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Return dispersion, stock market liquidity and aggregate economic activity

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ABSTRACT

This paper examines the effect of return dispersion on the dynamics of stock market liquidity, risk and return. Moreover, the importance of return dispersion in forecasting aggregate economic activity is rediscovered in the context of a regime switching model that accounts for stock market fluctuations and their association with the state of the economy. We find that there is a bidirectional, Granger-causal association between illiquidity and return dispersion in the U.S. stock market. The empirical results show that stock returns can help us predict both realized volatility as well as return dispersion. We report that there is a significant relation between economic conditions and the risk measures (return dispersion and realized volatility).

JEL classification: G10; C23; C32; C40; C51.

Keywords: Illiquidity; Aggregate Economic Activity; Realized Volatility; Regime Switching; Return Dispersion; Stock Market Liquidity.

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1. Introduction

Return dispersion (RD) is important in quantitative finance: it helps forecast the state of aggregate economic activity, while it explains the cross sectional variation in stock returns and assesses the quality of portfolio management. The emergence of dispersion has been attributed to a host of possible causes. Christie and Huang (1995) suggested that dispersion is inversely related to herding; stock returns can be diverse because diverse rational investors respond to market stimuli in a wide variety of ways, instead of a herd-like convergence to the market consensus. The dispersion of investor beliefs as a cause of RD has also been suggested by Connolly and Stivers (2003). They argued that abnormal RD can be caused by portfolio reallocations and indicate that the release of macroeconomic news is one cause of such possible reallocations. Garcia et al. (2011) suggested that as RD is associated with average idiosyncratic variance, it is induced by the trading behavior of investors who identify mispricing opportunities and reallocate their portfolios. In fact, shocks in share turnover, associated with portfolio relations, have been shown to be correlated with RD (Connolly and Stivers, 2003). The dispersion of stock returns is important at a practical level because RD helps to a) forecast the state of the economy, b) predict future stock returns, and c) evaluate fund managers (De Silva et al., 2001).

RD has important implications for policy makers since it is systematically associated with the state of economy. Loungani et al. (1990) showed that RD reflects sectoral shifts: as resources are reallocated from declining to expanding sectors of the economy, the demand for corporate securities is also reallocated, leading to increased dispersion in stock returns. Stivers (2003) demonstrated that RD in the US stock market has been consistently higher during recessions, while Gomes et al. (2003) reported, among others, that the cross-sectional dispersion in individual stock returns is related to aggregate stock market volatility and business cycle conditions. Furthermore, Garcia et al. (2011) produced evidence that RD is correlated with macroeconomic variables such as consumption growth volatility, inflation volatility and the term spread.

RD does not matter only for the policy maker; it matters for the choices and the performance of individual investors as well. The prediction of stock returns has constituted a central theme in the RD literature. Connoly and Stivers (2003) have found evidence that shocks in RD are correlated with equity index return in the US and also in Japan and the UK. Likewise, Stivers (2003) demonstrated that RD is positively associated with equity returns in US, Japan and UK. Similar evidence for the US market is produced in Wei and Zhang (2005). In an analysis of the value premium, Zhang (2005) showed that RD is positively associated with the industry cost of capital. Furthermore, Stivers and Sun (2010) showed that RD can help predict the value premium as well as the momentum premium of US stock returns. They argued that RD can also predict the performance of relative strength strategies. The most comprehensive account of the importance of RD in explaning stock returns has been suggested by Garcia et al. (2011). They argued that RD is a priced factor in the cross section of stock returns, extending the Fama and French (1993) three factor model.

There has also been a considerable amount of research oriented towards redefining performance evaluation and portfolio alphas based on RD. A clear argument on the portfolio implications of RD is given in Demirer and Lien (2004) who showed that RD across stocks is inversely associated to the correlation between stock returns. De Silva et al. (2001) and Ankrim and Ding (2002) were motivated by the increased dispersion in the performance of fund managers at the end 1990 and discovered that it was due to the increased dispersion in stock returns at that time. They also found that RD was an international phenomenon, and that it could not be attributed to stock market excesses like the dot.com bubble of the late 1990. More specifically, De Silva et al. (2001) found that RD was not captured by any of the Fama-French priced factors in the cross section of stock returns and suggested a modification to the portfolio alpha in order to account for RD. Gorman et al. (2010) also suggested a similar modification to the portfolio alpha and also discovered that the dispersion of alphas can be predicted by the volatility index of the S&P500 (VIX). Being able to predict the dispersion of alphas through VIX and RD, the authors showed that investors could profitably adjust the “activeness” of their portfolios. Yu and Sharaiha (2007) decomposed RD into beta dispersion and non-market dispersion and showed that an alpha-budgeting process can lead to profitable dispersion-based portfolio selection.

Drawing on the importance of RD in portfolio selection and policy making, this paper investigates the relationship between RD and dynamics of stock returns, variations in stock market liquidity and the dynamics of aggregate economic activity. Liquidity spillovers are essentially spillovers of trading activity. It is the dispersion of trading activity that ultimately drives the dispersion of stock returns (Bessembinder et al., 1996). Given that the cross sectional dispersion of stock returns captures aggregate idiosyncratic risk in the stock market (Garcia et al., 2011), the analysis of return, risk and liquidity spillovers has to accommodate the effect of RD; this is the main focus of this work. Our discussion of the intramarket causal association between (shocks in) liquidity, volatility and returns is motivated by the findings of Chordia et al. (2011) and Andrikopoulos and Angelidis (2010) for the US and the UK market, respectively.[1]

The contribution of this paper is fourfold: i) we demonstrate the effect of RD on variations of liquidity, ii) we uncover the Granger-causal effect of variations in liquidity on RD, realized variance and stock returns, iii) we expand the literature on liquidity spillovers by showing their regime-dependent effect on risk and return, iv) we extend the current literature on the association between stock market dynamics and macroeconomic fundamentals by incorporating the effect of risk (realized volatility and RD) and illiquidity into the discussion of the predictive power of stock market dynamics over fluctuations of aggregate economic activity. The paper shows that: a) RD and illiquidity are persistent in the US stock market; b) RD and illiquidity Granger-cause each other; c) RD, as well as the realized variance, can be predicted by the variations in stock returns; d) the variations in illiquidity and RD are sensitive to the regime of market dynamics; e) there is a negative relation between stock market illiquidity and (subsequent) aggregate economic activity; and finally that f) there is a statistically significant relation between the risk measures and the state of the economy, even though the sign of this relation is sensitive to the regime of aggregate financial variability.

The following section (section 2) reviews the properties of the dataset and presents the methodology, while section 3 presents the extension of the findings into a regime-switching setting. Section 4 demonstrates the ability of the financial variables to forecast the state of the US economy and section 5 concludes the paper.

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[1] Beyond the context of spillover analysis, the association of liquidity with both idiosyncratic and systematic risk has been documented in Benston and Hagerman (1974), the association between stock returns and idiosyncratic risk has been demonstrated by, e.g., Ang et al. (2009) and Goyal and Santa Clara (2003) and the explanatory power of liquidity with respect to cross sectional variations of stock returns has been shown by many authors such as Brennan and Subrahmanyam (1996), Amihud (2002) and Liu (2006).

2. Dataset and methodology

The data set is obtained from Thomson Datastream and covers all US stocks (dead or alive) from February 1, 1983 to December 31, 2010 (7037 daily observations).

Ince and Porter (2006) showed that equity data from Thomson Datastream must be handled with care, as, without data cleaning procedures, the economic inference may be misleading. Therefore, we impose the following filters[2] to minimize the risk of data errors:

1. We include in the database only the stocks that were characterized as "equities" (Stock type: EQ).
2. We exclude all the foreign companies by using the geography group code (Datastream data type: GEOG).
3. We exclude all companies not listed on the primary stock exchange (Datastream data type: EXMNEM).
4. We use Level 2, Level 3 and Level 4 sector names and the names of the companies to identify and exclude closed end funds, REITs, ADRs and preferred stocks.
5. We delete all zero returns, from the last observation to the first with non-zero return, in order not to include the returns of stocks that have stopped being traded.
6. We remove 5% of the stocks with the smallest capitalization, in order to address the outlier effect[3]. We only use the daily returns that are higher (lower) than the 2.5% (97.5%) of all the stock returns in a day.

We estimate the cross-sectional variance at day t (CSV_t) as:

$$CSV_{\mathrm{t}} = 252\frac{1}{N}\sum_{\mathrm{i=1}}^{\mathrm{N}}\left(\mathrm{r_{i,t}} - \mathrm{r_{m,t}}\right)^2, \tag{1}$$

where $\mathrm{r_{i,t}} = \log\left(P_{i,t}/P_{i,t-1}\right)$ is the i^{th} stock return, $P_{i,t}$ is the price of the i^{th} asset observed at day t, $\mathrm{r_{m,t}}$ is the value-weighted market return at day t, and N is the number of stocks. RD is equal to $\sqrt{CSV_{\mathrm{t}}}$. Stivers (2003) showed that $CSV_{\mathrm{t}} \cong$

[2] Hou et al. (2011), Guo and Savickas (2008), and Busse et al. (2013) impose similar filters to account for potential data errors.
[3] Simiraly to Ang et al. (2009).

$\sigma_\beta^2 (r_{m,t} - r_{f,t})^2 + \sigma_t^2$, where $r_{m,t} - r_{f,t}$ is the excess return of the market, σ_β^2 is the cross-sectional variance of betas and σ_t^2 is the idiosyncratic variance. Therefore, the cross sectional variation captures the two important elements of total risk: systematic and idiosyncratic risk.

Extended versions of ARCH (Engle, 1982) volatility specifications have been applied, enhancing our predictive ability in various areas such as option pricing, risk management, portfolio analysis, etc. In the past years, based on Andersen and Bollerslev's (1998) seminal paper, the use of intraday datasets has rekindled the interest of academics to forecast the variability of asset returns. The realized volatility[4], which is defined as the sum of the squared intraday returns, is mainly modeled by long memory volatility models (more information about realized volatility models is available in Andersen et al., 2003; Angelidis and Degiannakis, 2008; Degiannakis and Floros, 2013; Giot and Laurent, 2004; Koopman et al., 2005; and Thomakos and Wang, 2003, among others). The annualized realized volatility on day t is computed, based on the recent findings of Hansen and Lunde (2005), as below:

$$RV_t^{(HL)} = \sqrt{252\left(\omega_1\left(logP_{t_1} - logP_{t-1_\tau}\right)^2 + \omega_2 \sum_{j=1}^{\tau}\left(logP_{t_j} - logP_{t_{j-1}}\right)^2\right)} \quad (2)$$

where parameters ω_1 and ω_2 are estimated such as $min_{(\omega_1,\omega_2)} E\left(RV_t^{(\tau)} - \sigma^{2(IV)}\right)^2$. The P_{t_j} represents the asset prices that are observed at each j equidistant points of day t, with a sampling frequency of 5 minutes. Each daily time interval is partitioned in τ equidistant points. The intra-day realized variance, $RV_t^{(\tau)} = \sum_{j=1}^{\tau}\left(logP_{t_j} - logP_{t_{j-1}}\right)^2$, is partitioned into τ equidistant intra-day points. The $\sigma^{2(IV)}$ denotes the integrated volatility, which, according to the theory of quadratic variation of semi-martingales, can be consistently estimated by the realized volatility (see Barndorff-Nielsen and Shephard, 2002; 2005).

Even though trading activity is associated with liquidity, the two concepts are not equivalent (i.e. Chordia et al., 2007); an analysis of liquidity spillovers should not

[4] The intraday data were obtained from Tickdatamarket (www.tickdatamarket.com).

be structured on indirect proxies of liquidity (like trading volume) but on direct measures such as the measure of Amihud (2002). We estimate Amihud's (2002) daily illiquidity ratio as follows:

$$Il_t = N^{-1} \sum_{i=1}^{N} \frac{|r_{i,t}|}{Turnover_{i,t}}, \qquad (3)$$

where $Turnover_{i,t}$ and $|r_{i,t}|$ are the dollar trading turnover and the absolute return on stock i on day t, respectively.

2.1 Descriptive statistics

Panel A of Table 1 presents the descriptive statistics for the daily market returns, the illiquidity ratio, RD and annualized realized volatility. The average yearly RD is equal to 25.88% and exhibits significant variation as the minimum (maximum) is equal to 9.82% (126.14%), while the standard deviation of RD equals 9.32%. The minimum (maximum) occurred on 26/12/2003 (19/10/1987 – *Black Monday*). Cross-sectional variation is persistent with the first order autoregressive coefficient being close to 0.87, declining slowly and being significant even at the tenth lag (2 trading weeks). High (low) RD in one period is likely to be followed by higher (lower) than average RD for many subsequent periods. Realized volatility also exhibits high variability. The yearly average equals 12.74%, substantially lower than that of RD. The minimum (maximum) is equal to 9.1% (184.4%) and occurred on 26/12/1986 (20/10/1987 – A day after *Black Monday*[5]). Contrary to the evidence on the cross-sectional variation of stock returns, realized stock market volatility is less persistent. The average daily value of illiquidity is equal to 0.09% with a standard deviation equal to 0.07%. The range of the values is from 0.01% which may be related to the bull period[6] to 1.12% which is related to stock market downturn of 2002. Based on the autoregressive coefficients, the market remains illiquid form many days in a row. Finally, we observe that the average market return is positive with a yearly standard deviation close to 17%, and there is no indication that returns are affected by the previous ones.

[TABLE 1 HERE]

[5] The second highest value of realized volatility is observed on Black Monday.

[6] On May 30, 2007, the S&P 500 closed at 1,530.23, setting its first all-time closing high in more than seven years.

Panel B of Table 1 presents the correlation analysis of the four variables. We observe that average market return is negatively correlated with RD and realized volatility as well as with illiquidity. Therefore positive returns are expected when the market is liquid and the risk is relative low. We also observe that illiquidity is positively correlated with both RD and realized volatility, and, therefore, periods of high risk are also associated with illiquid periods. Periods of high risk coincide with periods of high RD, as the correlation coefficient between them equals 61.10%.

2.2 States of market returns, illiquidity, return dispersion, and realized volatility

It is well documented that stock returns are time-varying and are characterized by at least two distinct regimes, i.e. *bull* and *bear* markets (see Guidolin and Timmerman, 2005). Furthermore, Bekaert et al. (2012) document that at least 2 structural breaks occur in idiosyncratic risk, while Acharya et al. (2013) also verify the existence of two liquidity states as they show that the pricing of liquidity risk in the bond market is conditional on the state of the economy, with liquidity risk becoming more important in times of financial and economic distress**.**

Therefore, motivated by the findings in previous research, we estimate, for each variable, a two-state regime switching model which is described as follows:

$$y_t = \mu_{S_t} + \varepsilon_t,\ \varepsilon_t \sim N\left(0, \sigma_{S_t}\right), \tag{4}$$

where $y_t \equiv \left[Il_t, \sqrt{CSV_t}, RV_t^{(HL)}, r_{m,t}\right]'$, μ_{S_t} and σ_{S_t} are the mean and the standard deviation that are state dependent at time t. Following Hamilton (1989), we hypothesize that the process is first-order Markov and is described by a latent variable $S_t = 1,2$, while its transition matrix Π is characterized by constant probabilities (P,Q). P (Q) is the probability to stay in the low (high) risk regime. In order to evaluate the quality of regime classification, we follow the work of Ang and Bekaert (2002) and calculate the Regime Classification Measure (RCM): $RCM = 400\frac{1}{T}\sum_{t=1}^{T} p_t(1 - p_t)$, where $p_t = (S_t|\mathcal{J}_T)$. The RCM statistic takes values between 0 and 100 with low values indicating good regime classification[7].

[7] We also consider the Akaike, Schwarz, and Hannan-Quinn information criteria in order to evaluate the performance of the regime switching model. In all cases the state dependent specification describes better the underlying process than the single state one. We reach to the same conclusion when we perform likelihood ratio tests (these results are available from the authors upon request).

Table 2 presents the results from the estimation of equation (4), while Figure 1 plots the smoothed probability of state 1 (high risk environment), based on Kim's (1994) algorithm. In the same figure we also plot four financial variables (Illiquidity Ratio, RD, Realized Volatility, and Market Return). We observe that there is substantial fluctuation in the financial variables. A visual inspection of Figure 1 reveals that times of turbulence in market returns coincide with times of turbulence in risk and illiquidity (October 1987, summer of 1998 with the Russian and the Long-Term-Capital-Management crises, September 2001, credit-crisis events in 2008).

[FIGURE 1 HERE]

The statistical properties of the data are further explored in Table 2, which presents the estimated coefficients of equation (4). For the four variables, the RCM statistic ranges from 3.43 to 16.13 and, hence, there are strong indications that the two-state regime switching model correctly classifies periods of high and low risk. We also observe a typical characteristic of high-variance regimes: high variance regimes are associated with low mean returns and are constitutive of bear markets, while low variance are associated with high mean returns and are constitutive of bull markets (Guidolin and Timmerman, 2005, among others). The average daily return falls from 0.06% in bull markets to -0.1% in bear markets and the daily standard deviation of stock returns rises from 0.7% to 1.9% across the two regimes. Both states are persistent as the average probability of staying in the high (low) risk regime equals 0.96 (0.99). On average, the market stays in the high (low) risk environment 28 (97) days.

During turbulent periods (as given above), the market is 3.1 times more illiquid, RD is 1.7 times greater and realized volatility is 2.4 times higher than that during periods of financial stability. Furthermore, there is similar evidence for the standard deviation of market return, as it increases at least 2.7 times. Therefore, all the variables share a common characteristic: as stock market fluctuations increase in bear markets, the same happens to measures of stock market risk (RD and realized volatility) and stock market illiquidity (illiquidity being positively associated to both systematic and unsystematic risk; e.g. Benston and Hagerman, 1974).

[TABLE 2 HERE]

3. Spillovers: a single-state versus a two-state approach

A standard method in the investigation of the relation between risk, return and illiquidity is the regression of each variable against lagged values of all variables (e.g., Chordia et al., 2011; Andrikopoulos and Angelidis, 2010). However, previous research has extensively documented the presence of multiple regimes (e.g. Guidolin, 2011); furthermore, the regimes of stock market fluctuations are associated with the size of market-wide volatility and there is both a convincing theoretical argument and empirical evidence on the ability of RD to forecast market-wide volatility.[8] In this section, we propose a regime switching model which allows for an asymmetric relation between the variable of interest and lagged values of the other four variables, as given below:

$$y_t = \mu_{\mathrm{S_t}} + b_{\mathrm{S_t}} y_{t-1} + \varepsilon_t, \;\; \varepsilon_t \sim \mathrm{N}\left(0, \sigma_{\mathrm{S_t}}\right), \tag{5}$$

for $\mathrm{y_t} \equiv \left[\mathrm{Il_t}, \sqrt{CSV_{\mathrm{t}}}, RV_t^{(HL)}, \mathrm{r_{m,t}}\right]'$, $\mathrm{S_t} = 1{,}2$, where $\mu_{\mathrm{S_t}}$, $\sigma_{\mathrm{S_t}}$ and $b_{\mathrm{S_t}}$ are the mean, the standard deviation and the factor loading of state $\mathrm{S_t}$, respectively. Equation (5) models two states of the world with different slope coefficients, $b_{\mathrm{S_t}}$[9].

We explore the spillovers of risk, return and liquidity in the US stock market and also with an international sample. For the case of the US stock market, Panel A (B) of Table 3 presents evidence on the forecasting ability of the regime switching (single state) model. With respect to asset return predictability, daily stock returns cannot be consistently predicted based on previous evidence on returns, risk and liquidity; such results are consistent with previous results on the weak-form efficiency of the NYSE; e.g. Chordia et al. (2005). However, when we decompose market returns into low and high volatility regimes, statistically significant relations emerge. In both states, realized volatility positively affects subsequent stock market returns,

[8]The ability of RD to predict aggregate stock market volatility is first suggested in the real options model of Gomes et al. (2003). This theoretical argument finds empirical corroboration in Stivers (2003) who shows that the dispersion of monthly stock returns can help predict market level volatility in the US stock market. Connolly and Stivers (2006) demonstrate that the possibility of predicting stock market volatility is pervasive across industry-based, size-based and beta-based portfolios.

[9] The framework is based on Angelidis and Tessaromatis (2009) who use a regime switching model to study the relationship between idiosyncratic risk and subsequent stock market returns. They argue that the conflicting evidence (see Goyal and Santa Clara, 2003; and Bali et al., 2005) is due to the approach they followed which does not the volatility states of the market.

while lagged values of market returns are positively associated with future returns only when the market is in the low volatility state.

[TABLE 3 HERE]

The results for RD and realized volatility are statistically significant for almost all candidate explanatory variables. Both measures of risk are persistent since they are positively associated with lagged values of themselves and they are also Granger-caused by lagged values of illiquidity and returns. These results on the persistence of RD and realized standard deviation are in accordance with previous research findings on the persistence of idiosyncratic as well as systematic risk in US stock markets (see Ang and Chen, 2007; and McLean, 2010). Moreover, the regime switching decomposition enables us to shed more light on the relation. For example, illiquidity affects RD and realized volatility only during low volatility periods[10], while the coefficients of the variables between the two regimes differ significantly. Furthermore, even if realized volatility does not seem to affect RD in the single state environment, this is not true under the regime switching framework, as realized volatility in both states is positively related to subsequent changes of RD.

With respect to illiquidity, in the single state case, we observe that illiquidity is persistent (consistent with findings in Bekaert et al., 2007) and that RD Granger-causes the illiquidity of the stock market, consistent with previous findings that liquidity depends on the idiosyncratic risk undertaken by investors (see Benston and Hagerman, 1974; Andrikopoulos and Angelidis, 2010). In the state-dependent environment we observe slightly different results. Illiquidity is less persistent in the high risk state as the coefficient is lower than that of the high risk environment, while RD affects illiquidity only during low volatility periods.

In order to examine whether the results are sample-specific, we further investigate the robustness of the results by estimating the same models in two major European stock markets, the German (DAX) and the French one (CAC). The dataset was obtained from Thomson Datastream and covered the period from 2000 to 2010.

[10] We attribute this finding to the stronger presence of noise in times of high stock market volatility: as asset prices convey highly volatile and noisy signals, investors find difficulty in structuring their trading behavior on fundamentals such as risk and liquidity.

The findings[11] are qualitatively similar to with those from the US stock market; RD is persistent and is Granger causal for changes in illiquidity and realized volatility.

4. Macroeconomic significance of realized volatility, return dispersion, illiquidity, and market returns

The impact of RD is not limited to the Granger-causality of stock price dynamics. It is a state variable that carries important incremental information about the state of the current state of the economy; the countercyclical variations in RD can forecast sectoral shifts in the real economy and also the dynamics of aggregate economic activity (see Loungani et al., 1990; and Gomes et al., 2003). Beyond the argument about RD, there is also extensive research which documents that liquidity, volatility and return may also help forecast the state of the economy[12].

In an asset-pricing context, Liew and Vassalou (2000) argued that the differential performance of a set of size and value portfolios, in the context of Fama and French (1993), can be used to predict economic growth in the US. More to our point, the literature on the macroeconomic significance of financial variables has extensively discussed the possibility of forecasting economic growth based on the dynamics of stock market liquidity and volatility. Arestis et al. (2001) discussed the link between financial development and economic growth and -while concluding that banks are more effective for growth than stock markets- they argued that liquidity helps economic growth since when trades are easier the allocation of capital in competing alternatives is facilitated, and hence economic growth is fostered. On the other hand, they noted that excess liquidity can trigger noisy signals about asset values, thus hindering the allocation of capital assets in competing alternatives. Furthermore, Kaul and Kayacetin (2009) produced evidence on the possibility of

[11] To save space we do not report these results here, but they are available from the authors upon request.

[12] The findings on the macroeconomic implications of RD constitute part of a long and ongoing history of attempts to forecast the state of the economy, employing financial variables. A theoretical narrative for such explorations can be found in Greenwald and Stiglitz (1993) who argued that asymmetric information across risk-averse market participants can trigger cyclical movements in real wages, output and investment. Subsequent empirical work has documented that economic growth can be predicted by the dynamics of financial variables. In particular, Estrella and Mishkin (1998) produced a forecasting model of US recessions, by employing stock price indices, monetary aggregates, interest rates and interest rate spreads; extending the work of Estrella and Mishkin (1998), Hassapis (2003) developed a non-parametric model in which he forecast the state of the Canadian economy, with the use of Canadian and US financial variables.

predicting economic growth based on the illiquidity of stock markets: they discovered that changes in US real GDP and industrial production can be predicted with aggregate order flow on the New York Stock Exchange and also with order flow differentials (the difference in the order flow between small cap and large cap firms). As order flow differentials capture market-wide risk aversion and risk aversion is counter cyclical, order flow differentials may predict the state of the US economy. In the same line of argument, Naes et al. (2011) showed that, for the Norwegian and the US economy, stock market liquidity can help us assess the current as well as the subsequent state of the economy and that such effects can be explained through processes of portfolio restructuring and respective flights to liquidity.

The policy implications of macroeconomic forecasts and the macroeconomic importance of RD and stock market liquidity have motivated our research on the association between RD, liquidity and the state of the aggregate economy. As a proxy for aggregate economic conditions, we employed the index of Aruoba et al. (2009), the so-called ADS index. Table 4 presents the results of the framework we describe in section 3, by using as dependent variable the ADS index[13]:

$$ADS_t = \mu_{\mathrm{S_t}} + b_{\mathrm{S_t}} y_{t-1} + \varepsilon_{t,} \quad \varepsilon_{\mathrm{t}} \sim \mathrm{N}\left(0, \sigma_{\mathrm{S_t}}\right), \tag{6}$$

for $\mathrm{y_t} \equiv \left[\mathrm{Il_t}, \sqrt{CSV_{\mathrm{t}}}, RV_t^{(HL)}, \mathrm{r_{m,t}}\right]'$. We find that stock market illiquidity, RD, realized volatility and stock returns in the US market help predict (Granger-cause) the state of the US economy. Furthermore, the results confirm previous theoretical arguments as well as empirical findings on the possibility of predicting the state of the US economy based on the fluctuations of the stock market in terms of market returns (e.g. Estrella and Mishkin, 1998), RD (Stivers, 2003, and Garcia et al., 2011) and liquidity (Kaul and Kayacetin, 2009).

In the single state framework, all variables are negatively related to the ADS index and only the relation with the market return is statistically insignificant. An increase in RD leads to a deterioration in business conditions (the same holds for illiquidity and idiosyncratic volatility). Again, the causal relations are not constant, as the regime switching specification reveals. The market return is negatively related with the subsequent changes in ADS only during periods of high risk. Furthermore,

[13]We did not include a lagged value of ADS in equation (6) as we wanted to investigate if the four variables that are available in time *t* can forecast the ADS index, since there is a time delay in the calculation of the ADS values.

both RD and realized volatility are negatively related to future values of ADS in the high variance state as well as in the single-state context, in contrast to the observed negative relation in the low-variance regime. Illiquidity remains negatively related to ADS in both states, but the magnitude of the coefficient differs significantly (-129 versus -564). Therefore, we find that the state dependent framework is more appropriate -compared to a single state analysis- to uncover the relationship between the variables of interest, as the sign of RD and realized volatility alters between the two states, market return affects the business conditions only in the high volatility regime and the magnitude of the coefficient of illiquidity differs substantially.

[TABLE 4 HERE]

5. Concluding remarks

Investors' sentiment and information are transmitted through trading activity and, thus, investors drive fluctuations in liquidity and the prices of capital assets. Asset returns are volatile in markets of varying liquidity and manifest sensitivity to bull and bear regimes. Moreover, fluctuations in asset markets are associated with fundamental macroeconomic trends, helping us predict growth and recession in the economy. In this paper, we studied RD, realized volatility, illiquidity and stock returns as interconnected constituents of stock market dynamics; these are leading indicators of aggregate economic performance. Time varying RD is associated with the economic state (transitions) and provides information about future market volatility (Stivers, 2003). To the best of the authors' knowledge, this paper is the first to explain the interrelations between stock market returns, illiquidity, realized volatility and RD both under a single and state dependent environment. The aim is to uncover the hidden relations and examine if they depend on the state of the market. Specifically, in the single state environment no variable can forecast stock market returns, while in the state dependent realized volatility is related to subsequent stock market returns. Furthermore, RD is related to illiquidity only during low risk periods, while illiquidity is not related to future values of RD and realized volatility during high risk periods. Moreover, realized volatility and RD may increase (decrease) when the economy is in recession (expansion); a finding that could not be uncovered by using a single state equation. Therefore, the proposed specification in our study explains if these key variables are related and whether this relation is positive or negative.

Our empirical results show that, in the US stock market, RD and illiquidity are persistent and are connected with bidirectional (Granger) causality. Market returns cannot be predicted by RD (or past returns, illiquidity and realized volatility). However, market returns may help us predict aggregate systematic risk as well as RD in the US stock market. The evidence is robust to the dissolution of aggregate market fluctuations into bull and bear regimes and is also apparent in the German and French stock markets. Furthermore, we found that RD, the liquidity of the stock market and the dynamics of stock returns help us forecast the state of the US economy.

The above results are in accordance with most previous studies on the persistence of idiosyncratic as well as systematic risk in US stock markets (e.g. Ang and Chen, 2007; McLean, 2010), and those who report persistence of illiquidity (e.g. Bekaert et al., 2007). In addition, the findings are in line with those who argue and that liquidity depends on the idiosyncratic risk undertaken by investors (e.g. Benston and Hagerman, 1974; Andrikopoulos and Angelidis, 2010). Further, the results confirm previous studies on the possibility of predicting the state of the US economy based on the fluctuations of the stock market in terms of market returns (e.g. Estrella and Mishkin, 1998), RD (Stivers, 2003, and Garcia et al., 2011) and liquidity (Kaul and Kayacetin, 2009).

The present study can be extended in a plethora of ways. We could investigate the interplay between stock returns, illiquidity, RD, realized standard deviation in the context of intraday market fluctuations. Furthermore, the effect of RD and the realized standard deviation on stock returns and liquidity may be explored in the case of emerging stock markets with volatile dynamics and rapidly changing macroeconomic environment. Most importantly, future research should focus on mapping the behavioral links and the structural connection between investors' choices in the stock market and the resulting dynamics in aggregate economic activity.

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Tables

Table 1. Descriptive statistics and correlation analysis.

Panel A. Descriptive statistics

	Market Return	Illiquidity	Dispersion	Realized Volatility
Mean	0.02%	0.09%	25.88%	12.74%
Median	0.06%	0.08%	23.54%	10.60%
Maximum	10.36%	1.12%	126.14%	184.40%
Minimum	-19.13%	0.01%	9.82%	9.10%
Std. Dev.	1.10%	0.07%	9.32%	9.22%
Skewness	-1.13	2.31	2.53	4.87
Kurtosis	24.93	16.20	14.25	51.17
Jarque-Bera Statistic	142558	57322	44634	708235
1st Autoregressive	0.01	0.83	0.87	0.65
5th Autoregressive	-0.02	0.81	0.78	0.55
10th Autoregressive	0.01	0.80	0.75	0.45
Aug. Dickey-Fuller statistic	-61.97	-4.56	-6.63	-11.68

Panel B. Correlation analysis.

	Market Return	Illiquidity	Dispersion	Realized Volatility
Market Return	100%			
Illiquidity	-3.28% (-2.75)	100%		
Dispersion	-3.03% (-2.54)	38.32% (34.79)	100%	
Realized Volatility	-13.83% (-11.71)	25.61% (22.22)	61.10% (64.74)	100%

Panel A presents the descriptive statistics for the daily market returns, illiquidity ratio, RD, and realized volatility. Panel B presents the bivariate correlations between the four variables. In parentheses the t-statistics are presented. The sample is from February 1, 1983 to December 31, 2010.

Table 2. Estimation of the regime switching model.

State		Illiquidity	p-value	Dispersion	p-value	Realized Volatility	p-value	Market Return	p-value
Low variance	Mean	0.00043	0.00	0.22086	0.00	0.09992	0.00	0.0006	0.00
	Standard Deviation	0.00017	0.00	0.03709	0.00	0.03967	0.00	0.007	0.01
High variance	Mean	0.00135	0.00	0.38138	0.00	0.24124	0.00	-0.001	0.00
	Standard Deviation	0.00066	0.00	0.11265	0.00	0.14578	0.00	0.019	0.00
	P	99.46%	0.00	99.36%	0.00	98.01%	0.00	99.05%	0.00
	Q	99.52%	0.00	97.95%	0.00	91.73%	0.00	96.75%	0.00
	RCM	3.43		3.43		16.13		14.99	

The estimations of $y_t = \mu_{S_t} + \varepsilon_t$, $\varepsilon_t \sim N(0, \sigma_{S_t})$, where $y_t \equiv \left[Il_t, \sqrt{CSV_t}, RV_t^{(HL)}, r_{m,t}\right]'$, μ_{S_t} and σ_{S_t} are the conditional mean standard deviation that are state dependent at time t. The process is first-order Markov and is described by a latent variable $S_t = 1,2$, while its transition matrix Π is characterized by constant probabilities (P,Q). The regime classification measure is $RCM = 400 * \frac{1}{T}\sum_{t=1}^{T} p_t(1-p_t)$, where $p_t = (S_t|\mathcal{I}_T)$.

Table 3. Forecasting Market Returns, Illiquidity, Realized Volatility and Return Dispersion.

	Market Return		Illiquidity		Realized Volatility		Return Dispersion	
	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value
Panel A. Regime Switching Model								
Low Variance State								
Constant	0.0001	0.86	0.0000	0.00	0.0304	0.00	0.0489	0.00
Illiquidity	0.2789	0.11	0.8745	0.00	2.1612	0.01	6.3371	0.00
Realized Volatility	0.0091	0.00	0.0000	0.80	0.3080	0.00	0.0175	0.00
Return Dispersion	-0.0026	0.12	0.0002	0.00	0.1642	0.00	0.7517	0.00
Market Return	0.0632	0.00	-0.0002	0.19	-0.5775	0.00	-0.2527	0.00
High Variance State								
Constant	-0.0059	0.00	0.0005	0.00	0.0551	0.00	0.1172	0.00
Illiquidity	0.8616	0.15	0.5511	0.00	0.3330	0.96	3.7227	0.27
Realized Volatility	0.0077	0.02	0.0008	0.00	0.2549	0.00	0.0313	0.04
Return Dispersion	0.0044	0.34	0.0003	0.11	0.4119	0.00	0.6750	0.00
Market Return	-0.0232	0.27	0.0019	0.06	-1.7359	0.00	-0.7002	0.00
P	0.9911	0.00	0.9675	0.00	0.9703	0.00	0.9833	0.00
Q	0.9674	0.00	0.9098	0.00	0.8192	0.00	0.9294	0.00
σ_1	0.0069	0.00	0.0001	0.00	0.0371	0.00	0.0254	0.00
σ_2	0.0193	0.00	0.0006	0.00	0.1327	0.00	0.0866	0.00
Panel B. Single State Model								
Constant	0.0003	0.52	0.0000	0.00	0.0030	0.56	0.0351	0.00
Illiquidity	0.2576	0.33	0.8020	0.00	5.9668	0.00	6.7560	0.00
Realized Volatility	0.0041	0.18	0.0001	0.12	0.4782	0.00	0.0256	0.11
Return Dispersion	-0.0033	0.15	0.0005	0.00	0.2248	0.00	0.8280	0.00
Market Return	0.0102	0.61	0.0007	0.20	-1.2639	0.00	-0.5305	0.00

Panel A of Table 3 presents the estimation results of a regime switching model which allows for an asymmetric relation between the variable of interest and lag values of the other four variables. The model is described as: $y_t = \mu_{S_t} + b_{S_t} y_{t-1} + \varepsilon_t$, $\varepsilon_t \sim N(0, \sigma_{S_t})$, for $y_t \equiv [Il_t, \sqrt{CSV_t}, RV_t^{(HL)}, r_{m,t}]'$, $S_t = 1,2$, where μ_{S_t} and σ_{S_t} are the mean, the standard deviation and the factor loading of state S_t, respectively. We assume two states of the world in which the slope coefficients, b_{S_t}, might be different. Panel B presents the results of the single state model.

Table 4. Forecasting the ADS index.					
Regime Switching Model			Single State Model		
	Coefficient	p-value		Coefficient	p-value
Low Variance State					
Constant	-0.1712	0.00	Constant	0.6003	0.00
Illiquidity	-129.9883	0.00	Illiquidity	-389.9188	0.00
Realized Volatility	0.3613	0.00	Realized Volatility	-1.0753	0.04
Return Dispersion	0.9781	0.00	Return Dispersion	-0.7611	0.02
Market Return	-0.4671	0.14	Market Return	-1.0188	0.39
High Variance State					
Constant	1.4756	0.00			
Illiquidity	-564.0361	0.00			
Realized Volatility	-3.0992	0.00			
Return Dispersion	-2.4043	0.00			
Market Return	-2.4019	0.03			
P	0.9903	0.00			
Q	0.9846	0.00			
σ_1	0.2537	0.00			
σ_2	0.8663	0.00			

Table 4 presents the results of the framework that is described in section 3, by using as dependent variable the ADS index: $ADS_t = \mu_{S_t} + b_{S_t} y_{t-1} + \varepsilon_{t,}$ $\varepsilon_t \sim N(0, \sigma_{S_t})$, for $y_t \equiv [Il_t, \sqrt{CSV_t}, RV_t^{(HL)}, r_{m,t}]$.

Figures

Figure 1. Time series plots of regime-dependent stock market dynamics: returns, return dispersion, illiquidity and realized volatility.