determinants in the cross section of portfolios sorted by book-to-market and size. Therefore, we examine the following

cross-sectional regression:

$$R_{it+1} = \lambda_0 + \lambda_1 \hat{b}_{0it} + \lambda_2 \hat{b}_{1it} + \lambda_3 \hat{b}_{2it} + \lambda_4 \hat{b}_{3it} + \lambda_5 \hat{b}_{4it} \\ \lambda_6 \hat{c}_{0it} + \lambda_7 \hat{c}_{1it} + \lambda_8 \hat{c}_{2it} + \lambda_9 \hat{c}_{3it} + \lambda_{10} \hat{c}_{4it} + e_{it+1}, \quad (10)$$

where the λ terms are the prices of risk associated with the corresponding risk factors. If time-varying liquidity exposure is important for the cross section of expected returns, then the coefficients λ_7 , λ_8 , λ_9 , and λ_{10} should be jointly significant.

We use the Fama-MacBeth (1973) two-stage method to estimate the prices of risk from equation (10) over the entire sample period from January 1927 to December 2008. Our test assets consist of 25 portfolios sorted by size and book-to-market, as well as the same portfolios scaled by each one of the conditioning variables DIV, TERM, DEF, and TB.³⁰ Therefore, we have a total of 125 test assets that capture variation in expected returns across the book-to-market and size dimension, as well as variation through time. We compute the adjusted cross-sectional R^2 of the regression, which follows Jagannathan and Wang (1996). In addition, we compute t -statistics that have been adjusted for the errors-in-variables problem of estimated betas, following Shanken (1992).

Table 8 presents the results from the estimation of equation (10). The table shows that conditional liquidity betas are important determinants in the cross section of portfolios sorted by size and book-to-market. The prices of time-varying liquidity risk, represented by λ_7 , λ_8 , λ_9 , and λ_{10} , are jointly significant. The individually significant terms are λ_7 and λ_9 , which capture time-variation in the liquidity beta due to fluctuations in the dividend yield and the default spread. The explanatory power of the model is 82%.

³⁰Cochrane (2005) describes in detail how the scaling of portfolio returns with conditioning variables can capture conditioning information about expected returns. Lewellen, Nagel, and Shanken (2008) emphasize that it is important to expand the set of test assets beyond the 25 size and book-to-market portfolios in testing an asset-pricing model. Including the scaled portfolios is in line with their suggestion.

We now use the estimated price of time-varying liquidity risk to calculate the value premium, i.e., the expected profits to value-minus-growth strategies, implied by exposure to liquidity risk. We are interested in the magnitude of these expected profits relative to those observed in the data. Expected profit due to exposure to time-varying liquidity risk is defined as:

$$\begin{aligned}
E(High - Low) = & \hat{\lambda}_7(\hat{c}_{1High} - \hat{c}_{1Low}) + \hat{\lambda}_8(\hat{c}_{2High} - \hat{c}_{2Low}) \\
& + \hat{\lambda}_9(\hat{c}_{3High} - \hat{c}_{3Low}) + \hat{\lambda}_{10}(\hat{c}_{4High} - \hat{c}_{4Low}),
\end{aligned} \tag{11}$$

where High and Low refer to the book-to-market ratio of the portfolio.

The average realized returns for the *High - Low* strategy in each size quintile starting from the smallest one are 0.96%, 0.65%, 0.47%, 0.39%, and -0.85% per month, respectively. The corresponding estimates of $E(High - Low)$ from equation (11) are 0.33%, 0.50%, 0.79%, 0.44%, and -0.92%. The difference between the average realized *High - Low* return and $E(High - Low)$ is insignificant for all size quintiles except the smallest. Even in the case of the smallest size quintile, the spread in conditional liquidity betas between value and growth portfolios explains 35% of the difference in their average returns. Importantly, time-varying liquidity risk explains, on average, 100% of the value premium.

Next we examine the incremental explanatory power of time-varying liquidity risk in the cross section of portfolios sorted by size and book-to-market. To do so, we plot the fitted expected return of each portfolio against its realized average return in Figure 2. Each two-digit number in the figure represents a separate portfolio. The first digit refers to the size quintile (1 being the smallest and 5 the largest), while the second digit refers to the book-to-market quintile (1 being the lowest and 5 the highest). The fitted expected return is computed using the estimated parameter values from model (10). The realized average

return is the time series average of the portfolio return. If the fitted expected return and the realized average return for each portfolio are the same, then they should lie on a 45-degree line through the origin.

Panel A of Figure 2 shows the performance of the model in equation (10), while Panel B examines the case in which time-varying liquidity risk is dropped from the model in (10). It can be seen from the graphs that time-varying liquidity exposure plays an important role in explaining the spread in average returns. In Panel A, portfolios '11' and '15' are close to the 45-degree line, which suggests that the model is able to capture a large part of the value premium in the smallest quintile. In contrast, in Panel B portfolios '11' and '15' have a large difference in average realized returns, but the difference in their fitted expected returns is not that sizable. This implies that in the absence of time-varying liquidity risk, the small-stock value premium remains largely unexplained. In general, the rest of the portfolios tend to be closer to the 45-degree line in Panel A than in Panel B. Therefore, the results from Figure 2 show that time-varying liquidity risk is an important determinant of the expected returns of portfolios sorted by size and book-to-market.

VII. Conclusion

We provide evidence that time-varying liquidity risk explains part of the value premium. We find that the HML's portfolio sensitivity to liquidity risk is higher in bad times than in good times mainly because value stocks are more sensitive to liquidity risk in bad times and the opposite is true for growth stocks. In addition, we document that small value stocks have higher liquidity exposures than small growth stocks in worst times, while small growth stocks have higher liquidity exposures than small value stocks in best times. Our results are robust to different sample periods, various measures of value and growth strategies, and

different definitions of business cycles and liquidity risk.

Using buy-minus-sell trading order imbalance, we provide evidence that investors are more eager to sell value stocks than growth stocks in bad times. In addition, value stocks are less liquid than growth stocks and this relation becomes even more pronounced in bad times. Together these results suggest a flight-to-quality explanation for the countercyclical nature of the value premium. Shifts in risk cause investors to dislike riskier assets. This, in turn, affects the sensitivity of value and growth stocks to liquidity risk and leads to the observed patterns in the liquidity betas of HML across business cycles.

We estimate that exposure to time-varying liquidity risk captures 35% of the small-stock value premium and 100% of the large-stock value premium. On average, across all size quintiles, time-varying liquidity risk can account for 100% of the value premium.

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Table 1: Average Liquidity and Market Betas Across Business Cycles - 1927:2008

This table presents average fitted and rolling betas for value (High), growth (Low), value-minus-growth (HML), and small value-minus-growth (HMLs) portfolios for the period from 01/1927 to 12/2008. The rolling betas are estimated using 60-month rolling-window regressions, while the fitted betas are estimated from conditional regressions that contain the market return and aggregate liquidity. The conditioning variables are dividend yield, term spread, default spread, and one-month Treasury bill rate. In Panel A, there are four states of the world based on the expected market risk premium, which is estimated as a linear function of the conditioning variables. "Best" corresponds to the 10% lowest observations for the premium; "–" corresponds to the observations between 10% and 50%; state "+" corresponds to the observations between 50% and 90%; and "Worst" corresponds to the 10% highest observations for the premium. In Panel B, NBER recession dates define states of the world. "–" corresponds to recessions, while "+" corresponds to expansions. We report the average market (β_M) and liquidity (β_L) betas in each state, as well as the t-statistics adjusted for heteroscedasticity and autocorrelation of up to 60 lags. "Diff" is the difference between "Worst" and "Best" in Panel A, and between "–" and "+" in Panel B.

Panel A: Sort on Expected Market Risk Premium																
Fitted Beta																
HML				HIGH				LOW				HMLs				
	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$
Worst	0.626	22.8	0.204	10.3	0.869	28.8	1.179	110.3	0.243	20.5	0.975	89.1	0.298	4.0	-0.477	-18.8
-	0.317	16.3	-0.049	-2.3	0.595	45.4	1.047	96.1	0.278	35.6	1.095	97.3	-0.021	-1.1	-0.364	-18.8
+	0.176	13.7	-0.162	-10.9	0.466	53.3	0.966	115.4	0.291	61.6	1.129	157.7	-0.077	-7.5	-0.226	-14.0
Best	0.057	2.7	-0.269	-10.5	0.381	27.4	0.899	59.9	0.324	42.8	1.168	96.7	-0.023	-1.0	-0.140	-4.2
Diff	0.569	32.6	0.473	28.4	0.489	30.5	0.281	30.3	-0.081	-12.3	-0.193	-23.0	0.321	9.3	-0.337	-16.2
Rolling Beta																
HML				HIGH				LOW				HMLs				
	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$
Worst	0.506	9.9	0.059	1.1	0.763	15.5	1.085	30.0	0.257	29.4	1.026	55.4	0.223	1.2	-0.258	-4.0
-	0.323	4.1	-0.060	-0.9	0.612	9.7	1.030	25.5	0.288	11.8	1.090	36.9	-0.060	-0.6	-0.272	-3.8
+	0.229	2.6	-0.117	-1.9	0.537	8.8	1.044	27.0	0.308	9.3	1.162	42.1	-0.315	-4.3	-0.327	-4.9
Best	0.087	0.9	-0.225	-2.9	0.483	11.6	1.012	17.1	0.396	6.3	1.238	58.6	-0.233	-1.6	-0.500	-5.6
Diff	0.419	10.8	0.284	10.3	0.280	10.8	0.073	3.6	-0.140	-7.4	-0.211	-22.5	0.455	5.3	0.241	6.6
Panel B: Sort on NBER																
Fitted Beta																
HML				HIGH				LOW				HMLs				
	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$
-	0.363	8.4	-0.044	-1.1	0.643	17.4	1.034	46.8	0.280	27.4	1.078	60.6	0.159	2.8	-0.398	-11.7
+	0.242	15.2	-0.109	-7.1	0.528	43.4	1.005	117.6	0.286	61.2	1.114	153.9	-0.062	-4.9	-0.288	-20.6
Diff	0.120	6.1	0.065	3.6	0.115	6.9	0.029	2.8	-0.006	-1.2	-0.036	-4.4	0.221	8.7	-0.110	-6.7
Rolling Beta																
HML				HIGH				LOW				HMLs				
	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$
-	0.352	3.8	-0.025	-0.3	0.616	8.8	1.065	20.3	0.265	9.6	1.01	25.4	-0.101	-0.7	-0.281	-3.1
+	0.268	4.3	-0.098	-2.2	0.578	12.8	1.034	37.1	0.310	14.0	1.133	52.8	-0.159	-2.1	-0.320	-6.3
Diff	0.084	2.8	0.073	3.0	0.038	1.7	0.031	2.1	-0.046	-4.4	-0.042	-3.8	0.057	1.2	0.038	1.4

Table 2: Average Liquidity and Market Betas Across Business Cycles - 1935:2008

This table presents average fitted and rolling betas for value (High), growth (Low), value-minus-growth (HML), and small value-minus-growth (HMLs) portfolios for the period from 01/1935 to 12/2008. The rolling betas are estimated using 60-month rolling-window regressions, while the fitted betas are estimated from conditional regressions that contain the market return and aggregate liquidity. The conditioning variables are dividend yield, term spread, default spread, and one-month Treasury bill rate. In Panel A, there are four states of the world based on the expected market risk premium, which is estimated as a linear function of the conditioning variables. "Best" corresponds to the 10% lowest observations for the premium; "–" corresponds to the observations between 10% and 50%; state "+" corresponds to the observations between 50% and 90%; and "Worst" corresponds to the 10% highest observations for the premium. In Panel B, NBER recession dates define states of the world. "–" corresponds to recessions, while "+" corresponds to expansions. We report the average market (β_M) and liquidity (β_L) betas in each state, as well as the t-statistics adjusted for heteroscedasticity and autocorrelation of up to 60 lags. "Diff" is the difference between "Worst" and "Best" in Panel A, and between "–" and "+" in Panel B.

Panel A: Sort on Expected Market Risk Premium													
Fitted Beta													
HML				HIGH				LOW				HMLs	
β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$
Worst	0.596	10.2	0.059	1.9	0.828	19.3	1.079	58.7	0.232	14.1	1.021	63.6	–0.052
–	0.321	13.2	–0.088	–4.1	0.626	33.6	1.024	76.8	0.306	47.7	1.112	125.5	–0.095
+	0.182	12.7	–0.165	–10.8	0.508	43.9	0.994	94.5	0.326	76.7	1.159	211.3	–0.224
Best	0.097	5.0	–0.288	–9.0	0.430	25.8	0.922	38.3	0.333	39.4	1.210	132.6	–0.361
Diff	0.499	18.2	0.347	16.7	0.398	19.4	0.158	11.1	–0.101	–12.3	–0.189	–22.5	–0.138
Rolling Beta													
HML				HIGH				LOW				HMLs	
β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$
Worst	0.436	5.3	0.009	0.2	0.693	8.8	1.066	41.7	0.258	31.0	1.057	59.3	–0.093
–	0.327	3.9	–0.073	–1.1	0.614	9.4	1.020	27.1	0.287	11.5	1.093	38.5	–0.089
+	0.218	2.8	–0.127	–2.2	0.530	10.3	1.040	28.8	0.312	10.8	1.167	47.1	–0.311
Best	0.121	1.4	–0.221	–3.6	0.490	13.7	1.014	22.1	0.369	7.2	1.235	70.6	–0.175
Diff	0.315	7.7	0.230	8.1	0.204	7.4	0.052	2.6	–0.111	–5.8	–0.177	–17.1	0.082
Panel B: Sort on NBER													
Fitted Beta													
HML				HIGH				LOW				HMLs	
β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$
–	0.342	7.2	–0.154	–3.5	0.622	16.4	0.972	34.5	0.281	25.1	1.126	63.4	–0.014
+	0.260	14.3	–0.122	–8.4	0.575	40.7	1.013	120.3	0.315	66.5	1.135	172.1	–0.180
Diff	0.082	3.7	–0.032	–1.6	0.048	2.7	–0.041	–3.3	–0.034	–6.4	–0.009	–1.1	0.166
Rolling Beta													
HML				HIGH				LOW				HMLs	
β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$
–	0.336	3.4	–0.050	–0.5	0.603	8.1	1.056	19.1	0.267	8.7	1.106	25.5	–0.205
+	0.263	4.1	–0.110	–2.4	0.571	12.5	1.028	37.1	0.309	13.6	1.138	53.4	–0.183
Diff	0.074	2.3	0.060	2.4	0.032	1.4	0.028	1.8	–0.042	–3.7	–0.032	–2.8	–0.023

Table 3: Average Liquidity and Market Betas Across Business Cycles - 1963:2008

This table presents average fitted and rolling betas for value (High), growth (Low), value-minus-growth (HML), and small value-minus-growth (HMLs) portfolios for the period from 01/1963 to 12/2008. The rolling betas are estimated using 60-month rolling-window regressions, while the fitted betas are estimated from conditional regressions that contain the market return and aggregate liquidity. The conditioning variables are dividend yield, term spread, default spread, and one-month Treasury bill rate. In Panel A, there are four states of the world based on the expected market risk premium, which is estimated as a linear function of the conditioning variables. "Best" corresponds to the 10% lowest observations for the premium; "–" corresponds to the observations between 10% and 50%; state "+" corresponds to the observations between 50% and 90%; and "Worst" corresponds to the 10% highest observations for the premium. In Panel B, NBER recession dates define states of the world. "–" corresponds to recessions, while "+" corresponds to expansions. We report the average market (β_M) and liquidity (β_L) betas in each state, as well as the t-statistics adjusted for heteroscedasticity and autocorrelation of up to 60 lags. "Diff" is the difference between "Worst" and "Best" in Panel A, and between "+" and "–" in Panel B.

Panel A: Sort on Expected Market Risk Premium																
Fitted Beta																
HML				HIGH				LOW				HMLs				
	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$
Worst	0.169	3.0	-0.165	-4.7	0.502	19.8	1.015	34.3	0.333	10.3	1.180	110.0	0.104	1.2	-0.175	-4.5
-	0.123	5.4	-0.215	-12.5	0.462	44.4	0.971	64.6	0.339	24.8	1.186	273.6	0.004	0.1	-0.326	-18.2
+	0.004	0.2	-0.271	-11.7	0.391	28.7	0.941	48.8	0.387	31.8	1.211	248.5	-0.308	-9.0	-0.475	-17.1
Best	-0.137	-3.1	-0.476	-13.7	0.280	13.9	0.765	24.5	0.416	15.3	1.240	168.1	-0.495	-7.3	-0.804	-21.8
Diff	0.306	8.8	0.310	12.1	0.223	13.8	0.250	11.3	-0.083	-4.1	-0.060	-8.9	0.599	10.6	0.629	22.8
Rolling Beta																
HML				HIGH				LOW				HMLs				
	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$
Worst	0.176	2.6	-0.278	-6.9	0.472	8.1	0.914	28.0	0.296	16.9	1.192	102.1	0.092	1.2	-0.364	-6.0
-	0.025	0.3	-0.308	-6.7	0.375	6.6	0.903	27.0	0.350	9.5	1.211	73.6	-0.163	-1.3	-0.469	-5.8
+	0.076	1.5	-0.195	-4.0	0.432	19.2	1.022	25.2	0.355	10.1	1.217	88.8	-0.248	-3.3	-0.378	-5.9
Best	0.033	0.3	-0.302	-4.4	0.456	8.7	0.954	18.3	0.423	6.2	1.255	65.0	-0.223	-1.2	-0.595	-8.6
Diff	0.143	2.7	0.023	0.8	0.016	0.5	-0.040	-1.7	-0.127	-4.8	-0.063	-7.4	0.315	3.9	0.231	6.7
Panel B: Sort on NBER																
Fitted Beta																
HML				HIGH				LOW				HMLs				
	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$
-	0.228	4.1	-0.243	-7.0	0.492	18.9	0.931	32.5	0.264	8.4	1.174	106.9	0.150	1.5	-0.402	-10.9
+	0.038	2.1	-0.264	-16.4	0.417	39.1	0.944	69.8	0.379	41.5	1.209	348.2	-0.199	-6.4	-0.432	-17.5
Diff	0.190	6.3	0.021	1.0	0.076	4.9	-0.013	-0.8	-0.115	-7.3	-0.035	-5.4	0.349	6.5	0.031	1.2
Rolling Beta																
HML				HIGH				LOW				HMLs				
	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$
-	0.138	1.7	-0.247	-5.2	0.443	9.3	0.952	21.6	0.305	8.8	1.199	113.6	-0.021	-0.2	-0.446	-11.5
+	0.050	0.9	-0.261	-7.0	0.411	11.5	0.958	31.6	0.362	13.0	1.218	104.8	-0.204	-2.5	-0.433	-7.8
Diff	0.088	2.6	0.013	0.6	0.032	1.6	-0.006	-0.3	-0.057	-3.5	-0.019	-2.6	0.184	3.4	-0.013	-0.5

Table 4: Average Liquidity and Market Betas Across Business Cycles - Controlling for the Correlation between Book-to-Market and Liquidity

This table presents average fitted and rolling betas for value (High), growth (Low), value-minus-growth (HML), and small value-minus-growth (HMLs) portfolios for the period from 01/1963 to 12/2008. The rolling betas are estimated using 60-month rolling-window regressions, while the fitted betas are estimated from conditional regressions that contain the market return and aggregate liquidity. The liquidity factor, LIQ1 (Panel A) or LIQ2 (Panel B), controls for the correlation between the book-to-market ratio of a stock and its liquidity characteristic, as described in Section III.D. The conditioning variables are dividend yield, term spread, default spread, and one-month Treasury bill rate. In each panel there are two measures of economic states. The first one is the expected market risk premium, estimated as a linear function of the conditioning variables, that defines four states of the world. "Best" corresponds to the 10% lowest observations for the premium; "+" corresponds to the observations between 10% and 50%; state "-" corresponds to the observations between 50% and 90%; and "Worst" corresponds to the 10% highest observations for the premium. The second measure is based on NBER recession dates which define two states of the world: "-" corresponds to recessions, while "+" corresponds to expansions. We report the average market (β_M) and liquidity (β_L) betas in each state, as well as the t-statistics adjusted for heteroscedasticity and autocorrelation of up to 60 lags. "Diff" is the difference between "Worst" and "Best" or between "-" and "+".

Panel A: Liquidity Factor LIQ1									
Sort on Expected Market Risk Premium									
	HML		HIGH		LOW		HMLs		
	β_L	$t(\beta_L)$	β_L	$t(\beta_L)$	β_L	$t(\beta_L)$	β_L	$t(\beta_L)$	
Worst	0.044	0.8	0.436	15.0	0.392	13.1	0.000	0.0	
-	0.012	0.5	0.397	33.1	0.385	31.0	-0.097	-2.6	
+	-0.095	-3.9	0.321	22.5	0.416	38.0	-0.396	-11.5	
Best	-0.213	-4.6	0.217	9.3	0.430	17.7	-0.582	-8.5	
Diff	0.258	7.2	0.219	12.1	-0.038	-2.1	0.582	10.2	
Sort on NBER									
	HML		HIGH		LOW		HMLs		
	β_L	$t(\beta_L)$	β_L	$t(\beta_L)$	β_L	$t(\beta_L)$	β_L	$t(\beta_L)$	
-	0.108	2.0	0.428	15.3	0.320	12.4	0.029	0.3	
+	-0.075	-4.4	0.341	32.1	0.416	55.7	-0.300	-10.5	
Diff	0.183	6.4	0.088	5.5	-0.096	-7.2	0.329	6.3	
Panel B: Liquidity factor LIQ2									
Sort on Expected Market Risk Premium									
	HML		HIGH		LOW		HMLs		
	β_L	$t(\beta_L)$	β_L	$t(\beta_L)$	β_L	$t(\beta_L)$	β_L	$t(\beta_L)$	
Worst	-0.011	-0.2	0.406	15.8	0.417	15.6	0.014	0.2	
-	-0.035	-1.6	0.356	31.2	0.392	34.9	-0.094	-2.6	
+	-0.131	-6.4	0.265	21.9	0.395	43.4	-0.384	-12.1	
Best	-0.200	-4.5	0.174	7.4	0.374	16.9	-0.550	-7.9	
Diff	0.188	5.8	0.232	14.1	0.044	2.6	0.564	10.6	
Sort on NBER									
	HML		HIGH		LOW		HMLs		
	β_L	$t(\beta_L)$	β_L	$t(\beta_L)$	β_L	$t(\beta_L)$	β_L	$t(\beta_L)$	
-	0.063	1.3	0.386	13.9	0.323	14.9	0.027	0.3	
+	-0.112	-7.7	0.294	28.8	0.405	61.1	-0.288	-10.5	
Diff	0.175	7.1	0.092	6.3	-0.083	-7.5	0.315	6.7	

Table 5: Average Liquidity and Market Betas Across Business Cycles - Using Alternative Liquidity Measures

This table presents average fitted and rolling betas for value (High), growth (Low), value-minus-growth (HML), and small value-minus-growth (HMLs) portfolios for the period from 01/1927 to 12/2008. The rolling betas are estimated using 60-month rolling-window regressions, while the fitted betas are estimated from conditional regressions that contain the market return and aggregate liquidity. The conditioning variables are dividend yield, term spread, default spread, and one-month Treasury bill rate. We use three different liquidity factors based on Watanabe and Watanabe (2008), Pastor and Stambaugh (2003), and Liu (2006). In Panel A, there are four states of the world based on the expected market risk premium, which is estimated as a linear function of the conditioning variables. "Best" corresponds to the 10% lowest observations for the premium; "+" corresponds to the observations between 10% and 50%; state "-" corresponds to the observations between 50% and 90%; and "Worst" corresponds to the 10% highest observations for the premium. In Panel B, NBER recession dates define states of the world. "-" corresponds to recessions, while "+" corresponds to expansions. We report the average market (β_M) and liquidity (β_L) betas in each state, as well as the t-statistics adjusted for heteroscedasticity and autocorrelation of up to 60 lags. "Diff" is the difference between "Worst" and "Best" in Panel A, and between "-" and "+" in Panel B.

Panel A: Sort on expected market risk premium																								
Watanabe and Watanabe (2008)					Pastor and Stambaugh (2003)					Liu (2006)														
HML			HMLs		HML		HMLs		HML		HMLs													
β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$									
Worst	0.099	8.3	0.364	11.7	0.331	9.4	-0.450	-9.9	0.131	2.1	0.380	11.4	0.327	2.2	-0.381	-9.2	0.394	33.6	0.511	17.5	1.308	13.0	0.132	4.3
-	0.011	2.6	0.038	1.5	0.156	10.5	-0.373	-13.6	-0.040	-0.7	0.034	1.4	0.145	1.2	-0.359	-15.3	0.305	58.9	0.133	4.9	0.503	11.5	-0.151	-6.3
+	-0.019	-4.8	-0.136	-7.1	-0.111	-10.4	-0.193	-9.8	-0.127	-2.7	-0.140	-7.8	0.043	0.5	-0.249	-15.3	0.187	37.3	-0.088	-4.5	0.028	0.7	-0.257	-17.2
Best	-0.037	-4.3	-0.268	-7.9	-0.366	-26.5	-0.005	-0.1	-0.322	-3.4	-0.270	-8.6	-0.335	-1.9	-0.115	-3.6	0.076	11.2	-0.283	-8.6	-0.350	-4.3	-0.380	-15.5
Diff	0.136	19.7	0.633	27.8	0.697	37.0	-0.446	-15.6	0.453	8.2	0.650	28.8	0.661	6.0	-0.266	-10.9	0.318	45.6	0.794	35.2	1.659	26.5	0.512	26.1

Panel B: Sort on NBER																								
Watanabe and Watanabe (2008)					Pastor and Stambaugh (2003)					Liu (2006)														
HML			HMLs		HML		HMLs		HML		HMLs													
β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$	β_L	$t(\beta_L)$	β_M	$t(\beta_M)$									
-	0.043	3.9	0.037	0.7	0.070	2.3	-0.337	-8.9	-0.187	-2.0	0.047	0.9	-0.172	-1.0	-0.331	-10.6	0.261	17.7	0.124	2.2	0.669	6.3	-0.106	-2.8
+	-0.006	-1.7	-0.046	-2.4	0.002	0.1	-0.256	-12.7	-0.062	-1.7	-0.051	-2.7	0.133	2.0	-0.284	-17.9	0.240	28.3	0.021	0.9	0.222	5.1	-0.207	-12.3
Diff	0.049	9.8	0.082	3.4	0.069	4.0	-0.081	4.1	-0.125	-2.9	0.098	4.1	-0.305	-3.7	-0.047	-2.9	0.021	2.7	0.103	4.0	0.447	8.9	0.102	5.8

Table 6: Amihud Illiquidity Across Business Cycles

This table presents average Amihud illiquidity of value and growth portfolios across business cycles. We define four states by sorting on the expected market risk premium, which is estimated as a linear function of the dividend yield, term spread, default spread, and one-month Treasury bill rate. "Best" corresponds to the 10% lowest observations for the premium; "+" corresponds to the observations between 10% and 50%; "-" corresponds to the observations between 50% and 90%; and "Worst" corresponds to the 10% highest observations for the premium. The sample period is from 01/1963 to 12/2008. Panel A shows average illiquidity of value (High) and growth (Low) portfolios in a two-by-three sort on size and book-to-market. In Panel B, the average illiquidity of small value (Hs) and small growth (Ls) portfolios is obtained from a five-by-five sort on size and book-to-market. "Worst-Best" is the difference of the Amihud measures in "Worst" and "Best" times. "High-Low" represents the difference in the Amihud measures between value (high) and growth (low) portfolios. "Hs-Ls" reports the difference in the Amihud measures between small value (Hs) and small growth (Ls) portfolios. We also report the corresponding t-statistics for these differences.

Panel A: Average Amihud Illiquidity of Value(High) and Growth (Low) Portfolios

	Worst	-	+	Best	Worst-Best	t-statistic
High	1.040	0.984	0.901	0.563	0.478	14.69
Low	0.299	0.298	0.333	0.199	0.100	32.03
High-Low	0.741	0.687	0.568	0.364		
t-statistic	58.8	99.9	77.2	34.8		

Panel B: Average Amihud Illiquidity of Small Value(Hs) and Small Growth (Ls) Portfolios

	Worst	-	+	Best	Worst-Best	t-statistic
Hs	2.455	2.166	2.111	1.524	0.345	30.53
Ls	1.410	1.374	1.348	0.741	0.062	8.67
Hs-Ls	1.045	0.792	0.762	0.783		
t-statistic	16.2	21.3	21.9	15.4		

Table 7: Order Imbalance and Business Cycles

In Panel A, value-minus-growth portfolio equally-weighted scaled order imbalance in shares traded (OIBSHARES) at time t is regressed on DEF and TERM at time $t-1$, controlling for time $t-1$ excess market return (Excmrkt), portfolio return (Hml(s)), portfolio order imbalance (OIBHML(s)), time t market return (Mrkt), and time t short-term interest rate (R_f). The estimated coefficients, as well as the corresponding t -statistics adjusted for heteroscedasticity and autocorrelation of up to 60 months, are reported. Panel B uses value-minus-growth portfolio equally-weighted scaled order imbalance in dollar volume traded (OIBDOLLAR).

Panel A. OIBSHARES					Panel B. OIBDOLLAR			
	HML		HML(s)		HML		HML(s)	
	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic
Def	-1.206	-2.2	-1.864	-2.2	-1.173	-2.2	-1.828	-2.1
Term	0.349	2.5	0.404	2.3	0.351	2.58	0.419	2.4
Oibhml	0.456	5.0	0.415	4.5	0.462	5.16	0.419	4.6
Hml	-0.057	-1.0	-0.054	-0.7	-0.047	-0.83	-0.051	-0.6
Excmrkt	0.042	2.0	0.046	1.5	0.040	1.87	0.045	1.4
R_f	1.961	1.7	3.191	2.1	2.015	1.71	3.318	2.2
Mrkt	0.033	1.4	0.051	1.4	0.036	1.46	0.054	1.5

Table 8: Cross-Sectional Regression: Can Time-Varying Liquidity Risk Explain the Value Premium?

This table presents Fama-MacBeth cross-sectional regressions using the excess returns of 25 portfolios sorted by size and book-to-market, as well as the same portfolios scaled by the aggregate dividend yield (DIV), term spread (TERM), default spread (DEF), or the short-term T-bill rate (TB). The full-sample factor loadings, which are the independent variables in the regressions, are computed in one multiple time series regression:

$$R_{it+1} = \alpha_i + b_{0i}R_{Mt+1} + b_{1it}R_{Mt+1}DIV_t + b_{2it}R_{Mt+1}TERM_t + b_{3it}R_{Mt+1}DEF_t + b_{4it}R_{Mt+1}TB_t + c_{0i}LIQ_{t+1} + c_{1it}LIQ_{t+1}DIV_t + c_{2it}LIQ_{t+1}TERM_t + c_{3it}LIQ_{t+1}DEF_t + c_{4it}LIQ_{t+1}TB_t + \varepsilon_{it+1},$$

where R_{it+1} is the excess return of portfolio i , R_{Mt+1} is the excess market return, and LIQ_{t+1} is the liquidity factor. The Adjusted R^2 is computed as in Jagannathan and Wang (1996). The t -statistics are adjusted for errors-in-variables, following Shanken (1992). All coefficients are multiplied by 100. The sample period is from 01/1927 to 12/2008.

$R_{it+1} = \lambda_0 + \lambda_1 \hat{b}_{0it} + \lambda_2 \hat{b}_{1it} + \lambda_3 \hat{b}_{2it} + \lambda_4 \hat{b}_{3it} + \lambda_5 \hat{b}_{4it} + \lambda_6 \hat{c}_{0it} + \lambda_7 \hat{c}_{1it} + \lambda_8 \hat{c}_{2it} + \lambda_9 \hat{c}_{3it} + \lambda_{10} \hat{c}_{4it} + e_{it+1}$											
λ_0	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7	λ_8	λ_9	λ_{10}	R^2
0.01	0.55	0.00	-0.05	0.01	0.00	0.32	0.09	0.04	0.03	0.01	0.82
0.96	2.89	0.14	-2.05	0.52	0.81	0.95	2.75	1.88	2.56	1.46	

Figure 1. : Liquidity Factor

This figure plots the monthly time series of the liquidity factor, LIQ_t , for the period from 01/1927 to 12/2008. NBER recessions are represented by the vertical bars.

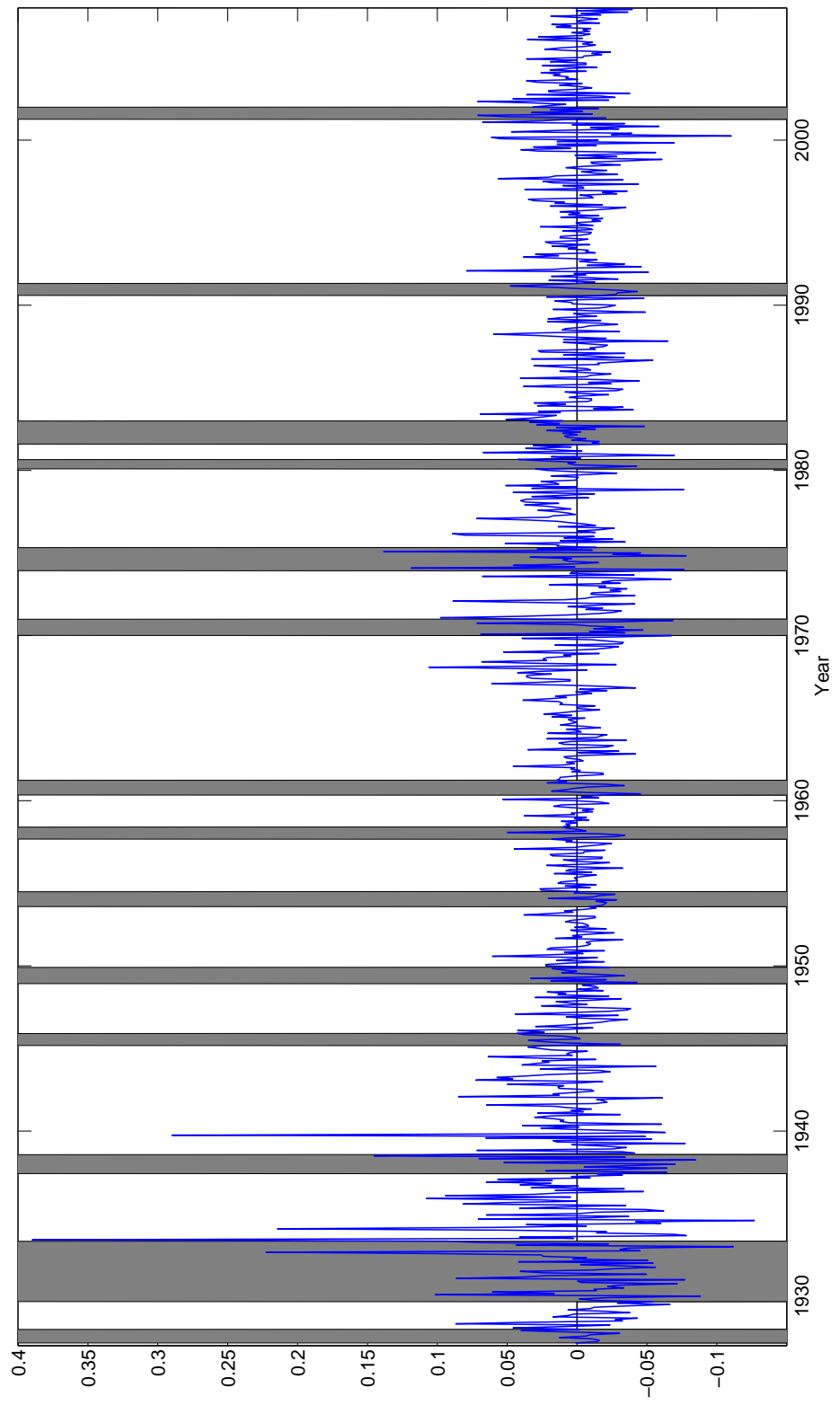
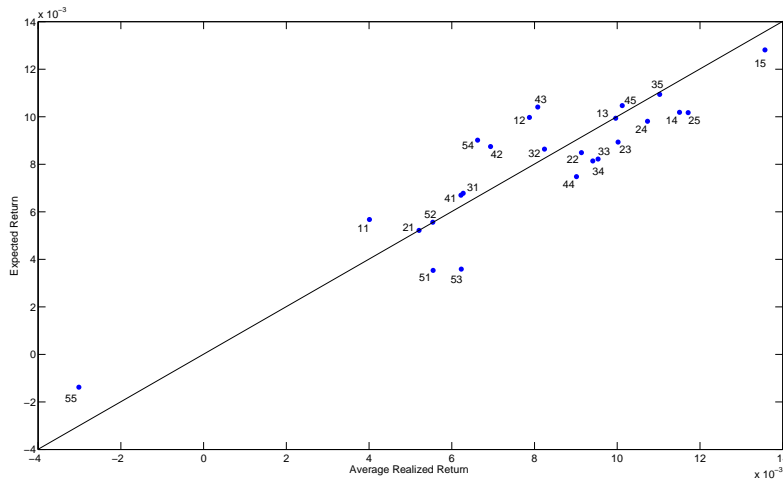


Figure 2. : Explanatory Power of Time-Varying Liquidity Risk

Panel A shows realized average returns on the horizontal axis and fitted expected returns on the vertical axis for 25 portfolios sorted by size and book-to-market relative to the conditional model in equation (10). Each two-digit number represents a separate portfolio. The first digit refers to the size quintile (1 being the smallest and 5 the largest), while the second digit refers to the idiosyncratic risk quintile (1 being the lowest and 5 the highest). For each portfolio, the realized average return is the time-series average of the portfolio return and the fitted expected return is the fitted value for the expected return from the corresponding model. The straight line is the 45-degree line from the origin Panel B shows realized average returns on the horizontal axis and fitted expected returns on the vertical axis for 25 portfolios sorted by size and book-to-market relative to the conditional model in equation (8), excluding the time-varying liquidity terms. The sample period is 01/1927-12/2008.

Panel A: The Model with Time-varying
Liquidity Risk



Panel B: The Model without Time-varying
Liquidity Risk

