THE JOURNAL OF FINANCE • VOL. LXVI, NO. 1 • FEBRUARY 2011

Stock Market Liquidity and the Business Cycle

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ABSTRACT

In the recent financial crisis we saw liquidity in the stock market drying up as a precursor to the crisis in the real economy. We show that such effects are not new; in fact, we find a strong relation between stock market liquidity and the business cycle. We also show that investors' portfolio compositions change with the business cycle and that investor participation is related to market liquidity. This suggests that systematic liquidity variation is related to a "flight to quality" during economic downturns. Overall, our results provide a new explanation for the observed commonality in liquidity.

In discussions of the current financial crisis, much is made of the apparent causality between a decline in the liquidity of financial assets and the economic crisis. In this paper we show that such effects are not new; changes in the liquidity of the U.S. stock market have been coinciding with changes in the real economy at least since the Second World War. In fact, stock market liquidity is a very good "leading indicator" of the real economy. Using data for the United States over the period 1947 to 2008, we document that measures of stock market liquidity contain leading information about the real economy, even after controlling for other asset price predictors.

Figure 1 provides a time-series plot of one measure of market liquidity, the Amihud (2002) measure, together with the National Bureau of Economic Research (NBER) recession periods (gray bars). This figure illustrates the relationship found between stock market liquidity and the business cycle. As can be seen from the figure, liquidity clearly worsens (illiquidity increases) well ahead of the onset of the NBER recessions.

Our results are relevant for several strands of the literature. One important strand is the literature on forecasting economic growth using different asset prices, including interest rates, term spreads, stock returns, and exchange rates. The forward-looking nature of asset markets makes the use

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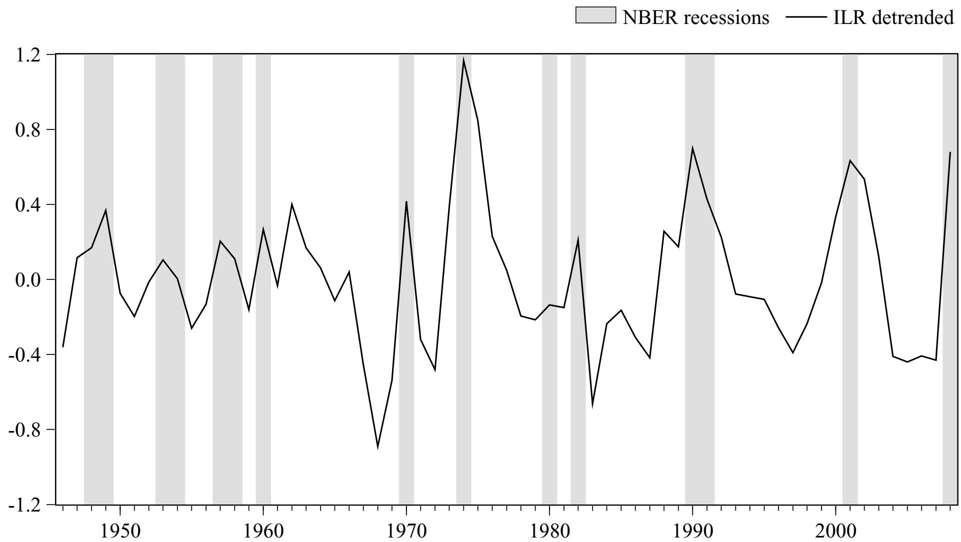

Figure 1. Liquidity and the business cycle. The figure shows time-series plots of the detrended Amihud (2002) illiquidity ratio (*ILR*) for the United States over the period 1947 to 2008. The gray bars indicate the NBER recession periods. *ILR* is an elasticity (price impact) measure of liquidity and reflects how much prices move in response to trading volume. *ILR* is first calculated for each stock for each year. Then the equally weighted cross-sectional average for each year is calculated. A more precise definition is found in equation (2) in the paper. Note that *ILR* reflects illiquidity, so a high value reflects a high price impact of trades (i.e., low liquidity). *ILR* is detrended using a Hodrick–Prescott filter.

of these prices as predictors of the real economy intuitive. If a stock price equals the expected discounted value of future earnings, it seems natural that it should contain information about future earnings growth. Theoretically, a link between asset prices and the real economy can be established from a consumption–smoothing argument. If investors are willing to pay more for an asset that pays off when the economy is thought to be in a bad state than for an asset that pays off when the economy is thought to be in a good state, then current asset prices should contain information about investors' expectations about the future real economy. In their survey article, however, Stock and Watson (2003) conclude that there is considerable instability in the predictive power of asset prices.

We shift focus to a different aspect of asset markets: the liquidity of the stock market (i.e., the costs of trading equities). It is a common observation that stock market liquidity tends to dry up during economic downturns. However, we show that the relationship between trading costs and the real economy is much more pervasive than previously thought. A link from trading costs to the real economy is not as intuitive as the link from asset prices, although several possible explanations are suggested in the literature.

One might speculate that the observed effects are a result of aggregate portfolio shifts from individual investors, where changes in desired portfolios are driven by changes in individuals' expectations of the real economy. We find some empirical evidence consistent with this "flight to quality" or "flight to liquidity" hypothesis (see for instance Longstaff (2004)).[1]

First, using data for the United States, we show that the informativeness of stock market liquidity for the real economy differs across stocks. In particular, the most informative stocks are those of small firms, which are the least liquid. Second, using data for Norway, for which we have unusually detailed information about stock market ownership, we show that changes in liquidity coincide with changes in the portfolio composition of investors of the hypothesized type. Specifically, before economic recessions we observe a flight to quality, where some investors leave the stock market altogether and others shift their stock portfolios into larger and more liquid stocks.

Brunnermeier and Pedersen (2009) provide an alternative explanation based on the interaction between securities' market liquidity and financial intermediaries' availability of funds. In the model, liquidity providers' ability to provide liquidity depends on their capital and margin requirements. During periods of financial stress, a reinforcing mechanism between market liquidity and funding liquidity leads to liquidity spirals. Reduced funding liquidity leads to a flight to quality in the sense that liquidity providers shift their liquidity provision toward stocks with low margins. In our Norwegian data set, we find that mutual funds have a stronger tendency to realize the value of their portfolios in small stocks during downturns than the general financial investor. This result provides some support for the model as mutual funds are most likely to face funding constraints during economic downturns (i.e., withdrawals from investors who have to realize the value of their portfolios). The current financial crisis has indeed shown that high systemic risk and funding liquidity problems in the financial sector can spread to the real economy.

Another possibility is that stock market liquidity affects the real economy through investment channels. For example, a liquid secondary market may make it easier for investors to invest in productive, but highly illiquid, long-run projects (Levine (1991), Bencivenga, Smith, and Starr (1995)). Empirical studies provide some support for this hypothesis. In a crosscountry regression, Levine and Zervos (1998) find significantly positive correlations between stock market liquidity and both current and future rates of economic growth after controlling for economic and political factors. Moreover, recent empirical evidence suggests that stock market liquidity is positively related to the costs of raising external capital.[2]

[1] The term "flight to quality" refers to a situation where market participants suddenly shift their portfolios toward securities with less risk. In Longstaff (2004), flight to liquidity is defined as a distinct phenomenon where market participants shift their portfolios from less liquid to more liquid bonds with identical credit risk, that is, from "off-the-run" to "on-the-run" Treasuries. We use the term flight to quality throughout the paper, although the portfolio shifts we analyze are also likely to have elements of flight to liquidity.

[2] See Lipson and Mortal (2009), who show a link between capital structure and liquidity. Also, for direct evidence, see Skjeltorp and Ødegaard (2010), who show that firms are willing to pay for improved liquidity before seasoned equity issues.

Even though there exist several possible explanations for a link between stock market liquidity and the real economy, it is still puzzling that liquidity measures provide information about the real economy that is not fully captured by stock returns. One explanation for why liquidity seems to be a better predictor than stock price changes is that stock prices contain a more complex mix of information that blurs the signals from stock returns (Harvey (1988)).

Two recent papers that investigate the relationship between equity order flow and macro fundamentals are closely related to our work. Beber, Brandt, and Kavajecz (2010) examine the information in order flow movements across equity sectors over the period 1993 to 2005 and find that an order flow portfolio based on cross-sector movements predicts the state of the economy up to 3 months ahead. They also find that the cross-section of order flow across sectors contains information about future returns in the stock and bond markets. Kaul and Kayacetin (2009) study two measures of aggregate stock market order flow over the period 1988 to 2004 and find that both measures predict future growth rates for industrial production and real GDP. The common theme of these two papers and our research is that the trading process in stock markets contains leading information about the real economy. Our results are by far the most robust, however, as they are based on a sample period that spans over 60 years and covers 10 recessions. The two order flow papers also find some evidence that order flow contains information about future asset price changes. Kaul and Kayacetin (2009) and Evans and Lyons (2008) argue that the extra information contained in order flow data can be explained by aggregate order flows bringing together dispersed information from heterogeneously informed investors.

A number of other papers are also related to our study. Fujimoto (2003) and Söderberg (2008) examine the relationship between liquidity and macro fundamentals. However, although they both investigate whether time-varying stock market liquidity has macroeconomic sources, they do not consider the possibility of causality going the other way. Gibson and Mougeot (2004) find some evidence that a time-varying liquidity risk premium in the U.S. stock market is related to a recession index over the 1973 to 1997 period.

Our paper also contributes to the market microstructure literature on liquidity. Several empirical studies have found evidence of commonality and time variation in stock market liquidity measures; see Chordia, Roll, and Subrahmanyam (2000), Huberman and Halka (2001) and Hasbrouck and Seppi (2001). It is also well documented that time variation in liquidity affects asset returns; see, for example, Pástor and Stambaugh (2003) and Acharya and Pedersen (2005). The phenomenon of commonality is so far not fully understood, however. The Brunnermeier and Pedersen (2009) model discussed above can explain commonality across stocks, although the model is probably most relevant during periods of financial stress.[3] Our finding that time-varying aggregate stock liquidity has a business cycle component is new and quite intriguing. In

[3] Coughenour and Saad (2004) investigate commonality in liquidity amongst stocks handled by the same New York Stock Exchange (NYSE) specialist firm and provide evidence in favor of the Brunnermeier and Pedersen (2009) model.

particular, it suggests that pricing of liquidity risk cannot be explained solely by uninformed investors requiring a premium for ending up with the stock that the informed investors sell, as suggested in O'Hara (2003). Hence, the traditional arguments for why market microstructure matters for asset returns might be too narrow.

By showing that microstructure liquidity measures are relevant for macroeconomic analysis, our paper also enhances our understanding of the mechanism by which asset markets are linked to the macroeconomy. We show that the predictive power of liquidity holds up to adding existing asset price predictors. Given the documented instability in the predictive power of asset prices, an incremental indicator that might react earlier or in some way differently to shocks in the economy should be useful for policy purposes.

The rest of the paper is structured as follows. First, in Section I we look at the data. We define the measures that we use, we discuss the data sources, and we present summary statistics. Next, in Section II we document that liquidity is related to the real economy using data for the United States for the period 1947 to 2008. In Section III, we look at the causes of this predictability by splitting stocks into size groups and showing that the main source of the predictability appears to be the liquidity variation of small, relatively illiquid stocks. In Section IV, we use Norwegian data to test the robustness of the U.S. results. We continue to find that stock market liquidity contains information about the macroeconomy. Further, we find some evidence on the causes of time variation in aggregate liquidity, by linking changes in liquidity to changes in the portfolio composition of all investors at the Oslo Stock Exchange. We construct several measures of changes in the portfolio composition of investors and show that the periods associated with liquidity tightening coincide with the periods associated with flight to quality in investors' stock portfolios. Section V offers concluding remarks.

I. Liquidity Measures and Data

A. Liquidity Measures

Given that there are numerous theoretical definitions of liquidity, there are also many different empirical measures used to capture liquidity. Because our focus is on the link between liquidity and the real economy, we are agnostic about the choice of measure. We therefore use a number of common measures. Our choices of liquidity measures are driven by our desire for reasonably long time series. Although many liquidity measures require intraday information on trades and orders, such information is not available for the long time period considered in this paper, and hence we employ measures that can be calculated using data available at a daily frequency. We consider the following four liquidity measures: relative spread (*RS*), the Lesmond, Ogden, and Trczinka (1999) measure (*LOT*), the Amihud (2002) illiquidity ratio (*ILR*), and the Roll (1984) implicit spread estimator (*Roll*). Goyenko and Ukhov (2009) and Goyenko, Holden, and Trzcika (2009) show that the "low-frequency" versions of these liquidity proxies do well in capturing the spread cost and price impact estimated using intraday data. We find that the relevant links are relatively independent of which liquidity measures we employ. Note that all the liquidity measures we employ in this study measure illiquidity. Thus, when the measures have a high value, market liquidity is low and it is costly to execute a trade.

Spread costs are observed in dealer markets as well as in limit order markets. The *RS* is calculated as the quoted spread (the difference between the best ask and bid quotes) as a fraction of the midpoint price (the average of the best ask and bid quotes) and measures the implicit cost of trading a small number of shares.

Lesmond, Ogden, and Trzcinka (1999) suggest a measure of transaction costs (*LOT*) that does not depend on information about quotes or the order book. Instead, *LOT* is calculated from daily returns. It uses the frequency of zero returns to estimate an implicit trading cost. The *LOT* cost is an estimate of the implicit cost required for a stock's price *not* to move when the market as a whole moves. To see the intuition behind this measure, consider the simple market model

$$R_{it} = a_i + b_i R_{mt} + \varepsilon_{it}, \tag{1}$$

where R_{it} is the return on security i at time t, R_{mt} is the market return at time t, a is a constant term, b is a regression coefficient, and ε is an error term. In this model, for *any* change in the market return, the return of security i should move according to (1). If it does not, it could be that the price movement that *should* have happened is not large enough to cover the costs of trading. Lesmond, Ogden, and Trzcinka (1999) estimate how wide the transaction cost band around the current stock price has to be to explain the occurrence of no price movements (zero returns). The wider this band, the less liquid the security. Lesmond, Ogden, and Trzcinka show that their transaction cost measure is closely related to the bid–ask spread.

We also employ as a liquidity measure the Roll (1984) estimate of the implicit spread. This spread estimator, also called the effective bid–ask spread, is measured from the serial covariance of successive price movements. Roll shows that, assuming the existence of a constant effective spread s, this can be estimated as $\widehat{s} = \sqrt{-Scov}$, where $Scov$ is the first-order serial covariance of successive returns.[4] We calculate the *Roll* estimator based on daily returns.

Our final liquidity measure, Amihud's (2002) *ILR*, is a measure of the elasticity dimension of liquidity. Elasticity measures of liquidity try to capture the sensitivity of prices to trading volume. Thus, cost measures and elasticity measures are strongly related. Kyle (1985) defines the price impact as the response of price to order flow. Amihud proposes a price impact measure that is closely

[4] This estimator is only defined when $Scov < 0$. Harris (1990) suggests defining $\widehat{s} = -2\sqrt{Scov}$ if $Scov > 0$, but this would lead to an assumed *negative* implicit spread. A negative transaction cost for equity trading is not meaningful. We therefore only use the *Roll* estimator for stocks with $Scov < 0$, and leave the others undefined.

related to Kyle's measure. The daily Amihud measure is calculated as

$$ILR_{i,T} = 1/D_T \sum_{t=1}^{T} \frac{|R_{i,t}|}{VOL_{i,t}}, \tag{2}$$

where D_T is the number of trading days within a time window T, $|R_{i,t}|$ is the absolute return on day t for security i, and $VOL_{i,t}$ is the trading volume (in units of currency) on day t. It is standard to multiply the above estimate by 10^6 for practical purposes. The Amihud measure is called an illiquidity measure because a high estimate indicates low liquidity (high price impact of trades). Thus, *ILR* captures how much the price moves for each volume unit of trades.

B. *Liquidity Data*

To calculate the liquidity measures, we use data on stock prices, returns, and trading volume. For the United States, we obtain sample data from CRSP for the period 1947 to 2008. To keep the sample as homogeneous as possible over the entire period, we restrict the analysis to the common shares of stocks listed at the NYSE. For Norway, we obtain similar data to the CRSP data from the Oslo Stock Exchange data service.[5] The Norwegian sample covers the period 1980 to 2008. For both the U.S. and Norwegian samples, we calculate the different liquidity measures each quarter for each security and then take the equally weighted average across securities for each liquidity variable.

In Table I, we present descriptive statistics for the liquidity measures of interest. Note that for the United States, we do not have complete data for bid–ask spreads and thus we have to leave these out in our time-series analysis for the United States.[6] Looking first at the descriptive statistics for the United States in Panel A of Table I, we see that the average *RS* for the full sample period is 2.1%, whereas the *RS* of the median firm is 1.4%. Looking at the subperiod statistics, we see some changes over time across all liquidity measures. Panel B shows the correlations between the liquidity proxies for the United States. We see that all the liquidity measures are positively correlated. The lowest correlation is between *ILR* and *Roll*, but the correlation is still as high as 0.32. In addition, the high correlation between *LOT* and *RS* indicates that *LOT* is a good estimator for the actual spread cost.

Panel C of Table I gives similar descriptive statistics for the Norwegian sample. The liquidity of the Norwegian market has improved over the sample, but has also varied across subperiods. In Panel D, we observe that all the liquidity proxies are strongly positively correlated also for Norway. Overall,

[5] We use all equities listed at the Oslo Stock Exchange with the exception of very illiquid stocks. Our criteria for filtering the data are the same as those used in Næs, Skjeltorp, and Ødegaard (2008), that is, we remove years in which a stock is priced below NOK 10, and remove stocks with less than 20 trading days in a year.

[6] This is due to bid and ask prices not being present in the CRSP data for the whole period. They have been backfilled for the early period, but in the 1950s through the 1970s there are essentially no bid and ask observations in the CRSP data.

Table I

Describing Liquidity Measures

Panels A and B show descriptive statistics for the U.S. liquidity measures. The U.S. sample covers the period from 1947 through 2008. The liquidity measures examined are the relative bid–ask spread (*RS*), the Lesmond, Ogden, and Trzcinka (1999) *LOT*, the Amihud (2002) *ILR* and the Roll (1984) implicit spread estimator (*Roll*). Note that the *RS* is not universally available; the CRSP database only includes full data on spreads starting in 1980, but there are some observations earlier. The liquidity measures are calculated for each available stock once each quarter. Panel A shows the mean and median of the liquidity measures, the number of securities used, the total number of observations (each security is observed in several quarters), and estimates of average liquidity measures for different subperiods. Panel B shows correlation coefficients between the liquidity measures. The correlations are calculated across all stocks and time, that is, the liquidity measures are calculated for each available stock once each quarter, and the correlations are pairwise correlations between these liquidity measures. Panels C and D show corresponding statistics for the Norwegian liquidity measures. The Norwegian sample covers the period from 1980 through 2008.

Panel A: Descriptive Statistics, U.S. Liquidity Measures

Liquidity Measure	Mean	Median	No. Secs.	No. Obs.	Means, Subperiods 1947–59	1960–69	1970–79	1980–89	1990–99	2000–08
RS	0.021	0.014	4,248	146,262	0.021	0.019		0.020	0.027	0.016
LOT	0.035	0.022	5,177	340,076	0.027	0.031	0.051	0.037	0.040	0.027
ILR	0.657	0.056	5,178	340,668	1.900	0.818	0.829	0.294	0.366	0.176
Roll	0.017	0.013	5,141	174,326	0.012	0.013	0.015	0.015	0.017	0.018

Panel B: Correlation Coefficients, U.S. Liquidity Measures

	RS	*LOT*	*Roll*
LOT	0.72		
Roll	0.40	0.62	
ILR	0.41	0.38	0.32

Panel C: Descriptive Statistics, Norwegian Liquidity Measures

Liquidity Measure	Mean	Median	No. Secs.	No. Obs.	Means, Subperiods 1980–1989	1990–1999	2000–2008
RS	0.042	0.029	788	14,942	0.041	0.046	0.040
LOT	0.054	0.039	753	14,852	0.055	0.064	0.049
ILR	0.772	0.205	770	15,092	1.149	0.875	0.452
Roll	0.027	0.021	663	7,209	0.027	0.026	0.026

Panel D: Correlation Coefficients, Norwegian Liquidity Measures

	RS	*LOT*	*Roll*
LOT	0.64		
Roll	0.65	0.51	
ILR	0.40	0.34	0.49

the high correlations between these measures suggest they contain some of the same information.

C. Macro Data

To proxy for the state of the real economy we use real GDP (*GDPR*), the unemployment rate (*UE*), real consumption (*CONSR*), and real investment (*INV*).[7] We also use a number of financial variables shown in the literature to contain leading information about economic growth. From the equity market we use *Excess market return* (er_m), calculated as the value-weighted return on the S&P500 index in excess of the 3-month T-bill rate, and *Market volatility* (*Vola*), measured as the cross-sectional average volatility of the sample stocks, where volatility is calculated as the standard deviation of daily returns over the quarter. We also use *Term spread* (*Term*), calculated as the difference between the yield on a 10-year Treasury bond benchmark and the yield on the 3-month T-bill, and *Credit spread* (*Cred*), measured as the yield difference between Moody's Baa credit benchmark and the yield on a 30-year government bond benchmark. Moody's long-term corporate bond yield benchmark consists of seasoned corporate bonds with maturities as close as possible to 30 years.[8] We use similar macro series for Norway.[9]

D. Time-Series Adjustment of Series

The sample period that we use covers more than 60 years. Over this long period changes in market structure, competition, technology, and activity in financial markets potentially generate nonstationarities in the liquidity series. Accordingly, we perform several unit root tests for each series to determine whether the series needs to be transformed to stationary series.

Although we want to avoid the risk of obtaining spurious results, we also want to avoid the risk of overdifferentiating our variables. We therefore employ two tests. The first test is the Augmented Dickey-Fuller (ADF) test with a null that the variable has a unit root. The second test is the test proposed by Kwiatkowski et al. (1992) (KPSS), where the null hypothesis is that the series is stationary. As noted by Kwiatkowski et al., their test is intended to complement unit root tests such as the ADF test. Among our liquidity proxies, *Roll* is the only variable for which we reject the null of a unit root using the

[7] The *GDPR* series is the real gross domestic product, *UE* is the unemployment rate for full-time workers, *CONSR* is real personal consumption expenditures, and *INV* is real private fixed investments. All series are seasonally adjusted. *GDPR* and *INV* are from the Federal Reserve Bank of St. Louis, *UE* is from the U.S. Bureau of Labor Statistics, and *CONSR* is from the U.S. Dept. of Commerce.

[8] The source of these variables is Ecowin/Reuters.

[9] *GDPR* is the real gross domestic product for mainland Norway (excluding oil production). *UE* is the unemployment rate, *CONSR* is the real households' consumption expenditure, and *INV* is real gross investments. All numbers are seasonally adjusted. The data source is Statistics Norway (SSB).

ADF test. We are also unable to reject the null (of stationarity) using the KPSS test. Both the *LOT* and *ILR* series are unit root processes according to the ADF test (both allowing for a drift and a deterministic trend), and in both cases the null of stationarity is rejected by the KPSS test.[10]

With respect to the other financial variables used in the analysis, the excess market return (er_m), stock market volatility (*Vola*), and the term spread (*Term*) are stationary. However, we cannot reject the null that the credit spread (*Cred*) has a unit root according to the ADF test. In addition, the null of stationarity is rejected by the KPSS test. The result that we cannot reject the null that the credit spread is a unit root has been documented previously by, for example, Pedrosa and Roll (1998) and Kiesel, Perraudin, and Taylor (2001). Thus, we transform *ILR*, *LOT*, and *Cred* to preserve stationarity.

Because we perform pseudo out-of-sample tests later in our analysis, we take care when transforming the series to only use the information available up to a given point in time. For this reason, we report results using a very simple method for making *ILR*, *LOT*, and *Cred* stationary, namely, by taking log differences.[11] We similarly use a simple differentiation of the macro variables.[12]

Table II shows the contemporaneous correlations between the different variables used in the analysis for the United States. All three liquidity measures are negatively correlated with the term structure and positively related to the credit spread. Thus, when market liquidity worsens, the term spread decreases and the credit spread increases. There is a positive correlation between all liquidity measures and market volatility, and a negative correlation between liquidity and the excess return on the market (er_m). Thus, when market liquidity is low, market volatility is high and market returns are low. This is consistent with the findings in Hameed, Kand, and Vishwanathan (2010) that negative market returns decrease stock liquidity. All liquidity variables are negatively correlated with growth in GDP, investments, and consumption, and positively correlated with the unemployment rate. Note that the macro variables are not known to the market participants before the following quarter. Thus, these correlations are a first indication that there is real time information about current underlying economic growth in market liquidity variables. Furthermore, we also see that the term spread has a significantly positive correlation with GDP growth and consumption growth, whereas the credit spread is negatively

[10] Also, looking at the correlograms for the different series, we see that the autocorrelation function for the *Roll* measure converges to zero relatively quickly (4 quarters). However, both the *ILR* and *LOT* measures are much more persistent with large and significant autocorrelations up to 24 quarters.

[11] We have also considered two alternative methods for making these three series stationary. One is to *demean* the series relative to a 2-year moving average of the series. The other is to use a Hodrick–Prescott filter. In the Internet Appendix, available at http://www.afajof.org/supplements.asp, we show that these alternative methods yield similar results.

[12] *dGDPR* is real GDP growth, calculated as $dGPDR = \ln(GDPR_t/GDPR_{t-1})$, *dUE* is the growth in the unemployment rate, calculated as $dUE = \ln(UE_t/UE_{t-1})$, *dCONSR* is real consumption growth, calculated as $dCONSR = \ln(CONSR_t/CONSR_{t-1})$, and *dINV* is real growth in investment, calculated as $dINV = \ln(INV_t/INV_{t-1})$.

Table II

Correlations between U.S. Variables

The table shows the Pearson correlation coefficients between the variables used in the analysis for the United States. The associated p-values are reported in parentheses below each correlation coefficient. *ILR*, *LOT*, and *Roll* are the three liquidity measures. The cross-sectional liquidity measures are calculated as equally weighted averages across stocks. *Term* is our proxy for the term spread and *Cred* is the credit spread. With respect to additional equity market variables, we examine market volatility (*Vola*), and excess market return (er_m). With respect to macroeconomic variables, *dGDPR* is real GDP growth, *dINV* is growth in investment, *dUE* is growth in the unemployment rate, and *dCONSR* is real consumption growth.

	Market Variables							Macro Variables		
	dILR	*dLOT*	*Roll*	*Term*	*dCred*	*Vola*	er_m	*dGDPR*	*dINV*	*dCONSR*
Term	−0.17	−0.14	−0.04							
	(0.00)	(0.04)	(0.55)							
dCred	0.32	0.34	0.42	−0.21						
	(0.00)	(0.00)	(0.00)	(0.00)						
Vola	0.30	0.57	0.47	−0.15	0.42					
	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)					
er_m	−0.53	−0.19	−0.35	0.33	−0.17	−0.33				
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)				
dGDPR	−0.16	−0.10	−0.31	0.16	−0.27	0.01	0.09			
	(0.02)	(0.15)	(0.00)	(0.02)	(0.00)	(0.87)	(0.19)			
dINV	−0.16	−0.17	−0.40	0.18	−0.26	−0.07	0.09	0.73		
	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)	(0.27)	(0.21)	(0.00)		
dCONSR	−0.27	−0.15	−0.38	0.21	−0.34	−0.08	0.16	0.68	0.57	
	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.24)	(0.01)	(0.00)	(0.00)	
dUE	0.16	0.15	0.33	−0.10	0.28	0.08	−0.04	−0.65	−0.62	−0.56
	(0.01)	(0.03)	(0.00)	(0.14)	(0.00)	(0.21)	(0.58)	(0.00)	(0.00)	(0.00)

correlated with GDP growth, investment growth, and consumption growth, and positively correlated with unemployment. The signs of these correlations are what we would expect. Stock market volatility and returns are not significantly correlated with any of the macro variables, except for consumption growth. Finally, as one would expect, all the macro variables are significantly correlated with each other and have the expected signs.

E. Norwegian Ownership Data

An important reason for including Norwegian data in the paper is the availability of data on stock market ownership for all investors at the Oslo Stock Exchange, which we use to investigate aggregate patterns in stock ownership.

Our data on stock ownership come from the centralized records on stock ownership in Norway. All ownership of stocks at the Oslo Stock Exchange is registered in a single, government-controlled entity, the Norwegian Central Securities Registry (VPS). From this source, we have access to monthly observations of the equity holdings of the complete stock market. At each date, we observe the number of stocks held by every owner. Each owner has a unique identifier, which allows us to follow each owner's holdings over time. For each owner, the data also include a sector code, which allows us to distinguish between such types as mutual fund owners, financial owners (which include mutual funds), industrial (nonfinancial corporate) owners, private (individual) owners, state owners, and foreign owners. This data set allows us to construct the actual monthly portfolios of all investors at the stock exchange. We can also calculate, for each stock, measures of ownership concentration and fractions held by different owner types.[13] Table III presents some descriptive statistics for the stock ownership data at the Oslo Stock Exchange.

II. Predicting U.S. Economic Growth with Market Illiquidity

A. In-Sample Evidence

We start by assessing the in-sample predictive ability of market illiquidity. The models we examine are predictive regressions of the form:

$$y_{t+1} = \alpha + \beta LIQ_t + \gamma' \mathbf{X}_t + u_{t+1}, \tag{3}$$

where y_{t+1} is the realized growth in the macro variable of interest over quarter $t+1$, LIQ_t is market illiquidity measured for quarter t, $\mathbf{X}_t$ is a vector of control variables (*Term*, *dCred*, *Vola*, er_m, and the lag of the dependent variable) observed at t, and γ' is the vector of coefficient estimates on the control variables. We use three different proxies for equity market illiquidity: *ILR*, *LOT*, and *Roll*. Our main dependent variable (y_{t+1}) is real GDP growth. However, we also examine three additional macro variables related to economic growth, namely, growth in the unemployment rate (*dUE*), real consumption growth (*dCONSR*), and real growth in private investments (*dINV*).

Table IV summarizes the results from the various regression specifications. The first specification only includes the liquidity variable and one lag of the dependent variable.[14] We see that the coefficient on market illiquidity ($\hat{\beta}$) is highly significant for most models regardless of which illiquidity proxy we use. An increase in market illiquidity predicts lower real GDP growth (*dGDPR*), an increase in unemployment (*dUE*), and a slowdown in consumption (*dCONSR*) and investment (*dINV*).

To shed more light on the significance of the liquidity variable, we report the $\bar{R}^2$ for models estimated with and without liquidity in the columns on the right of the table. We find, for example, that adding liquidity to the regression forecasting *dGDPR* improves the $\bar{R}^2$ from 3% to 13%.

It is at this point useful to interpret the coefficients to get at the magnitude of the estimated effects. Starting with the regression predicting changes in GDP as a function of changes in *ILR*, we ask how much growth changes. Let

[13] More details about these data can be found in, for example, Bøhren and Ødegaard (2001, 2006) and Ødegaard (2009).

[14] We have also estimated the models with different lag specifications with up to four lags of the dependent variable and the liquidity variables. This does not materially affect the results.

Table III

Descriptive Statistics for the Norwegian Ownership Data

The table shows summary statistics for the Norwegian ownership data. For each stock, we calculate the fraction of the stock held by its largest owner (Largest owner) and three largest owners (Three largest). We also calculate two Herfindahl indices: the sum of squared ownership fractions of all the firms' owners (Herfindahl index), and the sum of squared ownership fractions of all but the three largest owners (Herfindahl ex. three largest). We also show the total number of owners, only counting owners owning more than 100 shares (Total no. owners), and the fraction of the firm held by the five different mutually exclusive owner types: state, foreign, nonfinancial (industrial), individual (private), and financial owners. Finally, in the last line we show the fraction owned by the subgroup of financial owners that are mutual funds (note that these mutual funds are contained in the total holdings of financials in the line above.) Data from 1989 to 2007 (annual 1989 to 1992, monthly 1993 to 2007). The columns are Med.: the median value; vw: the value-weighted average, where firm value is used to do value weighting; and ew: the equally weighted average.

	1989–2007			1989–1994			1995–1999			2000–2007		
	Mean			Mean			Mean			Mean		
	vw	ew	Med.	vw	ew	Med.	vw	ew	Med.	vw	ew	Med.
Largest owner	37.2	27.5	21.1	28.4	26.2	20.8	29.4	27.0	21.0	44.8	28.2	21.3
Three largest	50.9	44.1	41.9	45.1	43.4	38.5	44.8	43.4	41.8	56.6	44.7	43.4
Herfindahl index	0.22	0.15	0.08	0.15	0.14	0.08	0.15	0.15	0.08	0.29	0.16	0.09
Herfindahl ex. three largest	0.03	0.04	0.03	0.03	0.04	0.03	0.03	0.04	0.03	0.02	0.04	0.02
Total no. owners	13,965	2,330	851	7,861	1,853	654	7,511	1,847	814	19,902	2,781	967
Fraction state owners	27.0	6.2	0.5	21.2	6.5	1.0	19.6	6.3	0.4	33.4	6.0	0.4
Fraction foreign owners	31.6	22.6	12.6	29.3	20.5	13.3	33.4	22.5	13.7	31.2	23.4	11.2
Fraction nonfinancial owners	19.1	35.1	28.9	25.6	41.0	40.8	20.9	33.6	28.8	16.0	34.2	28.0
Fraction individual owners	7.5	19.7	13.3	10.9	18.3	12.4	8.8	20.0	13.0	5.7	19.9	13.7
Fraction financial owners	16.8	18.7	16.6	18.5	20.6	18.1	20.5	21.0	19.4	13.9	16.8	14.2
Fraction mutual fund owners	5.5	6.8	4.9	4.5	5.8	5.2	6.6	7.2	6.1	5.0	6.8	4.4

Table IV

In-Sample Prediction of Macro Variables

The table shows the results from predictive regressions where we regress next quarter growth in different macro variables on three proxies for market illiquidity for the period 1947 to 2008. Market illiquidity (*LIQ*) is proxied by one of three illiquidity measures: the Amihud illiquidity ratio (*ILR*), the *LOT* measure, and the Roll measure (*Roll*). We use the log difference in *ILR* and *LOT* to preserve stationarity, whereas the Roll measure is not differenced. The cross-sectional liquidity measures are calculated as equally weighted averages across stocks. The model estimated is $y_{t+1} = \alpha + \beta^{LIQ} LIQ_t + \gamma' \mathbf{X}_t + u_{t+1}$, where y_{t+1} is real GDP growth (*dGDPR*), growth in the unemployment rate (*dUE*), real consumption growth (*dCONSR*), or growth in private investment (*dINV*). We also include one lag of the dependent variable (y_t) and *Term*, *dCred*, *Vola*, and er_m as control variables. The Newey-West corrected t-statistics (with four lags) are reported in parentheses below the coefficient estimates, and $\bar{R}^2$ is the adjusted R^2. The column on the far right, labeled "ex.liq. $\bar{R}^2$," gives the adjusted R^2 for a model *without* the liquidity variable.

Dependent Variable (y_{t+1})	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{Term}$	$\hat{\gamma}^{dCred}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$	$\bar{R}^2$	ex.liq. $\bar{R}^2$
Panel A: *ILR* Liquidity Measure									
dGDPR	0.006	−0.013	0.224					0.13	0.03
	(7.58)	(−5.38)	(3.68)						
dUE	0.003	0.074	0.300					0.13	0.07
	(0.61)	(3.68)	(5.14)						
dCONSR	0.006	−0.006	0.305					0.11	0.08
	(7.08)	(−3.33)	(4.46)						
dINV	0.006	−0.034	0.265					0.15	0.06
	(2.95)	(−6.19)	(3.97)						
dGDPR	0.006	−0.011	0.207	0.001	−0.012			0.17	0.10
	(5.14)	(−4.59)	(3.48)	(0.95)	(−2.91)				
dUE	0.014	0.055	0.298	−0.009	0.089			0.18	0.15
	(1.88)	(3.10)	(5.09)	(−2.61)	(3.01)				
dCONSR	0.004	−0.005	0.303	0.001	−0.003			0.13	0.12
	(3.81)	(−2.79)	(4.41)	(2.23)	(−0.94)				
dINV	0.002	−0.027	0.239	0.004	−0.035			0.23	0.17
	(0.57)	(−5.27)	(3.79)	(2.41)	(−3.93)				
dGDPR	0.006	−0.008	0.196	0.000	−0.012	0.000	0.015	0.17	0.15
	(5.82)	(−3.87)	(3.38)	(0.72)	(−2.99)	(0.07)	(1.95)		
dUE	0.005	0.021	0.302	−0.007	0.097	−0.033	−0.228	0.22	0.22
	(0.75)	(1.17)	(6.05)	(−2.44)	(3.16)	(−0.93)	(−4.54)		
dCONSR	0.005	−0.001	0.301	0.001	−0.003	0.002	0.026	0.17	0.18
	(4.65)	(−0.35)	(4.36)	(2.19)	(−1.21)	(0.39)	(3.38)		
dINV	0.003	−0.020	0.236	0.003	−0.037	0.007	0.045	0.24	0.22
	(1.21)	(−3.81)	(3.70)	(2.37)	(−3.87)	(0.50)	(2.02)		

(*continued*)

us look at a one-standard deviation change in *dILR*. The standard deviation of *dILR* is 0.26. Multiplying this by the estimated coefficient on *dILR* of −0.013 predicts a change in *dGDPR* of −0.003, that is, we would predict a 0.3% decrease in quarterly GDP growth for a one standard deviation increase in *ILR*. During the sample period, average GDP growth was 0.8% per quarter. The predicted change in GDP is thus about a third of average quarterly growth. A similar exercise for the *LOT* variable predicts a change in GDP growth of

Table IV—*Continued*

Dependent Variable (y_{t+1})	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{Term}$	$\hat{\gamma}^{dCred}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$	$\bar{R}^2$	ex.liq. $\bar{R}^2$
				Panel B: *LOT* Liquidity Measure					
dGDPR	0.007	−0.017	0.168					0.06	0.03
	(7.52)	(−2.78)	(2.59)						
dUE	0.003	0.129	0.261					0.10	0.07
	(0.47)	(3.14)	(4.42)						
dCONSR	0.006	−0.009	0.282					0.09	0.08
	(7.04)	(−1.74)	(3.86)						
dINV	0.007	−0.039	0.218					0.07	0.06
	(3.04)	(−2.56)	(3.21)						
dGDPR	0.006	−0.012	0.160	0.001	−0.014			0.11	0.10
	(5.20)	(−2.11)	(2.52)	(1.06)	(−3.48)				
dUE	0.014	0.088	0.269	−0.009	0.098			0.16	0.15
	(1.76)	(2.53)	(4.58)	(−2.73)	(3.26)				
dCONSR	0.004	−0.006	0.285	0.001	−0.004			0.12	0.12
	(3.94)	(−1.30)	(3.95)	(2.32)	(−1.21)				
dINV	0.002	−0.021	0.200	0.004	−0.043			0.18	0.17
	(0.71)	(−1.61)	(3.17)	(2.61)	(−4.60)				
dGDPR	0.007	−0.012	0.155	0.000	−0.014	0.006	0.028	0.16	0.15
	(6.29)	(−2.13)	(2.64)	(0.60)	(−3.48)	(1.03)	(3.63)		
dUE	0.004	0.110	0.285	−0.007	0.098	−0.085	−0.261	0.23	0.22
	(0.61)	(2.73)	(5.83)	(−2.32)	(3.17)	(−2.02)	(−5.44)		
dCONSR	0.005	−0.006	0.290	0.001	−0.003	0.005	0.027	0.18	0.18
	(4.94)	(−1.18)	(4.26)	(2.16)	(−1.22)	(0.90)	(4.41)		
dINV	0.005	−0.024	0.207	0.003	−0.041	0.017	0.075	0.22	0.22
	(1.67)	(−1.80)	(3.21)	(2.33)	(−4.38)	(1.14)	(3.85)		
				Panel C: *Roll* Liquidity Measure					
dGDPR	0.019	−0.811	0.136					0.10	0.03
	(5.94)	(−4.11)	(2.16)						
dUE	−0.074	5.206	0.236					0.12	0.07
	(−3.07)	(3.29)	(4.23)						
dCONSR	0.013	−0.436	0.269					0.11	0.08
	(4.23)	(−2.28)	(3.47)						
dINV	0.039	−2.192	0.188					0.13	0.06
	(4.26)	(−3.61)	(3.08)						
dGDPR	0.016	−0.716	0.133	0.001	−0.012			0.16	0.10
	(5.29)	(−3.79)	(2.15)	(1.91)	(−2.84)				
dUE	−0.051	4.639	0.248	−0.011	0.083			0.19	0.15
	(−2.23)	(3.15)	(4.64)	(−3.62)	(2.60)				
dCONSR	0.011	−0.465	0.268	0.001	−0.002			0.15	0.12
	(3.98)	(−2.54)	(3.47)	(3.00)	(−0.68)				
dINV	0.030	−2.007	0.177	0.005	−0.034			0.25	0.17
	(3.85)	(−3.80)	(3.25)	(3.56)	(−3.89)				
dGDPR	0.016	−0.614	0.135	0.001	−0.013	0.006	0.021	0.18	0.15
	(4.78)	(−3.03)	(2.30)	(1.39)	(−3.07)	(1.12)	(2.74)		
dUE	−0.044	3.559	0.270	−0.009	0.091	−0.065	−0.219	0.23	0.22
	(−1.80)	(2.25)	(5.90)	(−3.05)	(2.84)	(−1.71)	(−4.74)		
dCONSR	0.010	−0.318	0.282	0.001	−0.002	0.004	0.023	0.19	0.18
	(3.63)	(−1.76)	(4.03)	(2.71)	(−0.93)	(0.92)	(3.66)		
dINV	0.030	−1.895	0.179	0.005	−0.037	0.028	0.055	0.28	0.22
	(3.81)	(−3.43)	(3.17)	(3.20)	(−4.11)	(2.34)	(2.84)		

−0.2% (−0.00192) for a one standard deviation increase in *LOT*. Similarly, a one standard deviation increase in *Roll* predicts a change in GDP growth of −0.8% (−0.00796).

In sum, the results indicate that market illiquidity contains economically significant information about future economic growth. When market liquidity worsens, this is followed by a significant slowdown in economic growth.

Several other financial variables have been found to contain information about future macroeconomic conditions. We therefore also consider regression specifications in which we control for these variables. Table II shows that our liquidity proxies are correlated with the term spread, the credit spread, as well as the market return and volatility. This is what we would expect, because one hypothesis is that variation in market liquidity captures changes in expectations about future growth that should also be reflected in other financial variables. The main purpose of adding other financial control variables to the models is to determine whether liquidity provides an additional (or less noisy) signal about future macro fundamentals. We start by including two nonequity control variables (in addition to the lag of the dependent variable). These control variables are the term spread (*Term*) and credit spread (*Cred*). Harvey (1988) shows that *Term* is a strong predictor of consumption growth and a superior predictor of growth in *GNP* relative to stock returns (Harvey (1989)). With respect to *Cred*, Gilchrist, Yankov, and Zakrajsek (2009) show that credit spreads contain substantial predictive power for economic activity.

These regression specifications are also listed in Table IV. Looking first at the estimation results for GDP growth, we see that although *dCred* enters significantly in all three models, the coefficients on liquidity retain their level, sign, and significance. Interestingly, the coefficient on the term spread ($\hat{\gamma}^{Term}$) is not significant in the models that include *dILR* or *dLOT*. In specifications reported in the Internet Appendix we find that excluding the liquidity variables in these models restores the significance of *Term*. The results for the other macro variables yield the same results. The coefficients on liquidity are robust to the inclusion of the term spread and the credit spread in the models. However, the results suggest that both the term spread and the credit spread are important predictor variables, and a model that contains the two bond market variables in addition to liquidity has higher adjusted R^2 compared to the model just containing liquidity and the lag of the dependent variables.

As a final exercise, we include the equity market variables excess market return (er_m) and volatility (*Vola*) in the models, in addition to the term spread and the credit spread. In the models for GDP growth, we find that although market volatility is insignificant, market return enters significantly with a positive coefficient. However, this does not affect the significance of any of the liquidity coefficients. Market liquidity thus retains its predictive power for real GDP growth. In the models for the unemployment rate, the results are more mixed. In the model with *dILR*, we see that adding market return renders the *dILR* coefficient insignificant. However, in the models with *Roll* and *dLOT*, the coefficients are unaffected. In the models for real consumption growth, we see that market liquidity (regardless of liquidity measure) is rendered insignificant when the excess return on the market is included in the model. Finally, in the models for investment growth, the liquidity coefficients are unaffected by the inclusion of market return.

Overall, the results show that although other financial variables are clearly useful for predicting future economic growth, we find that there is additional information in market illiquidity, even after controlling for well-known alternative variables. Market liquidity seems to be a particularly strong and robust predictor of real GDP growth, unemployment, and investment growth. For future real consumption growth, however, there does not appear to be additional information in liquidity that is not already reflected in the term spread and market return.

A.1. Causality

We are primarily interested in predicting macroeconomic conditions with liquidity, but there is also the possibility of causality going in the opposite direction, with changes in economic conditions affecting market illiquidity. We know from earlier studies that monetary policy shocks have an effect on stock and bond market illiquidity (see, for example, Söderberg (2008) and Goyenko and Ukhov (2009)), whereas there is no effect of shocks to real economic variables on stock market illiquidity. However, neither of these studies considers the reverse causality from market liquidity to real economic variables. We look at this issue directly by performing Granger causality tests. We return to the specification with only liquidity and real variables and perform Granger causality tests between the different illiquidity proxies and real GDP growth.[15] Table V reports the results. The tests are conducted using a vector auto regression (VAR) framework. We perform the tests for the whole sample and for subsamples, where we split the sample period both in the middle and into five 20-year subperiods (overlapping by 10 years). The first row of Table V shows the number of quarterly observations in each sample period, and the second row shows the number of NBER recessions that occurred within each sample period. In Panel A of the table, we run Granger causality tests between *dILR* and *dGDPR*. Looking first at the column labeled "Whole sample," we see that the null hypothesis that GDP growth *does not* Granger cause *dILR* ($dGDPR \nrightarrow dILR$) cannot be rejected, whereas the hypothesis that *dILR does not* Granger cause GDP growth ($dILR \nrightarrow dGDPR$) is rejected at the 1% level. For the different subperiods, we see that the relation is remarkably stable. Thus, Panel A of the table shows strong and stable evidence of one way Granger causality from market illiquidity, proxied by *dILR*, to *dGDPR*, whereas there is no evidence of reverse causality from *dGDPR* to *dILR*. In Panels B and C of the

[15] Results from a much more comprehensive VAR specification are reported and discussed in the Internet Appendix. There we also examine the dynamic linkages between the other financial variables and liquidity as well as test for Granger causality between all the variables used in the analysis. Furthermore, we analyze the robustness of the response function of *dGDPR* to a shock in *dILR* for different orderings of the endogenous variables.

Table V

Granger Causality Tests

The table shows Granger causality tests between quarterly real GDP growth (*dGDPR*) and (a) the Amihud *ILR*, (b) the *LOT* measure, and (c) the Roll measure. The cross-sectional liquidity measures are calculated as equally weighted averages across stocks. The test is performed for the whole sample period and different subperiods. For each measure, we first test the null hypothesis that real GDP growth *does not* Granger cause market illiquidity and then whether market illiquidity *does not* Granger cause real GDP growth. We report the χ^2 and p-value (in parentheses) for each test. We choose the optimal lag length for each test based on the Schwartz criterion. For each illiquidity variable, the test is performed on the whole sample period (1947q1–2008q4), the first (1947Q1–1977Q4) and second (1978Q1–2008Q4) halves of the sample, and for rolling 20-year subperiods overlapping by 10 years. The first two rows report the number of quarterly observations covered by each sample period and the number of NBER recession periods within each sample. ** and * denotes a rejection of the null hypothesis at the 1% and 5% level, respectively.

	Whole Sample	First Half	Second Half	20-Year Subperiods				
	1947–2008	1947–1977	1977–2008	1950–1970	1960–1980	1970–1990	1980–2000	1990–2008
N (observations)	243	119	124	84	84	84	84	76
NBER recessions	11	6	5	5	4	4	2	3
Panel A: *ILR*								
H_0: $dGDPR \nrightarrow dILR$								
χ^2	4.08	1.66	3.13	3.66	3.56	3.35	2.83	2.66
p-value	0.13	0.44	0.21	0.16	0.17	0.19	0.24	0.26
H_0: $dILR \nrightarrow dGDPR$								
χ^2	31.97**	19.01**	14.50**	15.81**	8.89**	11.7**	11.64**	11.85**
p-value	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
Panel B: *LOT*								
H_0: $dGDPR \nrightarrow dLOT$								
χ^2	2.21	1.77	1.13	2.20	1.48	1.21	0.06	1.05
p-value	0.14	0.18	0.29	0.14	0.22	0.27	0.80	0.31
H_0: $dLOT \nrightarrow dGDPR$								
χ^2	9.55**	13.37**	1.45	8.24**	7.7**	6.81**	1.22	0.99
p-value	0.00	0.00	0.23	0.00	0.01	0.01	0.27	0.32
Panel C: *Roll*								
H_0: $dGDPR \nrightarrow Roll$								
χ^2	0.086	0.305	0.745	0.270	0.012	2.300	1.332	0.014
p-value	0.77	0.58	0.39	0.60	0.91	0.13	0.25	0.91
H_0: $Roll \nrightarrow dGDPR$								
χ^2	15.96**	5.56*	10.80**	2.95	10.74**	9.31**	4.43*	10.18**
p-value	0.00	0.02	0.00	0.09	0.00	0.00	0.04	0.00

table, we perform the same tests for the *dLOT* and *Roll* measures. For the full sample period, we find support for Granger causality from *dLOT* and *Roll* to GDP growth, although there is no evidence of reverse causality. Similarly, for the subperiods, we find support for one-way Granger causality from *Roll* to *dGDPR*, except for the first 20-year period for which we are only able to reject the null that the Roll measure does not Granger cause real GDP growth at the 10% significance level. Based on the subsample results for the *dLOT* measure, we cannot reject the null that *dLOT does not* Granger cause *dGDPR* in the second half of the sample. One potential reason *LOT* has become less informative over the sample period is the increase in trading activity. Recall that the transaction costs measure uses zero return days to identify a stock's implicit transaction costs. Thus, if the number of zero return days has decreased at the same time as trading activity has increased, *LOT* may have become a more noisy estimator of actual transaction costs in the last part of the sample.

A.2. Market Liquidity and NBER Recessions

The in-sample results on the predictive content of liquidity for macro variables can be visualized using an "event study." We take the onset of a recession to be the "event date," and plot the evolution of the various series of interest around this date. In Panel A of Figure 2, we plot changes in liquidity relative to the onset of a recession, as defined by the NBER. For each NBER recession, we first calculate the quarterly GDP growth starting five quarters before ($t = -5Q$) the first NBER recession quarter (NBER1) and ending five quarters after the end of each NBER recession ($t = 5Q$). Next, we average the GDP growth for each quarter across all recessions, and we accumulate the average GDP growth over the event window. We then do the same for *ILR*. Thus, the figure shows the average pattern in *ILR* before, during, and after U.S. recessions averaged across all 10 NBER recessions (shaded area) in our sample from 1947 to 2008.[16] From the figure in Panel A, we see that the liquidity starts to worsen from 4 quarters before the onset of the recession, despite the fact that the economy is still expanding. This style of analysis also allows us to make comparisons of the informational content of the different predictive variables. Panel B of Figure 2 shows similar plots, where we also add the financial control variables term spread, credit spread, excess market return, and volatility. Looking first at the term spread (dotted line) in picture (a), we see that there is a systematic decline in the term spread in all the quarters prior to the first NBER recession quarter (NBER1). This is consistent with the notion that the yield curve has a tendency to flatten and invert before recessions. We also see that the term spread increases again during the first quarters of the recession, predicting the end of the recession and increased growth. Thus, before the recession, the signal from both the term spread and market liquidity (solid line) seems to capture similar information about GDP growth. For the credit spread in picture (b), market liquidity and the credit spread appears to share a very similar path, although the liquidity series changes earlier than the credit spread. As we will

[16] Note that some NBER recessions only last for three quarters (e.g., 1980Q1–1980Q3), whereas some recessions last up to six quarters (e.g., 1973Q4–1975Q1 and 1981Q3–1982Q4). However, the most important point of the figure is that all NBER recessions are aligned to start at the same point (NBER1) in event time.

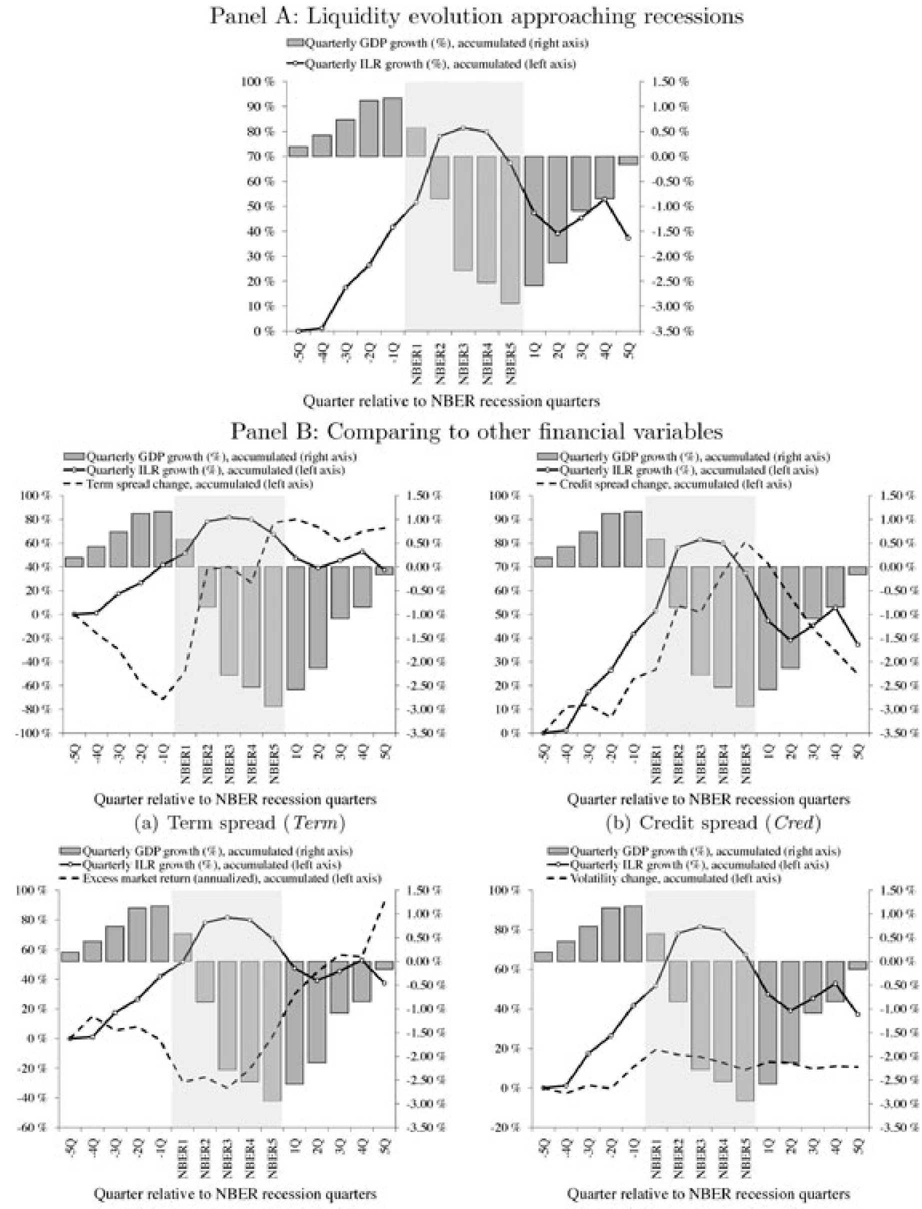

Figure 2. Market illiquidity around NBER recessions. The figure in Panel A shows the accumulated quarterly growth in *ILR* (solid line) and accumulated quarterly GDP growth (bars) averaged in event time across different NBER recession periods. All recession periods are aligned to start at NBER1, the first NBER recession quarter. The figure shows the results when looking at all 10 NBER recessions during the full sample period, 1947 to 2008. In Panel B, we show similar figures, adding evolutions of the cumulative average changes in (a) term spread, (b) credit spread, (c) excess market return, and (d) volatility.

see later in the out-of-sample analysis, the credit spread and market liquidity have very similar out-of-sample performance when predicting GDP growth. In picture (c), we see that the accumulated excess market return is relatively stable until the quarter just before the NBER recession starts, and, thus, it seems to be responding later than the other variables. Finally, in picture (d) we see that volatility increases in the quarter just before the NBER recessions starts. However, consistent with the regression results, the information in market volatility is small compared to the other variables.

B. Out-of-Sample Evidence for the United States

In the previous section, we find that market illiquidity has predictive power for economic growth for the whole sample period, for subperiods, and when controlling for other financial variables found in the literature to be informative about future economic growth. However, in-sample predictability does not necessarily mean that the predictor is a useful predictor out of sample. In this section, we examine whether market illiquidity is able to forecast quarterly real GDP growth out of sample.

B.1. Methodology and Timing of Information

When setting up our out-of-sample procedure, we need to be careful about the timing of the data so it reflects what would have been available to the forecaster when a forecast is made. Although the illiquidity variables and the other financial variables are observable in real time without revisions, real GDP growth is not. First, there is a publication lag of one quarter for GDP.[17] Second, there is an issue of later revisions in most macro variables. Although the publication lag is easily accounted for, the revisions are more tricky. Basically, the question is whether we want to forecast the first or final vintage of GDP growth. This depends on the question we are asking. If we were using macro variables to predict financial variables (e.g., returns), we would want to use the first vintage (real time version) of the macro variable because the later vintages (revised figures) would not be known to the forecaster (investor) when making his forecast. However, because the question we are asking is whether financial variables contain information about expected economic growth, we want to forecast the last vintage. The reason is that because the revisions are mainly due to measurement errors in the first/early vintage series, market participants' expectations about underlying economic growth should be unrelated to ("see through") measurement errors in the first vintages. Thus, we want to forecast the most precisely measured version of the macro variable, that is, the last vintage series.

In our out-of-sample analysis, we consider a rolling estimation scheme with a fixed width of 20 quarters (5 years). For all models, our first out-of-sample

[17] The Bureau of Economic Analysis releases the *final* GDP figure for quarter $t-1$ in the last month of the following quarter (t). However, it also releases an "advance" estimate in the first month of the following quarter as well as a "preliminary" release in the second month of the following quarter. Thus, at the end of t, a forecaster has the "final" number available for $t-1$ GDP growth.

forecast is made at the end of the first quarter of 1952 for GDP growth for the second quarter of 1952, using data from the first quarter of 1947 through the fourth quarter of 1951 (which is the most recent GDP observation available to the forecaster as of the end of the first quarter of 1952). We then produce a forecast of real GDP growth for the second quarter of 1952 based on the estimated model coefficients and the most recent observation of the predictor variable. Note that when the predictor variable is market liquidity or any of the other financial variables, these are observed for the same quarter as we use to construct our forecast for next quarter, that is, the first quarter of 1952. Next, we move the window forward by one quarter, reestimate the models, and produce a new forecast for the next quarter, and so on. The last forecast is made at the end of the fourth quarter of 2008 for GDP growth for the first quarter of 2009.

We compare the performance of a model with market liquidity as the benchmark predictor against models with other financial variables included individually, as well as against a model that looks at the contribution of adding liquidity to a benchmark model that contains all the financial market variables used in the previous analysis. We also compare the illiquidity model against a benchmark model in which we forecast GDP growth using an autoregressive model. In that case, the most recent observation of GDP available to the forecaster at the end of the first quarter of 1952, when we produce the first forecast of GDP growth for the second quarter of 1952, is GDP for the fourth quarter of 1951. Thus, we estimate the autoregressive model for GDP growth with data including the fourth quarter of 1951 and construct a forecast for the second quarter of 1952 based on the estimated coefficients and the most recent GDP observation available, which is the final figure for GDP growth for the fourth quarter of 1951.

B.2. Out-of-Sample Performance of Different Liquidity Measures

We begin by evaluating univariate forecast models for real GDP growth using the three different liquidity proxies. The models are evaluated by comparing the mean squared forecasting error (MSE) from the series of one-quarter ahead forecasts. Because we compare models for the same dependent variable, but with different predictor variables, the models are nonnested. We use two statistics to compare the out-of-sample performance of the different liquidity measures: the mean squared forecasting error (MSE) ratio and the modified Diebold-Mariano (MDM) encompassing test proposed by Harvey, Leybourne, and Newbold (1998), which has greater power than the original Diebold and Mariano (1995) test, especially in small samples. In addition, Harvey, Leybourne, and Newbold advocate comparison of the MDM statistic with critical values from the Student's t-distribution, instead of the standard normal distribution.

The Diebold and Mariano (1995) statistic (hereafter DM) is calculated as follows: Suppose we have a candidate predictor i and a competing predictor k. We want to test the null hypothesis of equal predictive accuracy that $E[\bar{d}] =$

$0 \, \forall \, t$, where $\bar{d} = P^{-1} \cdot \sum_t (\varepsilon^2_{k,t+1} - \varepsilon^2_{i,t+1})$, P is the number of rolling out-of-sample forecasts, and $\varepsilon^2_{k,t+1}$ and $\varepsilon^2_{i,t+1}$ are the squared forecast errors from the two models. The DM statistic is calculated as

$$DM = \frac{\bar{d}}{\left(\sigma^2_{\bar{d}}/P\right)^{1/2}}, \tag{4}$$

and the MDM statistic is calculated as

$$MDM = \left[\frac{P + 1 - 2h + P^{-1}h(h-1)}{P}\right]^{1/2} DM, \tag{5}$$

where DM is the original statistic, P is the number of out-of-sample forecasts, and h is the forecast horizon. The MDM statistic is compared with critical values from the Student's t-distribution with $(P - 1)$ degrees of freedom.

Panel A in Table VI shows the results when we compare different forecasting models for quarterly GDP growth using different proxies for market liquidity. The liquidity variables labeled in the first row (under Model 1) constitute the respective candidate variable (i), and the liquidity variables labeled in the first column (under Model 2) are the competing variables (k). For example, the first pair of numbers compares the MSE from a model (Model 1) that uses *dILR* as the predictor variable against a model (Model 2) that uses *dLOT* as the predictor variable. The first number shows the relative MSE between the two models, which is 0.89. This means that the model with *dILR* as a predictor variable has a lower MSE than the model that uses *dLOT*. The second number shows the MDM statistic, which provides a statistic to test for whether the MSE of Model 1 is significantly different from that of Model 2. The last row in the table shows the MSE for each model specification labeled under Model 1. Looking first at the last row, we see that the model with *dILR* has the lowest MSE across the models. Also, when comparing the forecast performance of the different models against each other, we see that the model with *dILR* in all cases has a significantly lower MSE compared to models with *dLOT* and *Roll* as predictor variables. The model with *dLOT* as the predictor variable has a lower MSE than the *Roll* model. The MDM statistic cannot, however, reject the null that the MSE of the *dLOT* model is not significantly different from the MSE of the *Roll* model.

Overall, the results in Panel A of Table VI show that *dILR* has the lowest forecast error for GDP growth among the three liquidity proxies we examine. This is consistent with the in-sample results where *dILR* was the strongest and most robust predictor of GDP growth. In the rest of the out-of-sample analysis we therefore use *dILR* as our liquidity predictor variable.

B.3. Out-of-Sample Performance of Illiquidity versus Other Variables

We next want to evaluate the out-of-sample predictive ability of *dILR* against different baseline models. We assess the out-of-sample performance of *dILR*

Table VI

Results of Out-of-Sample Tests

Panel A reports the results of one-quarter-ahead, nonnested forecast comparisons of models with different liquidity proxies. The variable being forecast is quarterly GDP growth (*dGDPR*). Each number in the table compares the out-of-sample MSE for models that use different liquidity variables as predictors. For each model pair, the table shows the relative MSEs between Models 1 and 2, and the MDM test statistic. An MDM statistic with ** or * denotes a rejection of the null hypothesis of equal forecast accuracy at the 1% and 5% level, respectively. The alternative hypothesis is that Model 1 has lower MSE than Model 2. Panel B reports the relative MSE, MSE-F, and ENC–NEW test statistics from nested model comparisons predicting quarterly real GDP growth out-of-sample one quarter and two quarters ahead. The first column shows the variables included in the unrestricted model, and the second column shows the variables included in the restricted (baseline) model. The last row in Panel B reports the out-of-sample results when we compare a restricted model containing all the financial variables with an unrestricted model where we add *dILR* to the model. ** and * denote a rejection of the null hypothesis (at the 1% and 5% level, respectively) of equal forecast precision for the MSE-F test, while it denotes a rejection of the null that the restricted model encompasses the unrestricted model for the ENC–NEW test. Panel C shows the model comparison results when the baseline model is an autoregressive model (of order one) for GDP growth. In that case, the unrestricted model adds *dILR* and each of the other financial variables to the restricted model.

Panel A: Predicting GDP Growth with Different Liquidity Proxies

		Model 1		
Model 2	Statistic	*dILR*	*dLOT*	*Roll*
dLOT	MSE_1/MSE_2	0.89	–	–
	MDM	1.74*	–	–
Roll	MSE_1/MSE_2	0.82	0.91	–
	MDM	1.89*	0.47	–
	MSE ($\times 10^3$)	0.088	0.099	0.108

Panel B: Forecasting GDP Growth: Illiquidity (*dILR*) versus Other Financial Variables

Unrestricted Model	Restricted Model	1-Quarter-Ahead Forecasts $\frac{MSE_u}{MSE_r}$	MSE-F	ENC–NEW	2-Quarters-Ahead Forecasts $\frac{MSE_u}{MSE_r}$	MSE-F	ENC–NEW
dILR, *Term*	*Term*	0.917	20.95**	41.96**	0.927	18.09**	31.49**
dILR, er_m	er_m	0.976	5.69**	14.39**	1.003	−0.59	12.33**
dILR, *dCred*	*dCred*	1.000	0.02	18.73**	0.964	8.53**	22.86**
dILR, *Vola*	*Vola*	0.889	28.76**	50.91**	0.895	26.88**	35.98**
dILR, *Term*, er_m, *dCred*, *Vola*	*Term*, er_m, *dCred*, *Vola*	1.016	−3.58	7.27**	1.030	−6.79	10.35**

Panel C: Forecasting GDP Growth: Financial Variables versus an Autoregressive Model

dILR, *dGDPR*	*dGDPR*	0.849	41.16**	60.17**	0.803	56.36**	40.60**
Term, *dGDPR*	*dGDPR*	0.988	2.91	34.75**	0.866	35.44**	28.99**
er_m, *dGDPR*	*dGDPR*	0.905	24.20**	45.54**	0.850	40.66**	30.91**
dCred, *dGDPR*	*dGDPR*	0.838	44.63**	51.37**	0.850	40.54**	28.77**
Vola, *dGDPR*	*dGDPR*	1.109	−22.77	9.92*	1.049	−10.81	1.26

against two types of baseline models. The first set of baseline models comprises models where GDP growth is regressed on *one* of the financial control variables (*Term*, *dCred*, *Vola*, er_m) that we used in the in-sample analysis. Each of these models is a restricted (nested) version of a larger model where GDP growth is regressed on the control variable *in addition* to *dILR*. We also look at the performance of a more comprehensive restricted model for *dGDPR* containing all the financial control variables, which we compare to an unrestricted model where we add *dILR*. The second type of baseline model that we compare *dILR* to is an autoregressive model for GDP growth. In this case, the autoregressive GDP model is a restricted version of a model where we include both lagged GDP growth and *dILR* as predictor variables for next quarter GDP growth. We also compare the models with the other financial variables to the restricted autoregressive model for GDP growth.

We evaluate forecast performance using two test statistics. The first test is the encompassing test (ENC–NEW) proposed by Clark and McCracken (2001). The ENC–NEW test asks whether the restricted model (the model that does not include *dILR*) encompasses the unrestricted model that includes *dILR*. If the restricted model *does not* encompass the unrestricted model, that would mean that the additional predictor (*dILR*) in the larger, unrestricted model improves forecast accuracy relative to the baseline. Clark and McCracken show that the ENC–NEW test has greater power than tests for equality of MSE. The ENC–NEW test statistic is given as

$$\text{ENC–NEW} = (P - h + 1) \cdot \frac{P^{-1} \sum_t \left[\varepsilon^2_{r,t+1} - \varepsilon_{r,t+1} \cdot \varepsilon_{u,t+1}\right]}{MSE_u}, \tag{6}$$

where P is the number of out-of-sample forecasts, $\varepsilon_{r,t+1}$ denotes the rolling out-of-sample errors from the restricted (baseline) model that excludes *dILR*, $\varepsilon_{u,t+1}$ is the rolling out-of-sample forecast errors from the unrestricted model that includes *dILR*, and MSE_u denotes the mean squared error of the unrestricted model that includes *dILR*.

The second test statistic we examine is an F-type test for equal MSE between two nested models proposed by McCracken (2007), termed MSE-F. This test is given by

$$\text{MSE-F} = (P - h + 1) \cdot \frac{MSE_r - MSE_u}{MSE_u}, \tag{7}$$

where MSE_r is the MSE from the restricted model that excludes *dILR*, and MSE_u is the mean squared forecast error of the unrestricted model that includes *dILR*. Both the ENC–NEW and MSE-F statistics are nonstandard and we use the bootstrapped critical values provided by Clark and McCracken (2001).[18]

Panel B of Table VI provides the results for nested model comparisons of one-quarter-ahead and two-quarters-ahead out-of-sample forecasts of GDP growth

[18] The bootstrapped critical values are available at http://www.kansascityfed.org/publicat/other/criticalvalues_tec.xls

for the full sample period, 1947 to 2008. The first column shows which variables are included in the unrestricted model, and the second column shows which variable constitutes the restricted (baseline) model. In columns three to five, we report the relative mean squared error between the unrestricted (MSE_u) and restricted (MSE_r) models, the MSE-F test statistic, and the ENC–NEW statistic for the one-quarter-ahead forecasts. In the last three columns we report the same test statistics for the two-quarters-ahead forecasts.

Looking first at the one-quarter-ahead forecasts in Panel B of Table VI, we see that the relative MSE is less than one for all model comparisons except in the case when the baseline model is the credit spread (*dCred*). The MSE-F test for equal MSE between the unrestricted and restricted models rejects the null of equal MSE in favor of the MSE_u being lower than MSE_r for all models except the case in which credit spread constitutes the baseline model. Based on the ENC–NEW test, we reject the null that the unrestricted models are encompassed by the restricted models at the 1% level of significance for all cases. These results provide strong support for the view that *dILR* improves forecast accuracy relative to all of the baseline models. For the two-quarters-ahead forecasts, we get similar results, although based on the MSE-F test, we cannot reject the null that the MSE of a model with *dILR* and er_m has lower MSE than a model with only er_m. The ENC–NEW test, however, supports the claim that *dILR* contains additional information relative to er_m.

In the last row in Panel B, we examine the effect on forecast performance of adding *dILR* to a more comprehensive restricted model that contains all the financial variables examined earlier. For both the one-quarter- and two-quarter-ahead forecasts we cannot reject the null that the MSE_u is equal to MSE_r, suggesting that there is no value in adding *dILR* to the restricted model. This is not surprising because above we see that adding *dILR* to a model with only *dCred* does not change the MSE. Thus, we would expect a similar result for a larger model containing *dCred* as one of the predictor variables in the restricted model. However, the ENC–NEW test still rejects (at the 1% level) the null that the restricted model encompasses the unrestricted model, suggesting that adding *dILR* to the restricted model improves forecast performance both at the one-quarter and two-quarter horizons.

In Panel C of Table VI, we change the baseline model to an autoregressive model for GDP growth and test whether adding *dILR* (or any of the other financial variables) improves forecast accuracy of GDP growth relative to an autoregressive model for GDP growth. Looking first at the one-quarter-ahead forecasts, we find that *dILR*, er_m, and *dCred* significantly improve the MSE relative to the baseline model. Adding the term spread or volatility to the model does not significantly reduce the MSE. The more powerful ENC–NEW test rejects the null that the baseline model encompasses the unrestricted model at the 1% level for all variables except for market volatility, where the null is rejected at the 5% level.

For the two-quarters-ahead forecasts, all variables except market volatility improve the forecast accuracy of the autoregressive baseline model. Note also that the unrestricted model that includes *dILR* shows the greatest improvement in MSE over the baseline model when giving two-quarters-ahead forecasts. One final observation from Panel C is worth noting. The model that adds the term spread does not improve the MSE relative to the restricted autoregressive model in the one-quarter-ahead forecast comparison. However, when we look at the two-quarter-ahead forecast comparison, the performance of the unrestricted model that adds *Term* to the restricted model is greatly improved. Thus, *Term* has better performance for longer-term forecasts.

III. Firm Size and the Information Content of Liquidity

Small firms are relatively more sensitive to economic downturns than large firms. Therefore, firm size might be of particular interest for the purpose of this paper. If the business cycle component in liquidity is caused by investors moving out of assets that have a tendency to perform particularly poorly in recessions, we would expect that the liquidity of small firms reflects this effect most strongly. In particular, we would expect the liquidity variation of small firms to be higher than the liquidity variation of large firms, and also the liquidity of small firms to be more informative about future macro fundamentals. To examine this more closely, we run in-sample predictive regressions with liquidity variables constructed for different firm size quartiles. Firms are assigned into size quartiles at the beginning of the year based on their market capitalization the last trading day of the previous year. We construct two versions of each liquidity variable, one calculated for the smallest quartile of firms (LIQ^{small}) and one for the largest quartile of firms (LIQ^{large}).

Table VII reports the results from regression models where we predict GDP growth using liquidity proxies calculated separately for small and large firms, and where we include the different control variables used earlier.[19] We find that the liquidity of small firms has a significant coefficient ($\hat{\beta}_S^{LIQ}$) for all three liquidity proxies. In contrast, the liquidity of large firms has an insignificant coefficient ($\hat{\beta}_L^{LIQ}$) for all liquidity proxies in all models. Comparison of the $\bar{R}^2$ of the different specifications, reported on the right in the table, yields a similar conclusion: a regression specification with *only* the liquidity of the large firms has no R^2 improvement relative to models without liquidity; all the improvement in R^2 comes from the liquidity of small firms. This result is also confirmed in Panel B in the table, which shows the results from Granger causality tests between the liquidity proxies for small and large firms and GDP growth. In the second and third columns, we report the χ^2 statistic and associated p-value from the test of the null that GDP growth does not Granger cause the respective liquidity variable. We cannot reject the null for any of the models. In the last two columns, we test the null that the liquidity variable does not Granger cause GDP growth. For all liquidity measures sampled for the small firms, we reject the null at the 5% level or better.

[19] In the Internet Appendix, we report the results for all three liquidity variables and the other macro variables.

Table VII

Predicting Macro with Market Liquidity–Size Portfolios

Panel A shows the multivariate OLS estimates from regressing next quarter GDP growth on current market illiquidity of small and large firms and four control variables. We examine three different proxies for market illiquidity. The cross-sectional liquidity measures are calculated as equally weighted averages across stocks. The estimated model is $y_{t+1} = \alpha + \beta_S^{LIQ} LIQ_t^{small} + \beta_L^{LIQ} LIQ_t^{large} + \gamma \mathbf{X}_t + u_{t+1}$, where y_{t+1} is real GDP growth, LIQ^{small} is the respective illiquidity proxy sampled for the 25% smallest firms and LIQ^{large} is the illiquidity of the 25% largest firms, $\mathbf{X_t}$ contains the control variables (*Term*, *dCred*, *Vola*, and er_m), and γ' is the vector of the coefficient estimates for the control variables. The Newey-West corrected t-statistics (with four lags) are reported in parentheses below the coefficient estimates, and $\bar{R}^2$ is the adjusted R^2. The three last columns report the adjusted $\bar{R}^2$ for the models estimated without any liquidity measures (ex. *LIQ* $\bar{R}^2$), only including the liquidity sampled for the 25% largest firms (ex. $LIQ^S\,\bar{R}^2$), and only including the liquidity sampled for the 25% smallest firms (ex. $LIQ^L\,\bar{R}^2$). Panel B shows the results of Granger causality tests between real GDP growth and the illiquidity of small and large firms for the three different illiquidity proxies. The first column denotes the liquidity variable, and columns two and three show the χ^2 and associated p-value for Granger causality tests where the null hypothesis is that GDP growth *does not* Granger cause the liquidity variables. Similarly, columns four and five show the results when the null hypothesis is that the liquidity variable *does not* Granger cause GDP growth. ** and * denotes a rejection of the null hypothesis at the 1% and 5% level, respectively.

Panel A: Predicting GDP with Various Liquidity Measures

Liquidity Variable	Const.	β_S^{LIQ}	β_L^{LIQ}	$\hat{\gamma}_1^{Term}$	$\hat{\gamma}_2^{dCred}$	$\hat{\gamma}_3^{Vola}$	$\hat{\gamma}_4^{er_m}$	$\bar{R}^2$	ex. *LIQ* $\bar{R}^2$	ex. LIQ^S $\bar{R}^2$	ex. LIQ^L $\bar{R}^2$
dILR	0.008	−0.008	0.003	0.000	−0.014	0.001	0.021	0.14	0.12	0.12	0.14
	(7.64)	(−3.74)	(1.09)	(0.54)	(−3.16)	(0.21)	(2.31)				
dLOT	0.009	−0.014	0.000	0.000	−0.015	0.009	0.029	0.14	0.12	0.12	0.15
	(7.52)	(−2.12)	(−0.06)	(0.42)	(−3.61)	(1.58)	(3.55)				
Roll	0.017	−0.306	−0.251	0.001	−0.013	0.007	0.022	0.15	0.12	0.14	0.15
	(5.14)	(−2.38)	(−0.91)	(1.39)	(−3.12)	(1.29)	(2.74)				

Panel B: Granger Causality Tests

Liquidity Variable (LIQ)	*dGDPR* $\nrightarrow$ *LIQ* χ^2	*dGDPR* $\nrightarrow$ *LIQ* p-value	*LIQ* $\nrightarrow$ *dGDPR* χ^2	*LIQ* $\nrightarrow$ *dGDPR* p-value
$dILR^S$	4.34	(0.23)	10.33*	(0.02)
$dILR^L$	6.86	(0.08)	1.32	(0.72)
$dLOT^S$	3.19	(0.07)	9.83**	(0.00)
$dLOT^L$	0.20	(0.65)	0.03	(0.87)
$Roll^S$	0.67	(0.72)	6.44*	(0.04)
$Roll^L$	0.19	(0.91)	5.60	(0.06)

Overall, the results in Table VII suggest that the illiquidity of smaller firms is most informative about future economic conditions. We view this result as consistent with our conjecture that variation in market liquidity is caused by portfolio shifts, from illiquid and more risky assets to safer and more liquid assets, due to changing expectations about economic fundamentals or binding funding constraints.

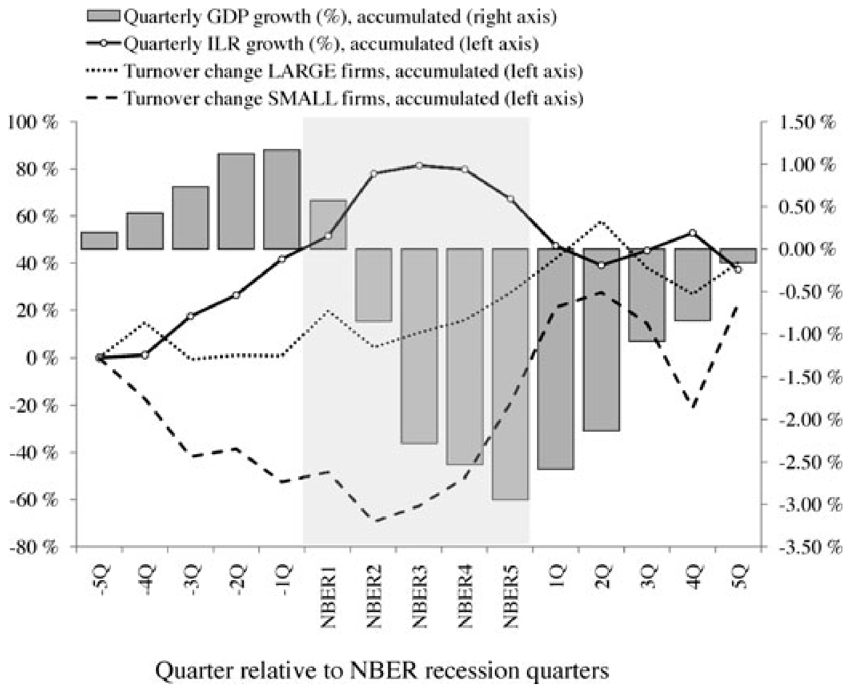

Figure 3. Market illiquidity and trading activity (turnover) around NBER recessions. The figure shows the accumulated average growth in *ILR* (solid line) and accumulated average GDP growth (bars) averaged in event time before, during, and after NBER recession periods. In addition, the dashed line shows the accumulated average change in turnover for the 25% smallest firms and the dotted line shows the accumulated average change in turnover for the 25% largest firms. Turnover is measured as the shares traded divided by the number of outstanding shares. All the NBER recession periods are aligned to start at NBER1.

Finally, if investors have a tendency to move out of small firms and this causes activity to drop and liquidity to worsen, we would expect this pattern to show up in the trading activity of these firms. We therefore investigate whether trading volume predicts economic growth. We find it to be less informative than other liquidity measures about real variables,[20] but looking at volume may still improve our understanding of the mechanisms. In Figure 3, we examine whether the change in turnover before and during NBER recessions is different for small and large firms. Turnover is measured as the shares traded divided by the number of outstanding shares. We sort firms into size quartiles at the end of each year and calculate the equally weighted average turnover for the first and fourth quartiles. As before, the bars show the cumulative average quarterly growth in real GDP and the solid line the cumulative average change in *ILR*. The dashed line shows the cumulative average change in turnover for small firms, and the dotted line shows the same series for large firms. The results

[20] In the Internet Appendix, we report the results from a comprehensive VAR specification that includes turnover as an alternative explanatory variable. We find that turnover has no predictive ability for *dGDPR*.

in the figure indicate a striking systematic difference in the trading activity in small and large firms before recessions. Although the turnover for large firms is essentially unchanged before the first recession quarter, the turnover for small firms falls steadily from four quarters before the first NBER recession quarter (NBER1). Furthermore, the turnover for both small and large firms starts increasing in the middle of the NBER recessions. Because this pattern is strongest for small firms, it indicates that investors increase their demand for equities in general, and for smaller firms in particular, when they start expecting future economic conditions to improve.

IV. Systematic Liquidity Variations and Portfolio Shifts: Evidence from Norway

In the introduction, we conjectured that the systematic liquidity variation that we find is linked to portfolio shifts and changes in market participation during economic downturns, that is, investors seek to move away from equity investments in general and from small, illiquid stocks in particular. Using special data on stock ownership from the Oslo Stock Exchange (OSE), we can examine this conjecture and provide a valuable robustness check of our results from the U.S. market.

A. The Norwegian Evidence of Predictability

We first check that we get similar results on predictability as in the U.S. case. For brevity we report the Norwegian results on predictability in the Internet Appendix and only summarize the main results here. We start by assessing the in-sample predictive ability of market liquidity for the macro variables' real GDP growth (*dGDPR*), growth in the unemployment rate (*dUE*), real consumption growth (*dCONSR*), and growth in investment (*dINV*). We use the Amihud *ILR* and *RS* as our liquidity proxies.[21]

We look at two model specifications. In the first specification, we use only market liquidity and the lagged dependent variable as predictors for next quarter growth in the respective macro variable. We find that regardless of the choice of liquidity proxy, the coefficient on market liquidity is highly significant across all models and has the expected signs. A worsening of market liquidity (increase in *RS* or *ILR*) predicts a decrease in next quarter GDP growth, consumption growth, and investment growth, and an increase in the unemployment rate.

In the second model specification, we control for other variables. In the U.S. analysis, we used four financial control variables: the term spread, credit spread, market returns, and market volatility. In Norway, no credit spread series are available for the length of our sample period. This is mainly due to a historically very thin credit market in Norway. Thus, we are only able to control for the other three variables. The results from regressions based on this

[21] Both the *ILR* and *RS* pass the stationarity tests in the Norwegian sample, so we do not transform any of the liquidity series.

specification show that the coefficient on market liquidity is highly significant for all models except when the dependent variable is real consumption growth. This is basically the same result that we find for the United States, where, after controlling for the term spread and stock market returns, the coefficient on *ILR* is rendered insignificant in the equation for *dCONSR*. However, none of the other financial variables have significant coefficients. It should be noted that if we exclude the *RS*, the term spread enters significantly in the models for *dGDPR* and *dUE*, although the adjusted R^2 of the models is more than halved. Thus, although *Term* is highly correlated with our liquidity proxies, there seems to be a significant amount of additional information in market liquidity. We also perform Granger causality tests for the Norwegian sample, between *dGDPR* and both *RS* and *ILR*. In that analysis, we are unable to reject the null that GDP growth does not Granger cause *RS*, whereas we reject the reverse hypothesis at the 1% level. This result is similar when we use the *ILR* as our liquidity proxy.

We also perform an out-of-sample analysis for Norway. In nested model comparisons between *RS* or *ILR* and the other financial control variables (*Term*, er_m, *Vola*), the MSE-F test suggests that the MSE of an unrestricted model (including *RS* as a predictor) has a significantly lower MSE across all models. When we use *ILR* as the liquidity proxy, we are only able to reject the null of equal forecast accuracy in the model where er_m is the competing predictor variable. Both for *RS* and *ILR*, the results are weaker with respect to the ENC–NEW test, and much weaker compared to the results for the United States. We are only able to reject the null at the 5% level that *RS* is encompassed by a model with er_m or *Vola*. For *ILR*, we only reject the null of encompassing when the restricted model contains er_m.

Similar to U.S. out-of-sample analysis, we also compare the out-of-sample forecast performance of liquidity to an autoregressive model for GDP growth. Adding either *RS* or *ILR* to the autoregressive GDP model significantly improves the MSE. In addition, the null that the restricted GDP model encompasses the unrestricted model that adds either *RS* or *ILR* is rejected at the 1% level.

Finally, we examine whether the informativeness of liquidity about future GDP growth also differs between small and large firms in Norway. We sort firms on the OSE into four groups based on their market capitalization at the end of the previous year, and calculate the average liquidity for each size group. We use the liquidity series for the smallest and largest groups as explanatory variables. The results are very similar to what we find for the United States in Table VII. Also, in the Granger causality tests, we reject the null hypothesis that both RS^S and ILR^S sampled for the small firms *does not* Granger cause *dGDPR*, whereas we are unable to reject the null when using the liquidity measured for the largest firms.

In summary, although the in-sample results and Granger causality tests for Norway are very similar to the U.S. results, the out-of-sample results are a bit weaker for Norway. Note, however, that the Norwegian sample is much shorter, and covers only about three business cycles. Overall, the results for Norway indicate that the result that stock market liquidity is related to future economic growth is robust to change of market, market structure, and trading system.

B. Portfolio Shifts and Liquidity

A possible channel through which the documented relationship between stock market liquidity and business cycles may work is changes in investors' portfolio composition. In this section, we investigate whether investors do in fact tilt their portfolios toward more liquid assets in economic downturns. Our Norwegian data set includes monthly ownership of all investors in all Norwegian companies listed on the Oslo Stock Exchange over the period 1992 to 2007. The challenge lies in constructing aggregate measures of changes in portfolio composition. We do this in two ways. First, we focus on market participation and look at the full portfolio of each investor. Next, we look at concentration and movements between owner types for individual stocks, without controlling for the portfolios *across* stocks.

B.1. Market Participation on an Investor-by-Investor Basis

Our ownership data let us construct the actual portfolios of all investors at the monthly frequency and also the changes in portfolio composition over time. We want a variable that can be informative about both the degree to which investors move in and out of the stock market and the degree to which the structure of their stock portfolios change. The measure should be influenced mainly by actual changes in stock ownership. This rules out measures based on wealth changes, because such measures have the undesirable characteristic that wealth can change due to stock price changes, even if investors do not make any active portfolio changes. We therefore use the *number of shares* owned by an investor as the basic observation of interest. We cannot sum the number of shares across stocks, because this is again sensitive to price differences across shares. Instead, we simply ask: When does an owner take significant amounts of money from his stock portfolio? The extreme example is when he sells *all* his stocks. Our measure of aggregate changes uses such cases to identify aggregate movements into and out of the market or a group of stocks, such as a size portfolio.

Our time series is constructed by comparing the set of participants at two dates. The set of investors who were present at the first date, but not on the second date, comprises the set of investors *leaving* the market entirely. Similarly, we count the number of investors present at the second date, but not on the first. This is the number of investors *entering* the market. The net change in investors is the number of investors entering the market less the number of investors leaving the market. This number is used as a measure of the change in portfolio composition. The net change in investors is calculated for all owners as well as for each of the owner types (personal, foreign, financial, nonfinancial (corporate), and state owners).[22] Panel A of Table VIII presents descriptive statistics for the net change in portfolio composition at the annual level. On average about 15,000 investors enter the market from one year to the next, which is about a quarter of the investors present at the beginning of the year. The net change is positive, which indicates that on average the number of investors on the exchange has been increasing over the sample period. Panel A also reports the average number of investors leaving and entering the market within each owner type. Note that in the calculations for different owner types, we only consider owners *of the given type*, that is, the fraction of investors is conditioned on the type. For example, the average of 51 financial owners entering corresponds to 14% of financial investors. As is clear from the table, the most common investor type is personal investors.[23]

As we saw for both the United States and Norway, the time series of small firms' liquidity has more predictive content than the time series of large firms' liquidity. To look into such issues, we construct measures of changes in participation for different size quartiles, that is, we sort the stocks at the OSE based on size and, for each year, construct four size-based stock portfolios. We then calculate the net number of new owners, but now *only* for the stocks in each size portfolio. So, for example, if an investor only had holdings in small stocks, but moved them to large stocks, we would count this as leaving the small stock portfolio and entering the large stock portfolio.

Panel B of Table VIII shows the correlations between liquidity, measured by the relative bid–ask spread (*RS*), and portfolio changes for various owner types. If liquidity worsens (*RS* increases) when the number of participants in the market falls, we should expect to see a negative correlation between *RS* and changes in the number of investors. Further, this relationship should be strongest for the least liquid stocks. That is exactly what we find. For the portfolio of the smallest stocks on the OSE, there is a significantly negative correlation between *RS*s and changes in participation. The correlation becomes smaller in magnitude when we move to portfolios of larger firms, the correlation being smallest in magnitude for the portfolio of the largest firms.

B.2. Movements between Owner Types for Individual Stocks

A disadvantage of the measure of participation above is that it *only* considers cases of complete withdrawal from the market. We therefore complement the analysis by looking at two alternative measures, namely owner concentration and owner type. These measures are much simpler to calculate than the pre-

[22] In implementing the calculation, we attempt to reduce noise by removing trivial holdings of less than a 100 shares, because this is the minimum lot size at the Oslo Stock Exchange.

[23] There is an institutional reason for the decrease in foreign investors: it is a reflection of the increased ownership through nominee accounts, as foreign owners register through a nominee account. The Norwegian Central Securities Registry does not have details on nominee ownership—it only has data on the total held in nominee accounts. The number of foreign investors that we use is the number of directly registered foreign owners, which has decreased, although the fraction of the OSE held by foreigners has increased throughout the period.

Table VIII

Changes in Portfolio Composition and Liquidity

Panel A describes changes in ownership participation measured at an annual frequency. Each year in the sample we calculate the number of investors leaving the market, entering the market, and the net change. We also normalize the numbers by calculating them as a fraction of owners at the beginning of the period. Panel B presents quarterly correlations between stock market liquidity measured by the average relative bid–ask spread and the change in stock market participation. Change in stock market participation is the change in the number of investors in the stock market, or the given portfolio, of the specified types. Numbers in parentheses are p-values. Panel C shows the correlations between changes in measures of ownership concentration and changes in liquidity. We calculate four concentration measures: the size of the largest owner and the total number of owners, as well as two Herfindahl indices (in the first version we include all owners, in the second version we exclude the three largest owners). The numbers in the tables are the correlations between the concentration measures and liquidity, measured by the relative spread (RS). Numbers in parentheses are p-values. Panel D shows correlations between liquidity and changes in the aggregate fraction of the firm owned by five different owner types. The numbers in the tables are the correlations between the ownership fraction by the given type and liquidity. Numbers in parenthesis are p-values. In the tables, we show statistics for five mutually exclusive owner types: individual (private), nonfinancial (corporate), state, foreign, and financial owners. In some tables, we also show data for mutual funds, which is a subgroup of financials. For annual data, we use each year from 1990 to 2006, giving 16 observations. For the calculations with quarterly data, we use data between January 1993 to December 2006, giving 56 quarterly observations.

Panel A: Describing Annual Changes in Portfolio Composition

Investor Type	Number of Investors			Fraction of Investors		
	Entering	Leaving	Net	Entering	Leaving	Net
All	15,220	11,934	3,286	24.1	18.5	5.6
Personal owners	13,445	10,087	3,358	24.3	17.5	6.8
Foreign owners	862	1119	−256	33.7	35.3	−1.6
Financial owners	51	44	6	14.8	12.4	2.4
Nonfinancial owners	1,013	838	175	24.4	19.6	4.8
State owners	14	11	3	20.8	15.1	5.7

Panel B: Correlation Liquidity and Change in Stock Market Participation

	All Firms		Firm Size Quartile: Q1 (Smallest)		Q2		Q3		Q4 (Largest)	
All owners	−0.07	(0.32)	−0.35	(0.00)	−0.10	(0.22)	−0.20	(0.07)	−0.11	(0.22)
Personal owners	−0.02	(0.45)	−0.33	(0.01)	−0.09	(0.25)	−0.18	(0.09)	−0.08	(0.28)
Foreign owners	−0.18	(0.09)	−0.30	(0.01)	−0.16	(0.12)	−0.25	(0.03)	−0.23	(0.04)
Financial owners	−0.06	(0.33)	−0.11	(0.21)	0.01	(0.46)	−0.09	(0.25)	−0.08	(0.27)
Nonfinancial owners	−0.16	(0.12)	−0.35	(0.00)	−0.11	(0.21)	−0.21	(0.06)	−0.20	(0.06)
State owners	−0.06	(0.34)	−0.20	(0.07)	0.19	(0.08)	−0.10	(0.23)	−0.06	(0.34)

(*continued*)

Table VIII—*Continued*

Panel C: Correlation Change in Liquidity and Change in Ownership Concentration

Concentration Measure	All Firms	Firm Size Quartile Q1 (Smallest)	Q2	Q3	Q4 (Largest)
Largest owner	0.07 (0.30)	0.13 (0.15)	0.13 (0.16)	0.09 (0.25)	−0.06 (0.31)
Herfindahl	0.09 (0.24)	0.20 (0.06)	0.10 (0.22)	0.18 (0.08)	−0.12 (0.18)
No. owners	0.37 (0.00)	−0.09 (0.23)	−0.22 (0.04)	−0.27 (0.02)	0.37 (0.00)
Herfindahl (ex 3 largest)	0.18 (0.08)	0.29 (0.01)	0.23 (0.04)	−0.07 (0.29)	−0.05 (0.36)

Panel D: Correlation Change in Liquidity and Movement Across Owner Types

Owner Type	All Firms	Firm Size Quartile Q1 (Smallest)	Q2	Q3	Q4 (Largest)
Financial fraction	−0.12 (0.18)	−0.14 (0.14)	−0.10 (0.21)	−0.07 (0.29)	0.24 (0.03)
Mutual fund fraction	−0.06 (0.32)	−0.13 (0.16)	−0.00 (0.49)	0.04 (0.37)	−0.18 (0.08)
Individual fraction	0.05 (0.35)	−0.03 (0.42)	−0.14 (0.13)	0.01 (0.46)	0.06 (0.32)
Nonfinancial fraction	−0.06 (0.34)	0.10 (0.22)	0.05 (0.36)	−0.14 (0.13)	−0.17 (0.09)
Foreign fraction	−0.08 (0.26)	−0.16 (0.11)	−0.04 (0.38)	−0.07 (0.29)	0.21 (0.05)
State fraction	−0.09 (0.23)	−0.30 (0.01)	−0.18 (0.08)	−0.07 (0.29)	0.22 (0.05)

vious measure, as they can be found on a stock-by-stock basis without looking at the full portfolio of individual investors.

We first look at several proxies for ownership concentration, such as the fraction of the company owned by the largest owner, and a couple of Herfindahl measures of concentration. We also look at the total number of owners. Ownership concentration is related to participation by the simple book-keeping argument that because all stocks must be held by somebody, if participation declines, the number of owners declines and ownership concentration increases. In Panel C of Table VIII, we show the results of looking at correlations between changes in liquidity and ownership concentration. The interesting numbers are the differences between the portfolio of small firms (quartile 1) and large firms. We see that, for example, when the spread increases, the concentration increases for the portfolio of small stocks (positive correlation), but decreases for the portfolio of large stocks. Similarly, when the spread increases, the number of owners decreases for the portfolio of small stocks but increases for the large stocks.

Changes in ownership participation may also be related to the prevalence of different ownership types. We therefore calculate the aggregate fractions of companies owned by five different owner types, and relate changes in these fractions to changes in liquidity. The results are given in Panel D of Table VIII. There are a number of interesting patterns in the table. First, we see that when liquidity worsens, this coincides with a movement *into* large stocks by individual investors, which is consistent with portfolio rebalancing and a flight to quality type of behavior among individual investors. Second, although financial investors may be expected to "take up the slack" in small firms, that turns out not to be the case. When the spread increases (liquidity worsens), financials also tend to decrease their stake in small stocks.

A potential explanation for this result relates to funding problems. Included in the group of financial investors are mutual funds. Because these entities have a tendency to experience outflows of funds in economic downturns, as investors sell off some of their portfolios to fund consumption, mutual funds face a funding problem and have to sell a part of their portfolios. To the extent that this is the case, we would expect outflows from small stocks to be more prevalent among mutual funds than other financial investors. We are able to investigate this conjecture because the database on ownership identifies which of the financial owners are mutual funds (bottom line, Panel D). When we rerun the calculation *only* for those financial owners that are mutual funds, the results show that indeed mutual funds have a *stronger* tendency to sell their holdings of small stocks. This is consistent with an explanation based on funding problems.

We observe that the group that appears to take up the slack in small firms, buying small stocks when liquidity is worsening, is foreign investors (which includes large international funds), although this number is not significant.

To sum up, using various measures of changes in portfolio composition, we find evidence consistent with our hypothesis that liquidity changes are related to portfolio shifts.

V. Conclusion

The prime contribution of this paper is to provide two empirical observations. First, we show that stock market liquidity contains useful information for estimating the current and future state of the economy. These results are shown to be remarkably robust to our choice of liquidity proxy and sample period. The relationship also holds for two different markets, the United States and Norway. Second, we find evidence that time variation in equity market liquidity is related to changes in participation in the stock market, especially for the smallest firms. Participation in small firms decreases when the economy (and market liquidity) worsens. This is consistent with a "flight-to-quality" effect, and with the finding that the liquidity of the smallest firms is more informative about future economic conditions compared to the liquidity of large firms. In addition to suggesting a new financial market-based predictor, our results provide a new explanation for the observed commonality in liquidity.

There are a number of interesting ways to expand on our results. First, our results showing that (Granger) causality goes from the stock market to the real economy has implications for prediction. The ability to improve forecasts and "nowcasts" (Giannone, Reichlin, and Small (2008)) of central macroeconomic variables such as unemployment, GDP, consumption, and the like would be of particular interest to central banks and other economic planners. For such purposes it would therefore be instructive to see more extensive comparisons of the predictive power of different liquidity proxies, or combinations of proxies. Second, although we find evidence of a link from observed liquidity to the economy using data for the United States and Norway, it would be interesting to look at a larger cross-section of stock markets. Finally, our finding that stock market participation is related to time variation in liquidity should be important to asset-pricing theorists attempting to understand why liquidity appears to be priced in the cross-section of stock returns.

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