HOW DO VOLATILITY REGIMES AFFECT THE PRICING OF QUALITY AND LIQUIDITY IN THE STOCK MARKET?

Tarik Bazgour, Cédric Heuchenne, Georges Hübner, Danielle Sougné

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Louvain Institute of Data Analysis and Modeling in economics and statistics

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Abstract

This paper shows how stock market volatility regimes affect the cross-section of stock returns along quality and liquidity dimensions. We find that, during crisis periods, low quality and low liquidity stocks experience relatively higher losses than predicted in normal times, while high quality and high liquidity stocks experience rather relatively lower losses. These findings lend strong support to the presence of cross-market and within-market flight-to-quality and to-liquidity episodes during crisis periods. During low volatility periods, however, low quality and low liquidity stocks earn relatively larger returns, while high quality and high liquidity stocks yield lower returns; suggesting that low volatility conditions benefit junk and illiquid stocks but not quality and liquid stocks. Finally, our results reveal that liquidity-level dominates liquidity-beta in explaining stock returns across the different market volatility regimes.

Keywords:
Financial crises, Quality, Liquidity, Liquidity risk, Market volatility regimes

1. Introduction

The unconditional pricing of quality and liquidity in the stock market has been extensively studied in the literature. Broadly speaking, quality is the ability of a stock to generate high profitability and stable returns (Sloan, 1996; Ang et al., 2006; Asness et al., 2019; Novy-Marx, 2013; Baker et al., 2014). Regarding liquidity, the literature distinguishes between two aspects namely liquidity-level (or simply liquidity) and liquidity risk (beta). The liquidity level is the ability of a stock to be easily traded without loss of value (Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996; Brennan et al., 1998; Datar et al., 1998; Narayan and Zheng, 2011), while the liquidity risk (beta) of a stock refers to the sensitivity of its return to unexpected changes in aggregate market liquidity (Pastor and Stambaugh, 2003; Liu, 2006; Watanabe and Watanabe, 2008; Narayan and Zheng, 2010; Lou and Sadka, 2011). Overall, most studies show that quality, liquidity level, and liquidity beta are all priced in the cross-section of stock returns. However, time-variation in the cross-sectional effects of these characteristics in the stock market has not been explicitly studied yet. To the best of our knowledge, there are only three studies that consider the conditional pricing of these characteristics. Asness et al. (2019) form a quality factor and show that their factor performs well during recession periods. Lou and Sadka (2011) use only data on the financial crisis of 2008-2009 and show that the cross-section of stock returns during the crisis is better-explained by liquidity risk than by liquidity level. Acharya et al. (2013) provide evidence of time variation in the liquidity risk premium of high and low book-to-market ratio stocks. In this paper, we extend these studies by investigating how market volatility regimes affect the cross-section of stock returns along quality, liquidity level, and liquidity beta dimensions. We contribute to the existing literature in two ways. First, we use a unified framework to investigate how investors price quality and liquidity conditional on different market conditions such as low and high volatility times. Second, given that the analysis of Lou and Sadka (2011) is based solely on the 2008-2009 crisis data, we revisit in this work the importance of liquidity level and liquidity risk in predicting stock performance using a sufficiently long sample period that includes several financial crisis episodes.

Our work is also related to the literature investigating the relation between stock returns and market volatility, such as Campbell and Hentschel (1992), Bekaert and Wu (2000), Kim et al. (2004), and Chung and Chuwonganant (2018). Most of these studies document a negative relation between stock returns and conditional volatility, but without explicitly considering the channels through which market volatility affects stock returns. The only exception is the recent work of Chung and Chuwonganant (2018), which examines how market volatility shocks affect stock returns through the liquidity channel. The authors show that, in response to an increase in market volatility, investors require greater illiquidity premiums on stocks with high liquidity sensitivity to market volatility. We add to this line of research by investigating how the negative relation between stock returns and market volatility depends on changes in the pricing of stock quality and liquidity across different market volatility conditions. Our study differs from Chung and Chuwonganant (2018) in two important aspects.

First, the authors consider the conditional pricing of stock liquidity sensitivity to market volatility. In our analysis, we rather consider the conditional pricing of two other important dimensions of stock liquidity, namely, liquidity level and liquidity risk. Second, Chung and Chuwonganant examine the relation between stock returns and market volatility shocks using the classical linear regression model. In this study, we use a Markov switching-regime model to capture the non-linear relationship between the two variables, which is not well described in the linear model.

Our motivation for linking quality and liquidity stock characteristics to market volatility conditions stems from the growing empirical evidence that their importance to investors increases during distress times. High quality and liquid assets become more desirable during volatile times. Vayanos (2004), for example, shows in a dynamic equilibrium model that preference for liquidity is time-varying and increasing with volatility; and that investors become more risk averse when volatility is high. These time-variations in the investors' risk aversion and preference for liquidity are closely related to the well known phenomena of flight-to-quality (when investors shift their portfolios toward high quality assets) and flight-to-liquidity (when investors tilt their portfolios toward liquid assets) that have been documented to be associated with volatile times in several empirical studies (Longstaff, 2004; Vayanos, 2004; Beber et al., 2009).

We address the question of how market volatility conditions affect the pricing of quality and liquidity by using a Markov-switching regime approach. The Markov-switching regime model was originally proposed by Hamilton (1989) and has become an enormously popular tool for modeling the dynamics of macroeconomic and financial time-series. Applications of this class of models are usually motivated by economic phenoma that appear to involve cycling between recurrent regimes such as bull and bear times or low and high volatility periods in the stock market. The major advantage of Markov-switching models is their flexibility in capturing these potential regimes without imposing strict periodicity. Examples of studies that have applied this technique to model stock market returns' time-series are Rydén et al. (1998), Kim et al. (1998), Billio and Pelizzon (2000), Perez-Quiros and Timmermann (2000), Guidolin and Timmermann (2007), Gulen et al. (2011) and Billio et al. (2012), among others.

We use an econometric framework very similar to the one of Billio and Pelizzon (2000) and Billio et al. (2012). Following these authors, we first use the market portfolio excess return time-series to identify stock market regimes. We then compute, conditional on each regime, the cross-sectional expected stock returns for quality, liquidity level, and liquidity beta deciles. In order to capture time-variation in the expected stock returns, we use a regime-switching beta model. We assume in particular that the market beta of a testing portfolio is time-varying across the different regimes that characterize the stock market but time-invariant within each regime. We run separate analyses with respect to the quality, liquidity level, and liquidity beta stock characteristics over a sample period from 1969 through 2017. Return time-series of quality-sorted portfolios are obtained from AQR Capital Management data library[1], while, liquidity-level and liquidity-beta sorted portfolios are formed using a sample of NYSE/AMEX/NASDAQ common stocks that satisfy our data requirements.

Our analysis reveals four main findings. First, during the 1969-2017 period, the US stock market was driven by three main regimes. the *normal* regime (that was prevailing most of the time); the *low volatility* regime; and the *crisis* regime. Second, during the *crisis* regime, low quality and low liquidity stocks experience relatively higher losses than would be predicted from normal times, while high quality and high liquidity stocks experience rather relatively lower losses. This is right in line with the presence of cross-market and within-market flight-to-quality and to-liquidity phenomena during volatile times. In these times, low quality and low liquidity stocks suffer large losses because of both cross-market and within-market flight-to-quality and to-liquidity, while high quality and high liquidity stocks experience reduced losses benefiting from the extra demand coming from investors who seek for quality and liquidity and choose to stay in the stock market. Third, during low volatility periods, low quality and low liquidity stocks earn relatively larger returns, while high quality and high liquidity stocks yield lower returns. We argue that this pattern can be explained by the fact that the *low volatility* regime is likely driven by a strong economy that boosts capital spending and allows junk and illiquid stocks to achieve higher returns. In contrast, high quality and liquid stocks underperform because they are subject to selling pressures from investors tilting their portfolios toward junk and illiquid stocks to seek portfolio gains. Finally, liquidity-level dominates liquidity-beta in predicting stock returns across the stock market volatility regimes. Our results here are thus in sharp contradiction with the claim of Lou and Sadka (2011) that, during crisis times, stock returns can be better explained by their liquidity-beta than by their liquidity-level. This contradiction can be justified by the fact that liquidity-beta becomes more important only when there is massive illiquidity, which is not the case of any crisis taking the history of US stock market crises. The findings of Lou and Sadka (2011) are thus specific to the last financial crisis of 2008-2009 that was characterized by massive illiquidity.

The remainder of the paper is organized as follows. Section 2 develops hypotheses. Section 3 describes data we use and our procedure to form quality, liquidity level, and liquidity beta portfolios. In section 4, we present our test to study how the cross-section pattern of stock returns along quality and liquidity dimensions varies across the different regimes and discuss the results we obtained. Section 5 concludes.

2. Hypotheses development :

As discussed in the introduction, stock quality, liquidity-level and liquidity risk are all priced characteristics in the cross-section of stock returns. In this paper, we take a step further and examine how the pricing of these characteristics is related to stock market volatility regimes. This section reviews the existing literature and develops hypotheses about this relation.

[1] `https://www.aqr.com/Insights/Datasets`

2.1. Market volatility regimes and the pricing of stock quality :

According to the existing literature, stock returns are negatively related to conditional volatility (Campbell and Hentschel, 1992; Bekaert and Wu, 2000; Kim et al., 2004). A large body of research attributes this negative relation between stock returns and market volatility to changes in investors' preference for the quality of the assets they hold in their portfolios (Fleming et al., 1998; Connolly et al., 2005; Jubinski and Lipton, 2012). During periods of low market volatility, investors are more willing to take on risk by investing in low quality assets, stocks, and drive stock prices upwards. During times of high levels of equity uncertainty, however, investors become more willing to reduce the risk level of their portfolios by investing in high quality assets (e.g., gold and treasury bonds) and push stock prices to decline. These cross-market rebalancing strategies are commonly referred to as flight-to-quality phenomenon. For example, Fleming et al. (1998) find evidence of strong volatility linkages across the stock, bond, and money markets and attribute this to common information and flight-to-quality phenomenon. Connolly et al. (2005) show that high stock market volatility periods are associated with higher treasury bond returns and negative stock-bond return correlations. The authors link their findings to flight-to-quality episodes. In a similar study, Jubinski and Lipton (2012) show that U.S. Treasuries and high quality corporate bonds yields fall in response to increases in implied stock market volatility, which is consistent with a flight-to-quality effect. Economic theory provides many explanations for this time-variation in investors' preference for the quality of the assets they hold. During volatile times, investors flee the stock market towards high quality assets and adjust the risk level of their portfolios because of (i) higher risk-aversion (Vayanos, 2004), (ii) tighter risk management practices (Garleanu and Pedersen, 2007), or (iii) fear of future losses and panic selling (Bernardo and Welch, 2004; Morris and Shin, 2004). These combined factors lead stock prices to decline (rise) during high (low) levels of stock market volatility.

Most prior studies have focused on flight-to-quality across markets. In this paper, we rather consider flight-to-quality within the stock market and study its implications on stock pricing. We argue that as stock market volatility changes, investors not only rebalance their portfolios between stocks and other high quality assets such as treasury bonds, but also between low and high quality stocks. We expect that in times of high volatility, low quality stocks suffer large losses because of both cross-market and within-market flight-to-quality, while high quality stocks experience reduced losses benefiting from the extra demand coming from investors who seek for quality and choose to stay in the stock market. To put it another way, due to flight-to-quality within the stock market, investors require an extra premium for holding low quality stocks and pay an extra price premium for holding high quality stocks in times of stress. During periods of low volatility, we expect, however, that investors become more willing to take on risk. Consequently, they require a lower premium for holding low quality stocks and pay a lower price premium for holding high quality stocks in these times. These arguments lead to the following two hypotheses :

Hypothesis 1a. *During high volatility periods, low (high) quality stocks experience larger (lower) losses than would be expected from normal times.*

Hypothesis 1b. *During low volatility periods, low (high) quality stocks earn larger (lower) gains than would be expected from normal times.*

2.2. Market volatility regimes and the pricing of stock liquidity :

A growing literature documents that the negative relation between stock returns and market volatility is not only due to changes in investors' preference for quality but also to changes in their preference for liquidity (Longstaff, 2004; Beber et al., 2009; Vayanos, 2004; Eisfeldt and Rampini, 2009). Investors are more willing to hold illiquid assets, stocks, during periods of low volatility. However, as market volatility increases, investors become more concerned about the liquidity of their investments and tilt their portfolios toward more liquid assets. These cross-market rebalancing strategies to meet investors time-varying liquidity needs are commonly known as flight-to-liquidity phenomenon. Longstaff (2004), for example, shows that investors flee towards liquid treasury bonds in times of market stress. Using data on the Euro-area government bond market, Beber et al. (2009) also demonstrate that investors chase liquidity during periods of market uncertainty. Vayanos (2004) argue that flight-to-liquidity occurs during volatile times because fund managers fear investors withdrawals and demand more liquid assets. While, Eisfeldt and Rampini (2009) show that flight-to-liquidity can also be attributed to the anticipation of binding financial constraints.

While the existing literature has focused on flight-to-liquidity across markets, in this study, we rather consider flight-to-liquidity within the stock market and its implications on stock pricing. We argue that as stock market volatility changes, investors not only rebalance their portfolios between stocks and other liquid assets but also between illiquid and liquid stocks. As a result, we expect that, during volatile times, illiquid stocks suffer large losses because of both cross-market and within-market flight-to-liquidity. While, liquid stocks experience reduced losses benefiting from the extra demand coming from investors who seek for liquidity and wish to stay in the stock market. Put differently, due to flight-to-liquidity within the stock market, investors require an extra premium for holding illiquid stocks and pay an extra price premium for holding liquid stocks in times of stress. We expect, however, that during low volatility times, investors become less concerned about liquidity and require a lower premium for holding illiquid stocks and pay a lower price premium for holding liquid stocks. The above discussions lead to the following two hypotheses :

Hypothesis 2a. *During high volatility periods, illiquid (liquid) stocks experience larger (lower) losses than would be expected from normal times.*

Hypothesis 2b. *During low volatility periods, illiquid (liquid) stocks earn larger (lower) gains than would be expected from normal times.*

2.3. Market volatility regimes and the pricing of stock liquidity risk :

A more recent line of research claims that, in times of stress, investors care not only about the liquidity level of their stocks but also about their liquidity betas, that is, the sensitivity of stock returns to unexpected changes in aggregate market liquidity (Lou and Sadka, 2011; Acharya et al., 2013). These studies build on prior work documenting that stock market liquidity tends to dry up during financial crises (Lesmond, 2005; Brunnermeier and Pedersen, 2009; Næs et al., 2011). The reasoning is that, as liquidity evaporates in crisis times, investors require higher premiums on stocks whose returns load significantly on market liquidity. In line with this assertion, Lou and Sadka (2011) show that stocks with high liquidity risk experienced large losses during the financial crisis of 2008-2009. In this paper, we extend this hypothesis and examine how stock liquidity risk is priced across the different stock market volatility regimes. We expect that, during volatile times, there is an extra demand for stocks with low liquidity risk and an extra selling pressure on stocks with high liquidity risk. We expect, however, that during low volatility times, investors require a lower premium for holding stocks with high liquidity risk and pay a lower price premium for holding stocks with low liquidity risk. These arguments give rise to the following hypotheses :

Hypothesis 3a. *During high volatility periods, high (low) liquidity risk stocks experience larger (lower) losses than would be expected from normal times.*

Hypothesis 3b. *During low volatility periods, high (low) liquidity risk stocks earn larger (lower) gains than would be expected from normal times.*

Our final hypothesis looks at the importance of liquidity level and liquidity beta in explaining stock returns across the different stock market volatility regimes. Lou and Sadka (2011) find that both liquid and illiquid stocks with high liquidity risk experienced large losses during the financial crisis of 2008-2009. While, losses are reduced for both liquid and illiquid stocks with low liquidity risk. The authors claim, therefore, that the cross section of stock returns is better explained by liquidity beta than by liquidity level during crisis periods. We extend this assertion and test the importance of those two characteristics in explaining the performance of stocks across the different volatility regimes. This leads us to our last hypothesis :

Hypothesis 3c. *Liquidity-beta dominates liquidity-level in explaining stock returns across the different market volatility regimes.*

3. Data and portfolio building

We start our analysis by forming stock portfolios based on quality, liquidity-level and liquidity-beta characteristics. To define the stock's quality, we follow the approach of Asness et al. (2019). Based on the Gordon's growth model, the authors define quality stocks as securities that have high profitability, high growth, and low risk, and high payouts. The authors calculate a score for each of the four components and, then, compute a single quality score by averaging the four proxies. In contrast to what asset pricing theory stipulates, they found that high quality stocks earn high risk adjusted returns as compared to junk (low quality) stocks. To define the stock's liquidity-level, we adopt the same definition as in the work of Lou and Sadka (2011) who describe it as "*the ability to trade large quantities of its shares quickly and at low cost, on average*". Amihud and Mendelson (1986) were the first to document that expected returns are negatively related to liquidity-level; suggesting that, illiquid stocks with low liquidity-level earn higher returns to compensate investors for bearing illiquidity costs. Since their seminal work, a substantial body of empirical evidence has confirmed this negative relationship (Brennan and Subrahmanyam, 1996; Brennan et al., 1998; Datar et al., 1998). Regarding the stock's liquidity-beta (risk), we rely on the concept of Pastor and Stambaugh (2003) who define it as "*the covariation of its returns with unexpected changes in aggregate liquidity*". The link between the liquidity risk of a stock and its expected return has been the focus of only more recent studies. Acharya and Pedersen (2005) have identified three sources of liquidity risk: (1) the covariance of the liquidity-level of a stock with aggregate liquidity; (2) the covariance of the return of a stock with aggregate liquidity and (3) the covariance of the liquidity-level of a stock with market returns. We focus, in our study, on the second type of liquidity risk which has been extensively investigated by many researchers such as Pastor and Stambaugh (2003), Liu (2006), Watanabe and Watanabe (2008) and Lou and Sadka (2011), among others. All these authors documented that this type of risk is priced in the US stock market.

In order to capture the different regimes that drive the market, a sufficiently long sample period is needed. To do so, we run our analysis over the period 1969-2017. This sample period includes several crisis and non-crisis episodes that had influenced the US stock market and can, hence, provide us with fruitful information about the different regimes that drove the stock market. We obtain the excess return time-series of 10 quality-sorted portfolios from AQR Capital Management data library. To form 10 portfolios sorted on liquidity-level and 10 portfolios sorted on liquidity-beta, we consider all NYSE/AMEX/NASDAQ common stocks. However, since reported volume on NASDAQ is upward biased due to the interdealer trades, we exclude NASDAQ stocks when forming portfolios based on liquidity-level. We obtained daily and monthly data on individual stocks from the Center for Research in Security prices (CRSP). Excess returns on the market portfolio and the risk-free rate (1-month T-bill rate) are from Kenneth French's website. Finally, Pastor-Stambaugh non-traded liquidity factor data are obtained from Lubos Pastor's web site[2]. In what follows, we will briefly describe the procedure that Asness et al. (2019) use to form 10 portfolios sorted on quality scores. After that, we will present our liquidity-level and liquidity-beta measures and describe our procedure to construct portfolios based on these two characteristics.

[2] `https://faculty.chicagobooth.edu/lubos.pastor/research`

3.1. Quality-sorted portfolios

Based on the Gordon's growth model, Asness et al. (2019) define quality stocks as securities that have *high profitability*, *high growth*, *low risk*, and *high payouts*. To compute a quality score for a stock, Asness et al. (2019) use several measures for each aspect of quality:

Profitability is computed as the average of z-scores of gross profits over assets, return on equity, return on assets, cash flow over assets, gross margin and low accruals. *Growth* is measured by averaging z-scores of 5-year growth rates in gross profits over assets, return on equity, return on assets, cash flow over assets, gross margin and low accruals. *Risk* is measured by averaging z-scores of minus market beta, minus idiosyncratic volatility, minus leverage, minus bankruptcy risk and minus earning volatility. *Payout* is computed as the average of z-scores of net equity issuance, net debt issuance and total net payout over profits. Finally, the four components are averaged to compute a single quality score.

To form 10 value-weighted quality-sorted portfolios, the authors use all available common stocks in the CRSP/XpressFeed database and assign stocks into portfolios using NYSE breakpoints (i.e. the deciles that are obtained considering only NYSE stocks). Table 1, Panel A reports summary statistics and the CAPM betas for the 10 quality portfolios as well as for the portfolio that is long the decile with high quality stocks and short the decile with low quality stocks. As documented by Asness et al. (2019), high quality stocks yield higher excess returns as compared to low quality stocks over the whole sample period 1969-2017. Stocks in the high-quality decile earn the highest average return, 0.625% monthly, whereas the low-quality decile performs most poorly, generating on average a negative return of -0.017% per month. The long/short portfolio generates an average return of 0.642%, which is economically large and statistically significant (t-statistic of 3.40). In addition, as expected, the CAPM betas of the portfolios indicate strong negative relation between quality and risk.

3.2. Liquidity-level sorted portfolios

As in Lou and Sadka (2011), we measure the liquidity-level of a share by the average of its daily Amihud (2002) ratio over the year. Amihud (2002) computes his liquidity metric as "*the daily ratio of absolute stock return to its dollar volume*". It has been widely used in the recent literature (Amihud, 2002; Acharya and Pedersen, 2005; Goyenko et al., 2009; Korajczyk and Sadka, 2008; Hasbrouck, 2009). In addition, Hasbrouck (2009) confirms that the ratio is highly correlated with high frequency liquidity measures and Goyenko et al. (2009) show that it does capture well the transaction costs and the price impact. In formal terms, we compute the liquidity-level of a share i at the end of year y as follows:

$$ILLIQ_{i,y} = \frac{1}{D_{i,y}} \sum_{i=1}^{D_{i,y}} \frac{|r_{i,d,y}|}{v_{i,d,y}} \tag{1}$$

where $ILLIQ_{i,y}$ denotes the (il)liquidity-level measure of share i at the end of year y. $D_{i,y}$ is the share i's number of trading days in year y. $r_{i,d,y}$ and $v_{i,d,y}$ are, respectively,

Table 1 :
Summary statistics for quality, liquidity-level, and liquidity-beta portfolios

Portfolios	Mean	25th percentile	Median	75th percentile	Standard deviation	CAPM Beta
Panel A : Quality portfolios						
(low) 1	-0.017	-3.984	0.107	4.520	7.130	1.413
2	0.267	-3.112	0.645	4.148	6.147	1.263
3	0.474	-2.515	1.071	3.902	5.312	1.115
4	0.502	-2.107	0.981	3.576	5.059	1.060
5	0.460	-2.101	0.717	3.192	4.738	0.996
6	0.494	-2.283	0.688	3.322	4.716	0.991
7	0.608	-2.259	0.966	3.527	4.581	0.970
8	0.528	-2.069	0.828	3.416	4.638	0.987
9	0.567	-1.903	0.763	3.405	4.426	0.947
(high) 10	0.625	-1.973	0.773	3.522	4.411	0.914
10 − 1	0.642	-1.965	0.701	3.367	4.582	-0.498
	(3.40)					(-13.66)
Panel B : Liquidity-level portfolios						
(liquid) 1	0.486	-1.960	0.855	3.226	4.379	0.930
2	0.532	-2.386	0.890	3.265	4.533	0.954
3	0.649	-2.409	0.850	3.752	4.914	1.025
4	0.650	-2.361	0.793	3.729	5.042	1.043
5	0.623	-2.304	0.830	3.819	5.054	1.030
6	0.728	-2.239	1.081	4.054	5.161	1.035
7	0.672	-2.305	1.018	4.104	5.250	1.043
8	0.719	-2.280	1.109	3.800	5.500	1.069
9	0.754	-2.353	1.065	4.299	5.598	1.064
(illiquid) 10	0.764	-2.299	1.176	4.042	5.407	0.996
10 − 1	0.278	-2.000	0.174	2.524	3.686	0.065
	(1.83)					(1.96)
Panel C : Liquidity-beta portfolios						
(low) 1	0.450	-3.076	0.714	4.243	5.626	1.134
2	0.498	-2.427	0.617	3.414	4.750	0.962
3	0.518	-1.912	0.747	3.248	4.481	0.895
4	0.555	-1.860	0.822	3.061	4.283	0.867
5	0.500	-1.989	0.811	3.122	4.404	0.894
6	0.555	-1.813	0.621	3.238	4.376	0.906
7	0.547	-2.100	0.888	3.193	4.338	0.883
8	0.495	-2.087	0.867	3.171	4.517	0.906
9	0.502	-2.301	0.594	3.603	5.057	1.026
(high) 10	0.535	-2.647	0.764	4.173	5.619	1.112
10 − 1	0.084	-1.912	0.060	1.974	3.493	-0.021
	(0.59)					(-0.68)

This table reports summary statistics and unconditional CAPM betas for quality, liquidity-level, and liquidity-beta portfolios. The portfolios are formed as described in section 3. Panels A, B and C display results for quality, liquidity-level, and liquidity-beta portfolios, respectively. T-statistics for the excess return and the CAPM beta on the long-short strategies are presented in parentheses. The statistics are computed over the sample period 1969-2017.

the daily return and the dollar volume of share i on the trading day d in year y.

At the end of each year between 1968 and 2016, we identified NYSE/AMEX common stocks with prices between \$5 and \$1000 and at least 100 valid observations of daily returns, prices and volumes over the year. We, then, sorted eligible stocks on the basis of their liquidity-level and assign them into 10 value-weighted portfolios using NYSE breakpoints (i.e. the deciles that are obtained considering only NYSE stocks). Table 1, Panel B provides summary statistics and the CAPM betas for the 10 liquidity-level portfolios as well as for the portfolio that goes long illiquid stocks and shorts liquid stocks . Over the sample period, illiquid stocks yield higher excess returns as compared to liquid stocks. The decile of most illiquid stocks earn the highest average return, 0.764% monthly, whereas the decile of most liquid stocks performs most poorly, generating on average a return of 0.486% per month. The long/short portfolio generates an average return of 0.278%, which is economically and statistically significant (t-statistic of 1.83). However, unlike quality portfolios, liquidity-level portfolios do not seem to significantly differ in their CAPM betas.

3.3. Liquidity-beta sorted portfolios

We follow Pastor and Stambaugh (2003) and measure the liquidity-beta of a share as the sensitivity of its returns to innovations in aggregate market liquidity. At the end of each year between 1968 and 2016, we identified NYSE/AMEX/NASDAQ common stocks with prices between \$5 and \$1000 and 60 non-missing monthly returns over the most recent five years. We, then, sorted eligible stocks on the basis of their liquidity betas and assign them into 10 value-weighted portfolios using NYSE breakpoints. To estimate liquidity betas, we use data over the previous five years and regress the share monthly excess returns on the Pastor-Stambaugh non-traded liquidity factor and the three Fama-French factors:

$$r^e_{i,t} = \alpha_{i,y} + \beta^{mkt}_{i,y} R^e_{m,t} + \beta^{smb}_{i,y} SMB_t + \beta^{hml}_{i,y} HML_t + \beta^{liq}_{i,y} LIQ_{m,t} + \varepsilon_{i,t} \tag{2}$$

where $r^e_{i,t}$ stands for the stock i's excess return. $R^e_{m,t}$,SMB_t and HML_t are the three Fama-French factors (market, size and value) and $LIQ_{m,t}$ is the Pastor-Stambaugh non-traded liquidity factor. $\beta^{mkt}_{i,y}$, $\beta^{smb}_{i,y}$, $\beta^{hml}_{i,y}$ and $\beta^{liq}_{i,y}$ denote, respectively, the historical exposures of the share i to the market, size, value and liquidity factors; as estimated at the end of year y.

Table 1, Panel C shows summary statistics and the CAPM betas for the 10 liquidity-beta portfolios as well as for the portfolio that is long the decile with high liquidity beta and short the decile with low liquidity beta. Over the sample period, stocks with high liquidity betas tends to slightly outperform those with low liquidity betas but the difference in excess returns is not statistically significant. In addition, in line with the findings of Pastor and Stambaugh (2003), liquidity-beta portfolios do not seem to significantly differ in their CAPM betas.

4. Empirical tests and results

In order to test the hypotheses developed in section 2, we relate the returns of quality, liquidity-level, and liquidity-beta portfolios to regime shifts in the stock market, using an econometric framework very similar to the one of Billio and Pelizzon (2000) and Billio et al. (2012). More specifically, we proceed in two steps. We first extract stock market regimes from the dynamics of the market portfolio excess return. We then test how the cross-section pattern of stock returns along quality and liquidity dimensions varies across the different regimes.

4.1. Stock market volatility regimes

In this section, we focus on the first step and present our approach to identify stock market volatility regimes as well as the results we obtained.

Let $R^e_{m,t}$ denotes the market portfolio excess return over the period t and assume that it is driven by the following K-state mean-variance switching regime process:

$$R^e_{m,t} = \mu_m\left(S_t^{R^e_m}\right) + \sigma_m\left(S_t^{R^e_m}\right)\varepsilon_t, \quad \varepsilon_t \sim iid.N\left(0,1\right) \tag{3}$$

where $\mu_m\left(S_t^{R^e_m}\right)$ and $\sigma_m\left(S_t^{R^e_m}\right)$ are the state-dependent expected return and volatility, respectively. $S_t^{R^e_m}$ denotes the state of the market and is assumed to be unobservable and to follow a K-state first order Markov process:

$$Pr\left(S_t^{R^e_m} = j \middle| S_{t-1}^{R^e_m} = i\right) = p_{i,j}, \quad i,j = 1,...,K \tag{4}$$

where $p_{i,j}$ denotes the likelihood of switching to regime j given that the market is in regime i.

The switching regime model (3) can be estimated using the maximum likelihood method. The log likelihood function of the model is given by:

$$LogL = \sum_{t=1}^{T} ln \sum_{j=1}^{K} \frac{1}{\sqrt{2\pi\sigma\left(j\right)^2}} exp\left[-\frac{\left(R^e_{m,t} - \mu_m\left(j\right)\right)^2}{2\sigma\left(j\right)^2}\right] Pr\left(S_t^{R^e_m} = j \middle| \Omega_t\right) \tag{5}$$

where $\Omega_t = \left\{R^e_{m,1}, ..., R^e_{m,t}\right\}$ and $Pr\left(S_t^{R^e_m} = j \middle| \Omega_t\right)$ are called *filtered probabilities* and are obtained through the Hamilton (1989) filter. Since the state of the market is unobservable, we can never know with certainty within which state the market is in. The Hamilton (1989) filter uses hence all past information to make inference about the state of the market at any given date t. In order to exclude very short lived and non-persistent regimes, we further require that the regimes have an expected duration of at least 3 months.

We estimated model (3) using the MS-Regress package for MatLab of Perlin (2012). For more details about the use of maximum likelihood method to estimate Markov-switching regime models, we refer the reader to Hamilton (2008) and Perlin (2012). Since the existing literature on switching regime models applied to the US stock market does not clearly provide us with an appropriate number of regimes driving the stock market, we started by estimating model (3) with two and three regimes. Table 2 shows, for each model specification, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values. As shown in the table, the AIC criterion favors the model with three regimes (AIC=3378.3), while the BIC criterion favors the two-regime model (BIC=3417.2). To choose between the two specifications, we follow Billio et al. (2012) and further performed an univariate ARMA analysis and a simulated likelihood ratio test. In the ARMA analysis, we use the AIC to select the appropriate order of the ARMA process. In the simulated likelihood ratio test, we simulated data (3000 times) under the null hypothesis that the two-regime specification is the true model. And then, from each simulation, we estimated both the two-regime and the three-regime models and computed the likelihood ratio statistic as follows:

$$Q_i = 2\left(logL_i^{3R} - logL_i^{2R}\right), \quad i = 1, 2, ..., 3000 \tag{6}$$

where $logL_i^{3R}$ and $logL_i^{2R}$ denote the log likelihood values for the three-regime and the two-regime specifications, respectively. As reported in Table 2, both tests favor the model with three regimes. The ARMA analysis shows that the ARMA representation of the three-regime model has an AIC value of 3437.6 which is lower than the AIC value of 3440.4 for the ARMA representation of the two-regime model. Regarding the simulated likelihood ratio test, the table shows that the observed likelihood ratio statistic is 17.88 and its corresponding p-value from the simulated outputs is 0.0056. The simulated likelihood ratio test rejects, thus, the null hypothesis and favors the three-regime model over the two-regime model with a confidence level of 99.44%. Accordingly, we assume in this analysis that the US stock market is governed by three regimes. Each regime is characterized by specific market risk levels in terms of the mean and volatility. To discuss and highlight the economic interpretation of the different regimes, we present in Table 3 parameter estimates for the three-regime model, the expected duration of each regime as well as the transition probability matrix. In addition, we plot in Figure 1 the corresponding state probabilities (smoothed probabilities).

We call regime 1 the *normal* regime because it had been prevailing most of the time during the sample period; with a normal mean excess return of 1.55% and a volatility of 4.11%. Despite of the prevalence of the *normal* regime the most of the full sample period, its expected duration is only about 7.61 months. This is because it is often destabilized by economic and financial crisis events.

Regime 2 is characterized by a negative mean excess return -2.21% and a high volatility 6.06%; we label it the *crisis* regime. Its expected duration is about 3.81 months and coincides with the most historical NBER (the National Bureau of Economic Research) economic recessions and financial crisis events such as the 1973 oil crisis, the 1987 crash, the 1997 Asian financial crisis and subsequent LTCM collapse in 1998, the Dotcom recession 2001-2002 and the 2008-2009 credit and liquidity crisis.

Finally, as regime 3 is characterized by low volatility, we call it the *low volatility* regime. It is a special regime because it developed mainly during the periods 1993-1996, 2003-2006, and 2012-2016. In this regime, the market portfolio earned a mean

Table 2 :
Identification of the number of stock market regimes

	Two-regime model	Three-regime model
1. Standard Model Selection Tests:		
AIC	3382.2	**3378.3**
BIC	**3417.2**	3443.9
2. Model Selection based on Univariate ARMA Analysis:		
AIC of ARMA representation	3440.4	**3437.6**
3. Model Selection based on Simulated Likelihood Ratio Test:		
Null Hypothesis: The two-regime model is the true model		
Alternative Hypothesis: The three-regime model is the true model		
Simulations	3000	
Empirical LR test	17.88	
p-value	**0.0056**	

This table reports the results of model selection methods used to test whether the market is governed by two or three regimes. We first estimated the following Markov-switching mean-variance model on the market portfolio excess return $R^e_{m,t}$; with two and three regimes:

$$R^e_{m,t} = \mu_m\left(S_t^{R^e_m}\right) + \sigma_m\left(S_t^{R^e_m}\right)\varepsilon_t, \quad \varepsilon_t \sim iid.N\left(0,1\right)$$

where $\mu_m\left(S_t^{R^e_m}\right)$ and $\sigma_m\left(S_t^{R^e_m}\right)$ are, respectively, the expected excess return and the standard deviation of the market portfolio in state $S_t^{R^e_m}$. The unobservable state of the market portfolio $S_t^{R^e_m}$ is assumed to evolve according to a two-state (three-state) first-order markov chain. In order to exclude very short lived and non-persistent regimes, we further require that the regimes have an expected duration of at least 3 months. After that, we used the following 4 model selection procedures to decide on the number of regimes driving the market: (1) Akaike Information Criterion (AIC); (2) Bayesian Information Criterion (BIC); (3) Univariate ARMA Analysis; and (4) Simulated Likelihood Ratio Test. The last test compares the statistical significance of the two-regime model (Null Hypothesis) against the three-regime model (Alternative Hypothesis). Data are simulated 3000 times under the null hypothesis that the two-regime specification is the true model. And then, from each simulation, both the two-regime and the three-regime models are estimated and the likelihood ratio statistic is computed as follows: $Q_i = 2\left(logL_i^{3R} - logL_i^{2R}\right), \quad i = 1,2,...,3000$ where $logL_i^{3R}$ and $logL_i^{2R}$ denote the log likelihood values for the three-regime and the two-regime specifications, respectively. Monthly excess returns for the market portfolio are obtained from Kenneth French's website and cover the period 1969-2017.

Table 3 :
Three-regime model – parameter estimates

	Regime 1 (*normal*)	Regime 2 (*crisis*)	Regime 3 (*low volatility*)
1. Switching parameters:			
mean (%)	**1.55**	**-2.21**	**1.00**
Standard deviation (%)	**4.11**	**6.06**	**2.41**
2. Expected duration (in months):	**7.61**	**3.81**	**30.99**
3. Transition Probabilities:			
Regime 1 (*normal*)	**0.87**	0.11	0.02
Regime 2 (*crisis*)	**0.26**	**0.74**	0.00
Regime 3 (*low volatility*)	0.03	0.00	**0.97**

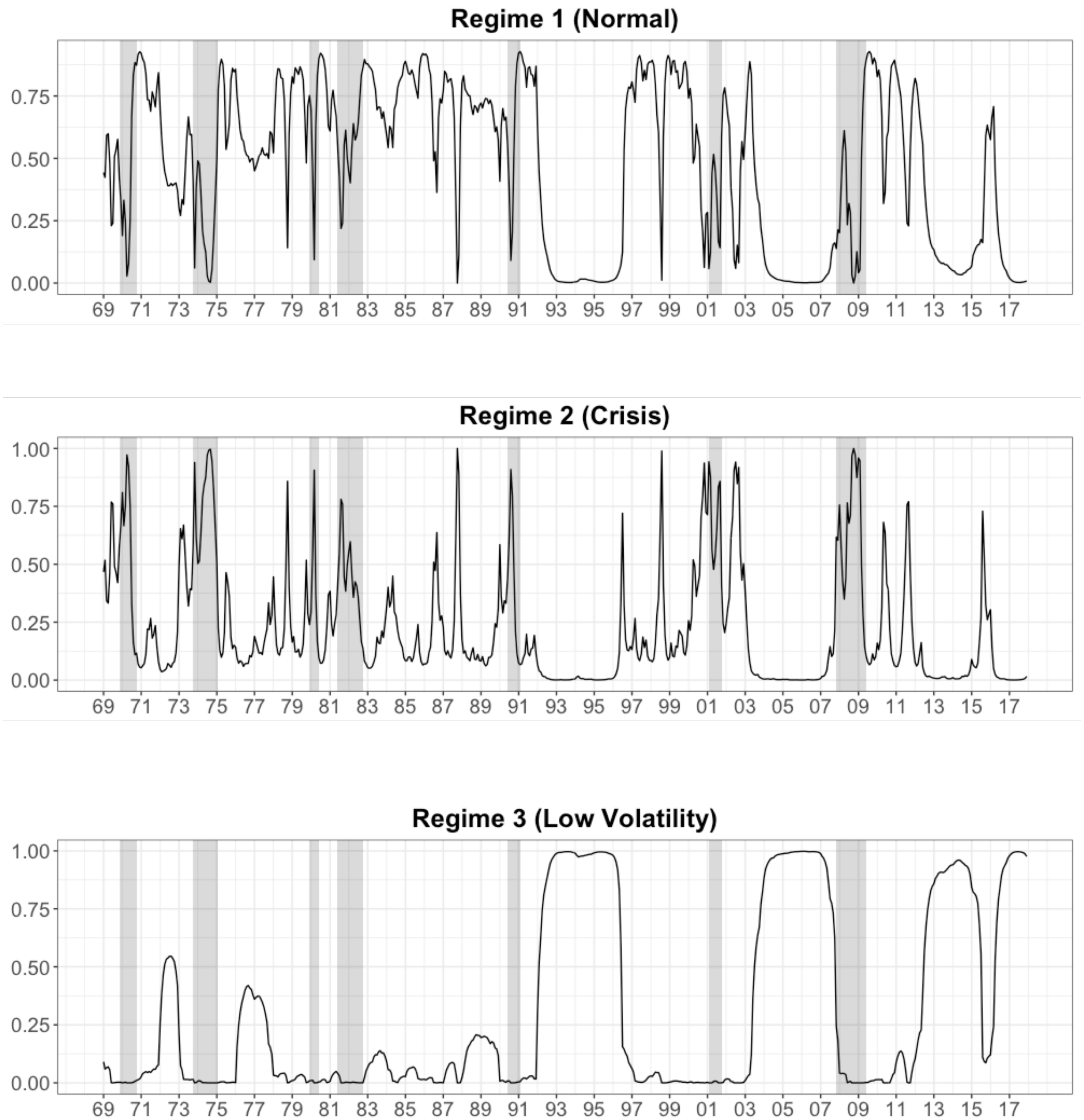
This table reports parameter estimates from a three-regime Markov switching mean-variance model for the market portfolio excess return $R^e_{m,t}$. We estimate the following model:

$$R^e_{m,t} = \mu_m \left(S_t^{R^e_m} \right) + \sigma_m \left(S_t^{R^e_m} \right) \varepsilon_t, \quad \varepsilon_t \sim iid.N\left(0, 1\right)$$

where $\mu_m \left(S_t^{R^e_m} \right)$ and $\sigma_m \left(S_t^{R^e_m} \right)$ are, respectively, the expected excess return and the standard deviation of the market portfolio in state $S_t^{R^e_m}$. The unobservable state of the market portfolio $S_t^{R^e_m}$ is assumed to evolve according to a three-state first-order Markov chain. In order to exclude very short lived and non-persistent regimes, we further require that the regimes have an expected duration of at least 3 months. The three states are labeled as follows: regime 1 (*normal*), regime 2 (*crisis*), and regime 3 (*low volatility*). Monthly excess returns for the market portfolio are obtained from Kenneth French's website and cover the period 1969-2017. In addition, the table presents the expected duration of each regime as well as the transition probability matrix (the likelihood of switching from one regime to another). Parameters that are significant at the 1% level are shown in bold type.

Figure 1 :

Three-regime model – smoothed probabilities



This figure plots the smoothed state probabilities from a three-regime Markov switching mean-variance model for the market portfolio excess return. The model specifications and the parameter estimates underlying these plots are presented in Table 3. The three states are labeled as follows: regime 1 (*normal*), regime 2 (*crisis*), and regime 3 (*low volatility*). Monthly excess returns for the market portfolio are obtained from Kenneth French's website and cover the period 1969-2017. The solid line in each plot represents the smoothed state probability, while the gray bars indicate NBER recession periods.

excess return of 1% with a low volatility of 2.41%. The *low volatility* regime is highly persistent with an average duration of about 31 months.

The transition probability matrix in Table 3 reports the likelihood of switching from one regime to another and has a meaningful form. If the market is in a crisis time, it will either stay in crisis with a probability of 74% or it will move to the *normal* regime with 26% chance. The *normal* and *low volatility* regimes are both highly persistent with 87% and 97% chance to persist respectively. However, the likelihood that a crisis occurs when the market is in the *normal* regime is about 11% while this probability is close to zero when the market is in the *low volatility* regime. This can be explained by the fact that, during low volatility times, the economy is generally strong and the chance of an eventual crisis to occur is very low.

4.2. Market volatility regimes and the pricing of stock quality and liquidity :

In the first step, we extracted stock market regimes from the dynamics of the market portfolio excess return. We found that the stock market is governed by three distinct regimes that we called *normal*, *crisis*, and *low volatility* regimes. In this second step, we relate the excess returns of quality, liquidity-level, and liquidity-beta portfolios to regime shifts in the stock market and test the hypotheses developed in section 2. More specifically, we follow Billio et al. (2012) and use a regime-switching beta model to compute regime-dependent expected returns for quality and liquidity deciles. Formally, we assume that the dynamics of a testing portfolio's excess return $r^e_{p,t}$ is specified by the following model:

$$r^e_{p,t} = \alpha_p + \beta_p \left(S_t^{R^e_m} \right) R^e_{m,t} + w_p \eta_{p,t}, \quad \eta_{p,t} \sim iid.N\left(0,1\right) \tag{7}$$

where $\beta_p \left(S_t^{R^e_m} \right)$ denotes the testing portfolio exposure to the market risk factor and is assumed to depend on the market risk factor regimes. However, for parsimony, we do not allow for non-linearity in the intercept coefficient α_p and the volatility of residuals w_p.

It should be noted here that the portfolio regime-dependent market beta in model (7) does not depend on the specific regimes driving the testing portfolio time-series but rather on the common regimes driving the whole stock market as obtained from Equation (5). The economic intuition behind this assumption is to closely assess the cross-sectional effects of quality and liquidity during market phases such as low and high volatility episodes. Given the specification in model (7), the expected excess return of the testing portfolio is related to the stock market regime and is defined by the sum of a regime-independent component α_p and a regime-dependent component $\beta_p \left(S_t^{R^e_m} \right) * \mu_m \left(S_t^{R^e_m} \right)$. The volatility of the testing portfolio excess return is also related to the stock market regime and is split into a regime-dependent component $\beta_p \left(S_t^{R^e_m} \right)^2 * \sigma_m \left(S_t^{R^e_m} \right)^2$ and a regime-independent component w_p^2.

We estimate the model above using the maximum likelihood method. To make inferences about the stock market regime at any date t, we rely on the Kim (1994) *smoothed probabilities* from model (3). Unlike the filtered probabilities that are obtained using only the past available information for a given date t, smoothed probabilities are more accurate to make inference about the state of the market because they are based on all available information; that is, all past and future information. In formal terms, the log likelihood function of model (6) is given by:

$$LogL = \sum_{t=1}^{T} ln \sum_{j=1}^{K} \frac{1}{\sqrt{2\pi w_p^2}} exp \left[-\frac{\left(r_{p,t}^{e} - \alpha_p - \beta_p\left(j\right) R_{m,t}^{e} \right)^2}{2w_p^2} \right] Pr\left(S_t^{R_m^e} = j \middle| \Omega_T \right) \quad (8)$$

Finally, in order to test our hypotheses about how investors price stock quality, liquidity-level, and liquidity risk conditional on market volatility, we proceed as follows. Since the *normal* regime was prevailing most of the time, we take it as our reference, and then, test whether the market betas of our quality and liquidity portfolios exhibit significant changes as market volatility shifts from *normal* regime to either *crisis* or *low volatility* regime. Formally, we test the null hypotheses that:

$$\beta_p\left(S_t^{R_m^e} = \text{crisis}\right) = \beta_p\left(S_t^{R_m^e} = \text{normal}\right) \quad (9)$$

AND

$$\beta_p\left(S_t^{R_m^e} = \text{low volatility}\right) = \beta_p\left(S_t^{R_m^e} = \text{normal}\right) \quad (10)$$

Any change in the market beta of a given portfolio during the *crisis* (*low volatility*) regime relative to the *normal* regime indicates a change in the pricing of the portfolio. Whereas, any persistent change in the market betas of quality or liquidity portfolios indicates a change in the pricing of the given characteristic in the cross section of stock returns. To assess the economic magnitude of the effect of volatility regimes on the pricing of these stock characteristics, we consider the lowest and the highest deciles in each characteristic and compute the extra return that investors require to hold these portfolios following a switch in market volatility from *normal* to either *crisis* or *low volatility* regime. Based on our model, the extra return that investors require to hold a given portfolio following a switch in market volatility from *normal* to *crisis* regime is given by $\Delta\beta_p * \mu_m\left(S_t^{R_m^e} = crisis\right)$. Since the expected excess return on the market portfolio is negative during the *crisis* regime, any increase (decrease) in the market beta of a portfolio during the *crisis* regime indicates that the portfolio experiences larger (lower) losses than would be predicted from the normal regime. In the same way, we compute the extra return that investors require to hold a given portfolio following a switch in market volatility from *normal* to *low volatility* regime as $\Delta\beta_p * \mu_m\left(S_t^{R_m^e} = low\ volatility\right)$. As the expected excess return on the market portfolio is positive during the *low volatility* regime, any increase (decrease) in market beta during that regime indicates that the portfolio earns larger (lower) returns than would be predicted from the *normal* regime.

We now proceed to test our Hypotheses 1a and 1b on how investors price stock quality conditional on the state of market volatility. To this end, we estimate model (7) using quality-based portfolios. Table 4 reports parameter estimates for the 10 portfolios. T-statistics are obtained using Newey and West (1987) standard errors with one lag. The table also displays, at the bottom, the outputs from the tests of the null hypothesis that market beta of a portfolio, in the *crisis* (*low volatility*) regime, is equal to its level in the *normal* regime. Several results emerge from Table 4. During the *crisis* regime, the four portfolios, containing stocks with the lowest quality scores, exhibit large positive and statistically significant changes in their market betas as compared to their levels during the *normal* regime. The market beta of the portfolios P1, P2, P3 and P4 moved, respectively, from 1.23, 1.09, 0.97, and 0.91 in the *normal* regime to reach 1.60, 1.44, 1.25 and 1.20 in the *crisis* regime; with a change of 0.37 (t=2.42), 0.35 (t=3.09), 0.28 (t=3.75) and 0.30 (t=3.80). Second, unlike low quality stocks, the market beta of high quality stocks decreases. The negative change in beta is not statistically significant for all portfolios but it persists across the 5 portfolios containing stocks with the highest quality scores. Our findings are also economically significant. Following a switch in market volatility from *normal* to *crisis* regime, the portfolio of stocks with the lowest quality scores experiences an extra loss of 0.82% ($0.37 * -2.21$) per month, while losses on the portfolio of stocks with the highest quality scores are reduced by 0.2% ($-0.09 * -2.21$). This pattern holds along the cross section of stock returns, which supports our hypothesis that, during high volatility periods, low (high) quality stocks experience larger (lower) losses than would be expected from normal times. We claim that this pattern is due to the presence of not only flight-to-quality across markets but also flight-to-quality within the stock market. During high volatility periods, low quality stocks suffer large losses because of both cross-market and within-market flight-to-quality, while high quality stocks experience reduced losses benefiting from the extra demand coming from investors who seek for quality and choose to stay in the stock market.

A similar pattern across the 10 quality-sorted portfolios is also observed in the *low volatility* regime. Low quality stocks exhibit increases in their market betas, while high quality stocks show decreases in their market betas. However, as the market premium is positive in these times, this pattern indicates that low quality stocks earn relatively larger returns than would be predicted from the market beta in the normal regime, while high quality stocks yield relatively lower returns. Following a switch in market volatility from *normal* to *low volatility* regime, the portfolio of stocks with the lowest quality scores earn an extra return of 0.13% per month, while gains on the portfolio of stocks with the highest quality scores are reduced by 0.1% per month. This evidence is in line with our hypothesis 1b and suggests that, during low volatility times, investors become more willing to take on risk. Consequently, they require a lower premium for holding low quality stocks and pay a lower price premium for holding high quality stocks in these times. Overall, our findings are consistent with the theoretical model of Vayanos (2004) who states that investors' risk aversion is an increasing function of market volatility.

We now turn to a test of Hypotheses 2a and 2b on how investors price stock liquidity-level conditional on the state of market volatility. To this end, we estimate model (7) using liquidity-level portfolios and present theresults in Table 5. As can

Table 4 :
Regime-dependent market betas – quality portfolios

	Low Quality	P2	P3	P4	P5	P6	P7	P8	P9	**High Quality**	**H-L**
α (%)	**-0.50**	**-0.17**	0.06	**0.14**	0.09	**-0.17**	0.02	**0.13**	-0.03	0.11	**0.61**
	(-2.54)	(-1.68)	(0.80)	(1.72)	(1.50)	(-2.74)	(0.28)	(2.12)	(-0.58)	(1.36)	(2.81)
β^{Normal}	1.23	1.09	0.97	0.91	0.88	1.12	1.06	0.90	1.03	0.97	**-0.26**
	(17.35)	(20.38)	(25.05)	(28.52)	(25.80)	(36.96)	(19.87)	(25.49)	(35.11)	(17.47)	(-2.57)
β^{Crisis}	1.60	1.44	1.25	1.20	1.11	0.85	0.89	1.06	0.87	0.88	**-0.72**
	(15.24)	(18.25)	(25.26)	(19.73)	(33.10)	(27.20)	(13.55)	(28.70)	(30.43)	(16.31)	(-5.01)
β^{Low}	1.36	1.24	1.14	1.04	0.93	1.01	0.97	0.95	0.99	0.87	**-0.49**
	(12.78)	(19.98)	(26.89)	(26.80)	(21.37)	(30.20)	(35.95)	(37.53)	(40.08)	(20.93)	(-3.87)
w (%)	3.09	2.18	1.59	1.52	1.40	1.38	1.28	1.24	1.08	1.54	**-1.55**
	(20.41)	(21.76)	(21.89)	(18.91)	(20.19)	(21.67)	(14.70)	(20.18)	(21.62)	(23.17)	(-10.48)
Null Hypothesis: β(state) =β (normal)											
$\beta^{Cris} - \beta^{Norm}$	**0.37**	**0.35**	**0.28**	**0.30**	**0.23**	**-0.27**	-0.17	**0.16**	**-0.16**	**-0.09**	**-0.46**
	(2.42)	(3.09)	(3.75)	(3.80)	(3.99)	(-5.92)	(-1.51)	(2.49)	(-3.34)	(-2.86)	(-2.07)
$\beta^{Low} - \beta^{Norm}$	**0.13**	**0.15**	**0.17**	**0.13**	0.05	**-0.11**	-0.09	0.04	-0.04	-0.10	**-0.22**
	(2.07)	(1.75)	(2.94)	(2.81)	(0.89)	(-2.38)	(-1.44)	(1.03)	(-1.09)	(-1.40)	(-1.94)

This table reports regime-dependent market betas of 10 quality-sorted portfolios. The market beta is assumed to depend on the stock market regimes and is estimated using the following model:

$$r^e_{p,t} = \alpha_p + \beta_p \left(S_t^{R^e_m} \right) R^e_{m,t} + w_p \eta_{p,t}, \quad \eta_{p,t} \sim iid.N\,(0,1)$$

where $r^e_{p,t}$ denotes the excess return of the testing portfolio and α_p and w_p are assumed to be fixed components over regimes. $\beta_p \left(S_t^{R^e_m} \right)$ is the testing portfolio market beta when the market portfolio is in state $S_t^{R^e_m}$. T-statistics are computed using Newey and West (1987) standard errors with one lag and are presented in parentheses. The table also presents, at the bottom, results of tests of the null hypotheses that market beta of the testing portfolio, in a given regime, is equal to its level in the normal regime. Parameters (with the exception of β(state) and w) that are significant at the 10% level are shown in bold type.

Table 5 :
Regime-dependent market betas – liq-level portfolios

	Liquid	P2	P3	P4	P5	P6	P7	P8	P9	**Illiquid**	**Illiq-Liq**
α (%)	**-0.10**	-0.00	0.06	0.07	**0.26**	**0.41**	**0.33**	**0.40**	**0.51**	**0.60**	**0.70**
	(-1.70)	(-0.07)	(0.69)	(0.08)	(2.89)	(4.08)	(2.67)	(2.22)	(4.87)	(5.68)	(3.98)
β^{Normal}	1.02	0.99	1.07	1.06	0.86	0.82	0.81	0.83	0.78	0.69	**-0.33**
	(43.83)	(22.52)	(16.30)	(2.34)	(19.15)	(16.36)	(15.31)	(14.30)	(15.83)	(13.56)	(-5.07)
β^{Crisis}	0.84	0.92	0.98	1.01	1.18	1.24	1.25	1.29	1.35	1.31	**0.47**
	(24.38)	(15.14)	(11.10)	(2.30)	(31.28)	(24.35)	(26.31)	(20.13)	(19.49)	(17.33)	(4.74)
β^{Low}	0.93	0.97	1.06	1.11	1.08	1.08	1.19	1.15	1.14	1.01	**0.08**
	(40.72)	(39.17)	(36.03)	(9.52)	(25.78)	(22.62)	(22.20)	(15.66)	(17.91)	(15.74)	(1.01)
w (%)	1.18	1.40	1.63	1.79	1.85	2.00	2.11	2.44	2.61	2.71	**1.52**
	(15.15)	(14.37)	(14.61)	(12.41)	(18.52)	(18.40)	(23.55)	(20.22)	(23.53)	(21.43)	(11.78)
Null Hypothesis: β(state) =β (normal)											
$\beta^{Cris} - \beta^{Norm}$	**-0.17**	-0.07	-0.09	-0.05	**0.32**	**0.42**	**0.44**	**0.46**	**0.57**	**0.62**	**0.80**
	(-3.86)	(-0.69)	(-0.59)	(-0.06)	(5.12)	(5.63)	(5.61)	(4.54)	(6.35)	(6.38)	(6.22)
$\beta^{Low} - \beta^{Norm}$	**-0.09**	-0.02	-0.00	0.04	**0.22**	**0.26**	**0.39**	**0.32**	**0.36**	**0.32**	**0.41**
	(-2.72)	(-0.37)	(-0.06)	(0.12)	(3.67)	(3.88)	(5.35)	(3.68)	(4.51)	(3.91)	(3.99)

This table reports regime-dependent market betas of 10 portfolios sorted on the basis of liquidity-level. The market beta is assumed to depend on the stock market regimes and is estimated using the following model:

$$r^e_{p,t} = \alpha_p + \beta_p \left(S_t^{R^e_m}\right) R^e_{m,t} + w_p \eta_{p,t}, \quad \eta_{p,t} \sim iid.N\left(0,1\right)$$

where $r^e_{p,t}$ denotes the excess return of the testing portfolio and α_p and w_p are assumed to be fixed components over regimes. $\beta_p \left(S_t^{R^e_m}\right)$ is the testing portfolio market beta when the market portfolio is in state $S_t^{R^e_m}$. T-statistics are computed using Newey and West (1987) standard errors with one lag and are presented in parentheses. The table also presents, at the bottom, results of tests of the null hypotheses that market beta of the testing portfolio, in a given regime, is equal to its level in the normal regime. Parameters (with the exception of β(state) and w) that are significant at the 10% level are shown in bold type.

be seen from Table 5, the variations in the market betas of liquidity portfolios across stock market volatility regimes have patterns similar to those of quality portfolios. In both *crisis* and *low volatility* regimes, liquid stocks exhibit a decrease in their market betas, while illiquid stocks show an increase in their market betas. For example, the market beta of the portfolios P7, P8, P9 and P10 increase by 0.44 (t=5.61), 0.46 (t=4.54), 0.57 (t=6.35) and 0.62 (t=6.38) following a switch in market volatility from *normal* to *crisis* regime, and by 0.39 (t=5.35), 0.32 (t=3.68), 0.36 (t=4.51) and 0.32 (t=3.91) in response to a switch in market volatility to *crisis* regime. Unlike illiquid stocks, the market beta of liquid stocks decreases following a switch in market volatility from *normal* to either *crisis* or *low volatility* regime. The negative change in market beta is not statistically significant for all portfolios but it persists across the 4 portfolios containing the most liquid stocks. The effect of switching regime in market volatility on the pricing of stock liquidity is also economically large. For example, following a switch in market volatility from *normal* to *crisis* regime, the portfolio containing the most illiquid stocks experiences an extra loss of 1.37% ($0.62 * -2.21$) per month, while losses on the portfolio with the most liquid stocks are reduced by 0.37% ($-0.17 * -2.21$). On the other hand, following a switch in market volatility from *normal* to *low volatility* regime, the portfolio with the most illiquid stocks earn an extra return of 0.32% per month, while gains on the portfolio containing the most liquid stocks are reduced by -0.09%. These results lend strong support to our hypotheses 2a and 2b. During high volatility periods, illiquid (liquid) stocks experience larger (lower) losses than would be expected from normal times. We argue that this pattern is due to the presence of not only flight-to-liquidity across markets but also flight-to-liquidity within the stock market in times of stress. During these periods, illiquid stocks suffer large losses because of both cross-market and within-market flight-to-liquidity, while liquid stocks experience reduced losses benefiting from the extra demand coming from investors who seek for liquidity and choose to stay in the stock market. During periods of low volatility, however, investors become less concerned about liquidity. Consequently, they require a lower premium for holding illiquid stocks and pay a lower price premium for holding liquid stocks. As a result, illiquid (liquid) stocks earn larger (lower) gains than would be expected from normal times.

We now test our hypotheses 3a and 3b and examine how the pricing of stock liquidity-risk is related to stock market volatility regimes. Table 6 reports the estimation results of model (7) using liquidity-beta portfolios. As can be seen from the table, there is no evidence that the pricing of stock liquidity-risk is related to stock market volatility regimes. During *crisis* regime, changes in the market betas of high liquidity-risk portfolios (P8, P9, P10) are not statistically significant. In addition, although the portfolio of stocks with the lowest liquidity betas shows a decrease in its market beta during the *crisis*, this pattern does not persist for the other portfolios (P2, P3). In the same way, unlike liquidity and quality portfolios, we do not observe any special pattern across liquidity-beta sorted portfolios during *low volatility* regime. Both low and high liquidity-beta stocks show no significant change in their market betas. These results do not support the claim of Lou and Sadka (2011) that, during crisis times, the stock returns can be better explained by their liquidity-beta than by their liquidity-level.

Table 6 :
Regime-dependent market betas – liq-beta portfolios

	Low Liq-Beta	P2	P3	P4	P5	P6	P7	P8	P9	**High Liq-Beta**	**H-L**
α (%)	**-0.34**	0.15	**0.21**	-0.03	0.15	0.01	-0.05	0.09	0.15	0.02	0.36
	(-2.72)	(1.55)	(2.32)	(-0.28)	(1.63)	(0.18)	(-0.60)	(0.69)	(1.36)	(0.12)	(1.09)
β^{Normal}	1.30	0.84	0.72	0.96	0.77	0.97	0.98	0.85	0.93	1.11	-0.19
	(21.92)	(14.61)	(12.94)	(18.61)	(14.60)	(24.66)	(36.59)	(10.95)	(18.27)	(7.45)	(-0.85)
β^{Crisis}	0.96	1.08	1.03	0.77	0.99	0.85	0.78	0.95	1.15	1.14	0.18
	(7.61)	(17.72)	(35.15)	(10.29)	(25.67)	(15.75)	(16.22)	(12.35)	(14.34)	(7.05)	(0.63)
β^{Low}	1.20	0.92	0.98	0.93	0.96	0.89	0.95	0.91	0.89	0.99	**-0.21**
	(20.44)	(23.98)	(23.45)	(25.51)	(23.17)	(24.85)	(28.46)	(19.96)	(20.04)	(17.90)	(-2.48)
w (%)	2.21	1.85	1.82	1.68	1.69	1.53	1.65	1.90	1.96	2.51	**0.29**
	(18.23)	(21.07)	(17.75)	(13.72)	(14.24)	(14.79)	(15.71)	(16.17)	(19.87)	(20.00)	(1.99)
Null Hypothesis: β(state) $=\beta$ (normal)											
$\beta^{Cris}-\beta^{Norm}$	**-0.34**	**0.24**	**0.31**	**-0.20**	**0.22**	-0.13	**-0.19**	0.10	**0.22**	0.03	0.37
	(-1.96)	(2.29)	(4.61)	(-1.68)	(2.79)	(-1.50)	(-3.02)	(0.66)	(1.87)	(0.09)	(0.74)
$\beta^{Low}-\beta^{Norm}$	-0.10	0.08	**0.26**	-0.03	**0.19**	**-0.09**	-0.02	0.06	-0.04	-0.13	-0.03
	(-1.18)	(1.27)	(3.89)	(-0.55)	(2.99)	(-1.77)	(-0.56)	(0.66)	(-0.59)	(-0.83)	(-0.13)

This table reports regime-dependent market betas of 10 portfolios sorted on the basis of liquidity-beta. The market beta is assumed to depend on the stock market regimes and is estimated using the following model:

$$r^e_{p,t} = \alpha_p + \beta_p\left(S_t^{R^e_m}\right)R^e_{m,t} + w_p\eta_{p,t}, \quad \eta_{p,t} \sim iid.N\left(0,1\right)$$

where $r^e_{p,t}$ denotes the excess return of the testing portfolio and α_p and w_p are assumed to be fixed components over regimes. $\beta_p\left(S_t^{R^e_m}\right)$ is the testing portfolio market beta when the market portfolio is in state $S_t^{R^e_m}$. T-statistics are computed using Newey and West (1987) standard errors with one lag and are presented in parentheses. The table also presents, at the bottom, results of tests of the null hypotheses that market beta of the testing portfolio, in a given regime, is equal to its level in the normal regime. Parameters (with the exception of β(state) and w) that are significant at the 10% level are shown in bold type.

Table 7 :
Regime-dependent market betas – 2by2 liq-level and liq-beta portfolios

	Low Beta and Liq.	**Low Beta and Illiq.**	**Illiq-Liq**	**High Beta and Liq.**	**High Beta and Illiq.**	**Illiq-Liq**
α (%)	-0.07	**0.40**	**0.47**	-0.00	**0.48**	**0.48**
	(-1.31)	(4.30)	(4.67)	(-0.05)	(5.23)	(4.49)
β^{Normal}	1.03	0.78	**-0.25**	0.99	0.78	**-0.21**
	(51.10)	(14.99)	(-4.42)	(18.06)	(18.51)	(-2.88)
β^{Crisis}	0.84	1.20	**0.36**	0.93	1.26	**0.33**
	(15.41)	(22.68)	(4.94)	(13.88)	(19.07)	(3.81)
β^{Low}	0.98	1.10	**0.12**	0.93	1.11	**0.18**
	(39.94)	(21.35)	(2.02)	(35.46)	(21.81)	(3.33)
w (%)	1.27	2.16	**0.90**	1.30	2.05	**0.75**
	(11.78)	(19.26)	(6.91)	(13.93)	(19.44)	(5.84)
Null Hypothesis: β(state) $=\beta$ (normal)						
$\beta^{Cris} - \beta^{Norm}$	**-0.19**	**0.42**	**0.61**	-0.06	**0.48**	**0.53**
	(-3.02)	(5.15)	(5.62)	(-0.48)	(5.69)	(3.75)
$\beta^{Low} - \beta^{Norm}$	-0.05	**0.32**	**0.37**	-0.07	**0.32**	**0.39**
	(-1.48)	(4.49)	(4.57)	(-1.20)	(4.95)	(4.62)

This table reports regime-dependent market betas of 2by2 portfolios, independently sorted on liquidity-level and liquidity-beta. The market beta is assumed to depend on the stock market regimes and is estimated using the following model:

$$r^e_{p,t} = \alpha_p + \beta_p \left(S_t^{R^e_m}\right) R^e_{m,t} + w_p \eta_{p,t}, \quad \eta_{p,t} \sim iid.N\left(0,1\right)$$

where $r^e_{p,t}$ denotes the excess return of the testing portfolio and α_p and w_p are assumed to be fixed components over regimes. $\beta_p\left(S_t^{R^e_m}\right)$ is the testing portfolio market beta when the market portfolio is in state $S_t^{R^e_m}$. T-statistics are computed using Newey and West (1987) standard errors with one lag and are presented in parentheses. The table also presents, at the bottom, results of tests of the null hypotheses that market beta of the testing portfolio, in a given regime, is equal to its level in the normal regime. Parameters (with the exception of β(state) and w) that are significant at the 10% level are shown in bold type.

Our last test looks at hypothesis 3c stating that liquidity-beta dominates liquidity-level in explaining stock returns across the different market volatility regimes. To test this hypothesis, we further form 2by2 portfolios based on liquidity-level and liquidity-beta and estimate model (7) using the four double sorted portfolios. Results are presented in Table 7. Once again, the results in Table 7 do not lend support to the assertion of Lou and Sadka (2011). We find rather that liquidity-level dominates liquidity-beta in predicting stock returns during *crisis* and *low volatility* regimes. Following a switch in market volatility from *normal* to either *crisis* or *low volatility* regime, the portfolios with the most liquid stocks exhibit a decrease in their market betas, while the portfolios with the most illiquid stocks show an increase in their market betas, regardless of the stocks' liquidity betas. We argue here that the findings of Lou and Sadka (2011)'study can not be generalized to every crisis period and are rather specific to the financial crisis of 2008-2009, which was characterized by massive illiquidity. In this study, we conjecture that, taking the history of US stock market crises, liquidity-level dominates liquidity-beta in predicting stock returns during *crisis* times. This can be justified by the fact that liquidity-beta becomes more important only when there is massive illiquidity, which is not the case of any crisis.

5. Conclusion

This paper offers a study on time-variation in the pricing of quality and liquidity in the US stock market. We use in particular a regime-switching beta model and study how the cross-sectional effects of quality and liquidity varies across the stock market regimes. Following Billio and Pelizzon (2000) and Billio et al. (2012), we first use the market portfolio excess return time-series to identify stock market regimes. We then compute, conditional on each regime, the cross-sectional expected stock returns for quality and liquidity deciles.

Four main conclusions can be drawn from this study. First, the US stock market is driven by three main regimes: the *normal* regime (that is prevailing most of the time); the *low volatility* regime; and the *crisis* regime. Second, during the *crisis* regime, on one hand, low quality and low liquidity stocks experience relatively higher losses than would be predicted from normal times. On the other hand, high quality and high liquidity stocks experience rather relatively lower losses. These findings are consistent with the presence of cross-market and within-market flight-to-quality and to-liquidity phenomena during periods of high volatility. During episodes of market stress, low quality and low liquidity stocks suffer large losses because of both cross-market and within-market flight-to-quality and to-liquidity. Whereas, high quality and high liquidity stocks experience reduced losses in these times, benefiting from the extra demand coming from investors who seek for quality and liquidity and choose to stay in the stock market. Third, during low volatility periods, low quality and low liquidity stocks earn relatively larger returns, while high quality and high liquidity stocks yield lower returns. We conjecture that this finding can be explained by the fact that the *low volatility* regime is likely driven by a strong economy that boosts capital spending and allows junk and illiquid stocks to achieve higher returns. In contrast, The underperformance of high quality and liquid stocks can be attributed to the selling pressures from investors tilting their portfolios toward junk and illiquid stocks to seek portfolio gains. Finally, regarding the importance of liquidity-level and liquidity-beta in predicting stock returns across the stock market regimes, we do not find evidence for the assertion of Lou and Sadka (2011) who claim that liquidity-beta is more important than liquidity-level during crisis times. Contrary to their claim, we find that liquidity-level dominates liquidity-beta in predicting stock returns during the *crisis* regime.

Overall, our analysis in this paper shows that the effect of liquidity and quality on stock returns is a function of market volatility regimes. We therefore claim that market volatility could be a valuable guide to investors and portfolio managers on how to actively reallocate investments across liquid (quality) and illiquid (junk) stocks to potentially increase returns and reduce exposure to market risk.

This analysis can be extended in several ways. First, we considered only a one factor model. This model can be extended to a multi-factor model including size, value and momentum factors that have been documented in several studies to have an important effect on stock returns. Second, to proxy for liquidity-level, we use the Amihud (2002) measure which is highly correlated with the size characteristic. One direction for future research is to isolate the component of liquidity from size. Finally, future research could also extend our study by adding other macroeconomic indicators to the market risk factor when identifying stock market regimes.

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