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Abstract

Purpose – The purpose of this paper is to predict real gross domestic product (GDP) growth and business cycles by using information from both liquidity and volatility measures.

Design/methodology/approach – The paper estimates liquidity and volatility measures from over 5,000 NYSE rms and extracts a common factor, which the paper calls uncertainty. In-sample and out-of-sample forecasting tests are used to determine the ability of the uncertainty factor to predict growth in real GDP, industrial production, consumer price index, real consumption and changes in real investment.

Findings – The paper finds that on average, positive shocks to the uncertainty factor occur in the quarters preceding and at the beginning of a recession. During the quarters toward the end of recessions, there are negative shocks to uncertainty on average.

Originality/value – Previous research has explored using either liquidity or volatility to forecast economic activity. The paper bridges the two branches of research and finds a link to real GDP growth and business cycles.

Keywords Uncertainty, Forecasting, Volatility, Liquidity

Paper type Research paper

1. Introduction

Recently, there has been a large branch of literature that examines market liquidity. Pástor and Stambaugh (2003), Acharya and Pedersen (2005), Chen (2005) and Sadka (2006), all look into systematic liquidity risk. Additionally, as there are several different measures of liquidity, many studies have focused on identifying a common systematic liquidity factor (Chordia *et al.*, 2000; Hasbrouck and Seppi, 2001; Eckbo and Norli, 2002; Korajczyk and Sadka, 2008). Amihud, Hameed, Kang and Zhang (2015) examine 45 countries and find evidence that the illiquidity premium exists in a number of international markets. With the most recent financial crisis, there has been an interest in the apparent causal link between a reduction in liquidity and an economic slowdown. Czauderna *et al.* (2015) find a bidirectional link between liquidity (as measured using exchange traded funds) and market returns in the German stock market between July 2006 and June 2010. Wagner and Winter (2013) include liquidity risk in models to evaluate daily mutual fund performance for funds focused on the European market. When using a six-factor model including liquidity and idiosyncratic risk, they find that a large number of funds have significant loadings on both the liquidity and idiosyncratic risk factors. In measuring exposure to the liquidity risk factor, they find that on average, fund managers prefer liquid stocks.

In a paper by Næs *et al.* (2011), they show that this link between liquidity and recessions is not a recent phenomenon but has existed in past recessions as well. They find that, on average, there is an increase in illiquidity before a recession followed by an increase in liquidity during the tail end of the recession. Furthermore, measures of liquidity help in

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forecasting future real gross domestic product (GDP) growth. Switzer and Picard (2016) also examine measures of aggregate liquidity and their relation to economic cycles. Rather than using a linear model, as was done by Næs *et al.* (2011), Switzer and Picard (2016) use nonlinear models and find the relationship between aggregate liquidity measures and the real economy to be significantly less pronounced. In addition to linking liquidity to business cycles, several papers have explored stock market volatility and its relation to real macroeconomic variables and business cycles (Schwert, 1989; 1990; Hamilton and Gang, 1996). Hamilton and Gang (1996) find that stock volatility may be useful in forecasting economic activity.

We merge these two trains of thought and check if there is any added benefit from considering liquidity and volatility jointly. In Carlston (2012), multiple daily liquidity and volatility measures are estimated from daily stock prices and returns. Common factors, what we will term as "uncertainty", are extracted across all of the liquidity and volatility measures. He finds that this common risk factor carries a significant premium and helps explain the cross section of expected returns. In this paper, we follow the methodology of Næs *et al.* (2011) to explore a possible link between this common liquidity and volatility measure and the real economy and business cycles.

In addition to the literature on liquidity and volatility, if one considered the common factor between liquidity and volatility risk as a measure of uncertainty, this work would also relate to the literature exploring various measures of uncertainty and their links to the real economy and financial markets. Loudon (2017) examines the effect of financial market uncertainty on the risk-return relationship for multiple stock markets using a regime-switching model. Bloom (2014) discusses many of the current measures of uncertainty including stock market volatility, GDP volatility and mentions of "uncertainty" in the news, disagreements among forecasters and the dispersion of firm productivity shocks. He discusses how uncertainty, as measured by a number of different proxies, seems to increase during recessionary periods. Baker *et al.* (2016) construct a measure of economic policy uncertainty based on the frequency of news articles that contain the words relevant to policy and economic uncertainty. They expand on their measure and develop several uncertainty measures for specific topics and categories such as countries, financial regulation and taxes. When performing firm-level regressions, their measure of policy uncertainty has an impact on stock volatility, investment and employment. They also find that firms in the defense, healthcare and financials sectors are more sensitive to their sector specific policy uncertainty measures. Jurado *et al.* (2015), use hundreds of macroeconomic and financial data series to estimate an aggregate measure of uncertainty based on implied forecast errors. They find that periods of significant uncertainty events occur with much less frequency than suggested by simply using stock market volatility as a proxy. Furthermore, their measure tends to be much more persistent than using the common proxy of stock market volatility. Similar to Jurado *et al.* (2015), our measure is constructed using multiple measures, but we focus solely on liquidity and volatility measures rather than spanning hundreds of macroeconomic and financial measures. Both Baker *et al.* (2016) and Jurado *et al.* (2015) provide access to their uncertainty estimates on their respective websites[1]. We find that shocks to our measure have a correlation of 0.37 and 0.65 to the uncertainty measures respectively. Because our measure of uncertainty and that of Jurado *et al.* (2015) are both based on financial data, it is expected that they will be more highly correlated.

When plotting real GDP growth and shocks to our uncertainty measure before, during and after recessions, we find that on average, in quarters preceding a recession, there are positive shocks to uncertainty. Similarly, on average, at the beginning of a recession, there are positive shocks to uncertainty. However, toward the end of a recession and in the quarters following a recession, there are, on average, negative shocks to our uncertainty measure. In-sample test results indicate that this uncertainty measure helps predict several macroeconomic variables, including real GDP growth, growth in industrial production, CPI growth, real consumption growth and changes in real investment. Additionally, out-of-sample forecasting tests indicate that a forecasting model including the uncertainty measure outperforms an AR(1) forecasting model for real GDP growth. When comparing the out-of-sample performance between models with our uncertainty measure and models involving just liquidity measures, we find there is no statistical difference between their expected mean squared forecast error (MSFE). Our results suggest that while there is a definite link between our uncertainty measure and the real economy, it doesn't appear to offer an improvement over liquidity measures in forecasting business cycles.

The paper is organized as follows. Section 2 discusses the specific liquidity and volatility measures as well as the method for extracting the risk factor, Section 3 presents the in-sample and out-of-sample forecasting tests and Section 4 concludes.

2. Data and methodology

2.1 Macroeconomic and financial data

The primary series that is explored in this paper is real GDP growth, calculated as the log difference of the quarterly real GDP[2]. Other macroeconomic variables considered in this paper are industrial production (IP), consumer price index (CPI), unemployment rate (UE), real personal consumption expenditure (Cons) and real gross private domestic investment (Inv). Additionally, we also use the term spread and credit spread (Cred). Term is calculated as the difference between the yield on the ten-year treasury bond and the yield on the three-month treasury bill, and Cred is the difference between the yield on Moody's Baa rated bonds and the yield on a ten-year government bond. All of these data were taken from the Federal Reserve Economic Data (FRED) available through the Federal Reserve Bank of St. Louis.

Similar to Carlston (2012), this paper uses data from the daily CRSP databases for stocks traded on the NYSE and follows their steps in estimating the common liquidity and volatility risk factor. The time range is from January 1947 to December 2012. As trading on the NASDAQ uses a different trading mechanism relying heavily on market makers, only stocks traded on the NYSE are considered in the analysis. Additionally, only assets with a CRSP share code of 10 or 11 (ordinary common shares) are considered, which will eliminate certificates, Americus Trusts components, American depository receipts (ADRs), shares of beneficial interest, closed-end funds, REIT's and ETFs. Stocks with a price lower than \$1 are excluded as well as those observations with a volume = 0. After appropriate filtering, we are left with a total of 5,281 firms over a total of 264 quarters.

2.2 Liquidity and volatility measures

There is a wide range of proposed measures of liquidity. We implement a total of four liquidity measures at a quarterly frequency from the daily stock data. The first is the measure based on Amihud (2002). We define the Amihud measure for stock i in month t as follows:

$$A_{i,t} = \frac{1}{d_t}\sum_{j=1}^{d_t}\frac{|r_{i,j}|}{dvol_{i,j}} \tag{1}$$

where $r_{i,j}$ is the return on asset i on day j of quarter t, d_t is the number of trading days in the quarter and $dvol_{i,j}$ is the dollar volume for asset i on day j of quarter t. Following both

Acharya and Pedersen (2005) and Korajczyk and Sadka (2008), the quarterly measure $A_{i,t}$ is scaled by the ratio of the market capitalization of the CRSP market index at time $t-1$ and at the reference date of July 1962. For the quarterly measure to be included in the sample, a stock is required to have at least 45 daily observations in the quarter. This measures the price impact of trades, suppose you see a large price change (high numerator) for a low volume trade (a small denominator). This would represent an illiquid asset and would correspond with a large value of the Amihud measure.

The second liquidity measure used is the turnover, the ratio of quarterly volume and shares outstanding. It is defined as follows:

$$TO_{i,t} = \frac{\sum_{j=1}^{d_t} vol_{i,j}}{SO_{i,t}} \tag{2}$$

where $SO_{i,t}$ is the number of shares outstanding at the end of quarter t. Once again, it is required that a stock have at least 45 daily observations in quarter t to be included in the sample.

The relative spread is calculated as the difference between the bid and the ask, divided by the midpoint price (average of the bid and ask):

$$RS_{i,t} = \frac{1}{d_t} \sum_{j=1}^{d_t} \frac{Ask_{i,j} - Bid_{i,j}}{midpt_{i,j}} \tag{3}$$

This is calculated at the daily frequency and then aggregated by taking the quarterly average of the daily measures. The purpose of the relative spread is to measure the implicit cost of trading a small number of shares.

The final liquidity measure used is that of Roll (1984). Assuming the existence of a constant spread s, Roll shows that the spread can be estimated as $\hat{s} = 2\sqrt{-Scov}$, where $Scov$ is the covariance of adjacent daily returns. This is estimated each quarter using daily returns, where a minimum of 45 daily returns is required to be included. As this is undefined when $Scov > 0$, whenever a stock has $Scov > 0$ for a given quarter, the Roll measure is set to missing for that quarter, as in Næs *et al.* (2011)[3].

Two different estimates of quarterly volatility are used in the following analysis. The first is an estimate formed from the daily realized variance measure. We implement the adjustment from French *et al.* (1987) to account for possible autocorrelation with the variance estimated as the sum of the squared daily returns plus two times the sum of products of the adjacent returns:

$$RV_{i,t} = \sum_{j=1}^{d_t} r_{i,j}^2 + 2\sum_{j=1}^{d_t-1} r_{i,j} r_{i,j+1} \tag{4}$$

where, again, $r_{i,j}$ is the return of asset i on day j of quarter t and d_t is the number of trading days in quarter t.

The other estimate of quarterly volatility for each asset is obtained by estimating an EGARCH(1, 1) model[4] over an expanding window with a minimum of eight quarterly returns required for estimation. Formally, the monthly variance for our EGARCH(1, 1) model is defined as follows:

$$r_t = c + \epsilon_t \qquad \epsilon_t \sim N\left(0, \sigma_t^2\right) \tag{5a}$$

$$\ln \sigma_t^2 = \alpha_0 + \alpha_1 \frac{\epsilon_{t-1}}{\sigma_{t-1}} + \gamma_1 \left(\frac{|\epsilon_{t-1}|}{\sigma_{t-1}} - \sqrt{\frac{2}{\pi}} \right) + \beta_i \ln \sigma_{t-1}^2 \tag{5b}$$

To reduce the effects of outliers, each quarterly estimate of liquidity and volatility is Windsorized at the 1st and 99th cross-sectional percentiles for each quarter[5].

This results in an unbalanced panel of 4 liquidity and 2 volatility measures over 5,281 NYSE firms, spanning a total of 264 quarters. The various liquidity (volatility) measures will be used to derive a common liquidity (volatility) factor. A common cross-sectional factor will be extracted from the combined liquidity and volatility measures which we will refer to as the common uncertainty factor.

2.3 Factor decomposition of liquidity and volatility measures

We will examine the common uncertainty factor across the various liquidity and volatility measures using a process similar to that of Korajczyk and Sadka (2008). As the units are not comparable for the various liquidity and volatility measures, each measure is standardized using the mean and standard deviation in the cross section using all available data prior to quarter t. Specifically, let M^i be the $n \times T$ matrix of estimator i (this could be either a liquidity or a volatility estimator). Define $\hat{\mu}_{t-1}^i$ and $\hat{\sigma}_{t-1}^i$ as the cross-sectional mean and standard deviation for measure i estimated for all the samples up to $t - 1$. Then, the standardized measure is calculated as $S_{j,t}^i = \left(M_{j,t}^i - \hat{\mu}_{t-1}^i\right)/\hat{\sigma}_{t-1}^i$. The estimator S^i is assumed to follow the factor model:

$$S^i = B^i F^i + \epsilon^i, \tag{6}$$

where F^i is a $k \times T$ matrix of shocks to the liquidity (volatility) measure that are common across the set of n assets, B^i is a $n \times k$ matrix of sensitivities to the common factor and ϵ^i, is the $n \times T$ matrix of asset specific shocks to the liquidity (volatility) measure. Connor and Korajczyk (1986) show that n-consistent estimates of the factors, F^i, are obtained by calculating the eigenvalues of:

$$\Omega^i = \frac{S^{i\prime} S^i}{n}. \tag{7}$$

While this estimator relies on a balanced panel, it does vastly simplify the calculations as we are now simply calculating the eigenvectors of a $T \times T$ matrix, which is independent of the number of stocks in our sample. To accommodate the fact that our panel is unbalanced, we follow the estimation technique of Connor and Korajczyk (1987), which will essentially estimate the elements of Ω using only the observed data. To implement this method, all of the missing observations in S^i are replaced with zeros, and the resulting balanced panel will be called S^{i*}. Define N^i as a $n \times T$ indicator matrix, where each element takes a value of 1 if the element in S^i is observed or 0 if the corresponding element in S^i is missing. Now, we can construct an unbalanced equivalent of Ω that only uses the cross-sectional averages of the observed data:

$$\Omega^{i,u}_{t,\tau} = \frac{\left(S^{i*\prime}S^{i*}\right)_{t,\tau}}{\left(N^{i\prime}N^{i}\right)_{t,\tau}} \tag{8}$$

The estimates of the k latent factors $\hat{F}^{i}$ can be calculated as the eigenvectors ($T \times 1$) of the k largest eigenvalues of $\Omega^{i,u}$. Following Connor and Korajczyk (1986), the eigenvectors are normalized so that the rows have a mean-square of 1.

Common factors across all of the liquidity (volatility) measures are extracted. This can be accomplished by stacking the multiple liquidity (volatility) measures and then using the stacked matrix to form Ω. The factors extracted from the stacked liquidity (volatility) measures will be referred to as the common, or across-measure, liquidity (volatility) factors. The sign of the liquidity factors is chosen so that an increase in the factor will correspond to an increase in liquidity. This is done by choosing the sign so that the within-measure factors are negatively correlated with the cross-sectional mean of the measure (although for turnover it will be positively correlated). In addition to across-measure liquidity and volatility factors, a common "uncertainty" factor is extracted using all of the quarterly liquidity and volatility measures. The majority of the analysis will center on examining the relationship between this uncertainty factor and the macro-economy, with special attention given to business cycles.

3. Results

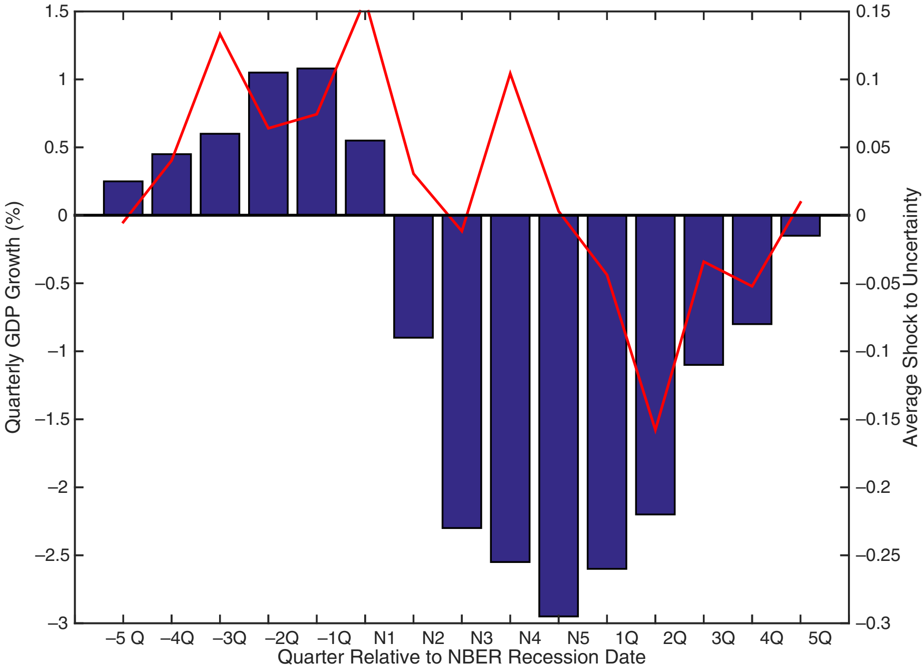
3.1 Data transformation

Frequently, there is a need to transform macroeconomic series owing to the presence of a unit root. We perform various Augmented Dickey–Fuller (ADF) tests to determine whether a variable contains a possible unit root, including specifications with and without trend components. Not surprisingly, we fail to reject the null that the series does not possess a unit root for the macroeconomic variables not including the term spread. The presence of a unit root in the series of shocks to the uncertainty, liquidity and volatility factors was also rejected by the ADF test. We are also potentially interested in the various liquidity measures upon which our factors are based. We therefore calculate the equally weighted cross-sectional quarterly mean for both the Amihud and Roll measures.

To achieve stationarity in the series used in this study, we transform the necessary variables by taking the first log difference. For example, we construct dGDP (real GDP growth) as $\mathrm{dGDP} = \ln\left[\frac{GDP_t}{GDP_{t-1}}\right]$. The other variables, for which we could not reject the presence of a unit root, undergo a similar log-difference transformation as in Næs *et al.* (2011).

3.2 Uncertainty shocks and business cycles

It is widely accepted that in the most recent recession, there was a strong connection between the decline in liquidity in financial markets and the financial crisis. We also saw an increase in the volatility of returns. We begin our exploration of this relationship by first examining Figure 1. In this figure, we follow the method of Næs *et al.* (2011) in constructing a bar graph of the accumulated average quarterly real GDP growth before and after the NBER defined recession. For each of the recessions in the sample, there are a total of 11 defined NBER recessions between 1947Q1 and 2012Q4; we construct a window that begins five quarters before the date of the peak (beginning of the recession) and extend that for five quarters after the recession ends. We, then, average the growth rates across the recessions, remembering that each is aligned so that N1 is the first quarter of the recession on the x-axis of Figure 1. The average growth rates are then accumulated over the even window. The



Notes: We construct a window around each of the NBER recession start dates that spans 5 quarters prior to the recession, 5 quarters during the recession, and 5 quarters after the recession. We plot the accumulated average quarterly GDP growth in a bar chart. Also included is a plot of the average shock to our uncertainty measure (based on multiple liquidity and volatility measures) during the same quarters. We find that in the quarters leading up to a recession, there are positive shocks. Toward the end of the recession and during the start of the recovery, we see that on average there are negative shocks to uncertainty. Data from 1947Q1 to 2012Q4

Figure 1.
Average quarterly real GDP growth

average shocks to our uncertainty measure (as derived from a variety of liquidity and volatility measures) during the same window are also included in Figure 1. The heavy black line coincides with the 0 value for the uncertainty shocks and is included to simply make the figure more quickly legible.

As we note, averaging over all of the recessions since 1947Q1, there is positive growth to real GDP in the five quarters leading up to the recession. During the recession, the average growth rate becomes negative and then begins to improve in the quarters after the recession, exactly as we would expect given the definition of an economic recession. The true interest in Figure 1 is the behavior of the average shocks to our uncertainty measure around the NBER recession dates. We see a pattern in the uncertainty shocks where there are positive shocks (increased uncertainty) preceding the recession and in the beginning of the recession. Then, on average, the shocks become negative (decreased uncertainty) as the economy begins to leave the recession. This seems to suggest a possible relationship between our measure of uncertainty and changes in real GDP growth.

3.3 Correlations

In Table I, we present the contemporaneous correlations between the US macroeconomic variables as well as our measures of uncertainty, liquidity and volatility. A brief examination of the table reveals some interesting relationships. Our uncertainty measure is negatively correlated with several key macroeconomic series including real GDP growth (dGDP), the growth in real industrial production (dIP), real consumption growth (dCons) and growth in real private investment (dInv). This suggests that as uncertainty increases (in other words, we see a decrease in assets' liquidity and an increase in the volatility of stock returns) the growth rates of real GDP, real consumption, real private investment and real industrial production will decrease. Should there be a large enough spike in uncertainty, the economy may slide into a recession. Another interesting feature of Table I is that the shocks to the across-measure volatility factor (VOL) do not appear to be significantly correlated to any of the series except for the uncertainty measure. This may suggest that there is little improvement in the forecasting of GDP growth by including the volatility measures in addition to liquidity measures (i.e. forecasts from a model with UNC may not be significantly better than those from a model using LIQ). Recall that LIQ measures liquidity while both Amihud and Roll measure illiquidity, which explains the opposite signs on their correlations. The signs of the correlations for both the term spread (Term) and the credit spread (dCred) are what we would expect. Furthermore, nothing unusual appears in the correlations for the macroeconomic variables.

3.4 In-sample predictability

In this subsection, we explore both the ability of our uncertainty measure to predict GDP growth in-sample as well as any Granger causality between the series. The models under consideration are of the following form:

$$y_{t+1} = \alpha + \beta\, UNC_t + \gamma' X_t + \eta_{t+1} \tag{9}$$

where UNC_t is our uncertainty measure and X_t is a matrix of additional regressors including $Term_t$, *dCred* and the lagged dependent variable. The dependent variable we are primarily interested in is real GDP growth, but we also include the growth in the unemployment rate (dUE), the growth in real industrial production (dIP), real consumption growth (dCons) and the growth in private investment (dInv).

The results of the various regressions are presented in Table II. We first consider models that include only UNC_t and the lagged dependent variable. Additional regressions are performed with the inclusion of Term and dCred.

One important note is that $\hat{\beta}$ is significant in every specification, suggesting that shocks to our proposed uncertainty measure help predict the gap growth in the following quarter. Specifically, a positive shock (increase) in "uncertainty" (corresponding with a decrease in liquidity and an increase in volatility) predicts lower GDP growth, lower industrial production growth (dIP), increased growth in the unemployment rate, decreased growth in real consumption and decreased growth in real private investment. Consider the following illustration to better understand the coefficients. Suppose we have a one standard deviation change in uncertainty measure. The standard deviation of *UNC* is 0.2004. Thus, this one standard deviation increase would result in a predicted 0.2004 × − 0.010 = −0.0020 or 0.20 per cent drop in the quarterly real GDP growth. The average quarterly real GDP growth over our sample period is 0.78 per cent, which means a one standard deviation increase would lower the real GDP growth forecast by about 26 per cent of its historical average.

Table I. Contemporaneous correlations

	UNC	LIQ	VOL	Amihud	Roll	Term	dCred	dGDP	dUE	dCons	dInv
LIQ	−0.87 (0.00)										
VOL	0.48 (0.00)	−0.07 (0.23)									
Amihud	0.15 (0.01)	−0.14 (0.03)	0.10 (0.49)								
Roll	0.35 (0.00)	−0.31 (0.00)	0.30 (0.00)	0.55 (0.00)							
Term	−0.18 (0.01)	0.14 (0.02)	−0.01 (0.85)	−0.13 (0.05)	0.03 (0.66)						
dCred	0.26 (0.00)	−0.38 (0.00)	−0.12 (0.06)	0.17 (0.01)	0.22 (0.00)	−0.18 (0.01)					
dGDP	−0.21 (0.00)	0.20 (0.00)	−0.09 (0.15)	−0.23 (0.00)	−0.32 (0.00)	0.21 (0.00)	−0.35 (0.00)				
dUE	0.12 (0.05)	−0.10 (0.12)	0.10 (0.11)	0.28 (0.00)	0.31 (0.00)	−0.15 (0.02)	0.29 (0.00)	−0.58 (0.00)			
dCons	−0.14 (0.02)	0.16 (0.01)	−0.04 (0.51)	−0.14 (0.02)	−0.24 (0.00)	0.17 (0.01)	−0.31 (0.00)	0.60 (0.00)	−0.29 (0.00)		
dInv	−0.23 (0.00)	0.18 (0.00)	−0.11 (0.06)	−0.19 (0.00)	−0.29 (0.00)	0.26 (0.00)	−0.33 (0.00)	0.78 (0.00)	−0.49 (0.00)	0.21 (0.00)	
dIP	−0.22 (0.00)	0.23 (0.00)	−0.04 (0.54)	−0.23 (0.00)	−0.33 (0.00)	0.19 (0.00)	−0.43 (0.00)	0.70 (0.00)	−0.44 (0.00)	0.49 (0.00)	0.66 (0.00)

Notes: Quarterly measures of liquidity (LIQ), volatility (VOL) and what we term "uncertainty" (UNC) are derived from liquidity and volatility measures calculated from daily CRSP data. The sample includes 5281 NYSE stocks from January 1947 to December 2012. The macroeconomic series span 1947Q1 to 2012Q4 and were obtained from the FRED as provided by the Federal Reserve Bank of St. Louis. p-values are listed in parentheses beneath the correlation coefficients

y_{t+1}	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{Term}$	$\hat{\gamma}^{dCred}$	R^2
dGDP	0.006	−0.010	0.216			0.09
	(7.39)	(−3.67)	(3.46)			
	0.005	−0.009	0.215	0.001	0.001	0.12
	(3.61)	(−3.03)	(3.07)	(1.97)	(0.31)	
dIP	0.007	−0.023	0.155			0.07
	(4.28)	(−3.49)	(2.66)			
	0.003	−0.020	0.113	0.002	−0.004	0.11
	(1.38)	(−3.39)	(1.70)	(2.03)	(−0.41)	
dUE	0.001	0.058	0.244			0.08
	(0.22)	(2.92)	(3.36)			
	0.017	0.044	0.221	−0.011	0.064	0.16
	(2.31)	(2.20)	(2.59)	(−3.19)	(2.07)	
dCons	0.006	−0.005	0.321			0.12
	(6.97)	(−2.05)	(4.59)			
	0.005	−0.004	0.312	0.001	0.007	0.14
	(4.68)	(−1.82)	(4.17)	(2.01)	(1.86)	
dInv	0.009	−0.065	0.128			0.07
	(2.67)	(−4.82)	(2.09)			
	0.001	−0.057	0.069	0.006	−0.024	0.13
	(0.23)	(−3.86)	(1.08)	(2.32)	(−1.23)	

Notes: Quarterly measures of what we term "uncertainty" (UNC) are derived from liquidity and volatility measures calculated from daily CRSP data. The sample includes 5281 NYSE stocks from January 1947 to December 2012. The macroeconomic series span 1947Q1 to 2012Q4 and were obtained from the FRED as provided by the Federal Reserve Bank of St. Louis. The estimated models are of the form $y_{t+1} = \alpha + \beta UNC_t + \gamma' X_t + u_{t+1}$ where UNC_t is our uncertainty measure and X_t contains additional regressors including the lagged dependent variable. The Newey and West (1987) adjusted t-stats with 4 lags are presented in parentheses beneath the parameter estimates

Table II.
In-sample predictive regressions

Similar to the contemporaneous correlations, the $\hat{\beta}$s have the expected signs. A positive shock to our uncertainty measure will result in a lower forecast for real GDP growth (dGDP), real industrial production growth (dIP), growth in real consumption expenditures (dCons) and growth in real private investment (dInv). It will also lead to an increased forecast of the growth in the unemployment rate (dUE). While Carlston (2012) shows that the commonality between liquidity and volatility risk (our uncertainty measure) carries a significant risk premium for investors, we show that changes in the uncertainty measure impact predictions of future economic growth not limited to the financial sector.

3.5 Granger causality

In addition to looking at using our uncertainty measure to help predict various macroeconomic series, we will examine a possible causal relationship going in the opposite way as well. Næs *et al.* (2011) performed several Granger causality tests to better understand the relationship between GDP growth and three different measures of liquidity. They found evidence of a one-way Granger casualty from liquidity measures to GDP growth. We will similarly examine whether macroeconomic conditions affect our uncertainty measure or if it is primarily a one direction causal relationship.

The Granger causality tests are performed using a VAR setup, where the optimal number of lags for each VAR system was chosen using the Bayesian Information Criterion (BIC)[6]. The tests were performed over the entire sample as well as the two subsamples created by splitting the sample in half. Table III contains the results of the tests for Granger causality between various macroeconomic variables and our uncertainty measure derived from liquidity and volatility measures.

Examining Table III, we notice strong evidence that our uncertainty measure Granger causes real GDP growth and real industrial production growth, but the Granger causal relationship does not run in the opposite direction. What is surprising is that the relationship doesn't hold for the second half of the sample for growth in the unemployment rate and real consumption growth, even though there is evidence that

Table III. Granger causality

Test	Entire sample 1947-2012	First half 1947-1979	Second half 1980-2012
H_0: $dGDP \nrightarrow UNC$			
χ^2	0.01	0.21	0.03
p-value	0.92	0.65	0.86
H_0: $UNC \nrightarrow dGDP$			
χ^2	12.81**	8.25**	6.89**
p-value	0.00	0.00	0.01
H_0: $dIP \nrightarrow UNC$			
χ^2	0.36	0.01	0.73
p-value	0.55	0.94	0.73
H_0: $UNC \nrightarrow dIP$			
χ^2	8.08**	6.60**	3.05*
p-value	0.00	0.01	0.08
H_0: $dCons \nrightarrow UNC$			
χ^2	0.84	1.66	0.03
p-value	0.36	0.20	0.85
H_0: $UNC \nrightarrow dCons$			
χ^2	4.34**	5.89**	0.54
p-value	0.04	0.02	0.46
H_0: $dUE \nrightarrow UNC$			
χ^2	1.95	2.42	0.40
p-value	0.16	0.12	0.53
H_0: $UNC \nrightarrow dUE$			
χ^2	3.63*	6.95**	0.14
p-value	0.06	0.01	0.71

Notes: Quarterly measures of what we term "uncertainty" (UNC) are derived from liquidity and volatility measures calculated from daily CRSP data. The sample includes 5281 NYSE stocks from January 1947 to December 2012. The macroeconomic series span 1947Q1 to 2012Q4 and were obtained from the FRED as provided by the Federal Reserve Bank of St. Louis. A VAR specification is used in the tests of Granger causality where the number of included lags was chosen using the Bayesian Information Criterion (BIC). Here the null is that there is no Granger causality between the variables so a statistically significant test rejects the null of no Granger causality

UNC Granger causes those variables for the entire sample and the first half of the sample. It may be interesting in future work to gain a better understanding of the reason for this breakdown.

3.6 Out-of-sample predictability

Up to this point, our analysis has focused on the in-sample predictive power of UNC for various macroeconomic series. In this subsection, we will evaluate the out-of-sample performance of forecasts for real GDP growth that rely on our uncertainty measure (UNC). Specifically, we will compare several nested and non-nested models to determine if there are any statistically significant gains to including UNC in the forecasting models for real GDP growth.

Before discussing the statistical tests for out-of-sample forecast evaluation, we will discuss the general methodology for constructing our forecasts. The forecasts are calculated by first estimating the model over a rolling, a fixed 5-year window (20 quarters). When constructing the forecast from the estimated parameters, we use financial variables (e.g. UNC) from the previous quarter but GDP growth is lagged two quarters owing to the delay in reporting its most recent value (Næs *et al.*, 2011). This means the first out-of-sample forecast is for 1952Q2 using parameters from the regression spanning 1947Q1 to 1952Q1. The financial variables for the 1952Q2 forecast are from 1952Q1, while the lagged GDP growth value is from 1951Q4. From there, everything is shifted one quarter, repeated and then shifted forward again.

When comparing non-nested models, we rely on the Diebold and Mariano (1995) statistic (DM), while nested models are compared using both the encompassing test proposed by Clark and McCracken (2001) and the test for equal mean squared forecast error between two nested models proposed by McCracken (2007). The DM test statistic tests the null hypothesis of equal predictive accuracy. Let $d_t = L\left(\epsilon^1_{t+h|t}\right) - L\left(\epsilon^2_{t+h|t}\right)$ where $L(s^2)$ is simply the squared loss function. Then, the null of equal predictive accuracy can be rewritten as H_0: $E[d_t] = 0$.

Now, let us look more closely at the tests for nested models. The ENC–NEW test proposed by Clark and McCracken (2001) tests whether the restricted model (the model with fewer regressors; in our case, the model without UNC) encompasses the unrestricted model. If we reject the null hypothesis that the restricted model encompasses the unrestricted model, then, we would conclude that the additional regressors improve the accuracy of the forecasts. The test statistic is given by:

$$\mathrm{ENC-NEW} = (P - h + 1)\frac{P^{-1}\sum_t \left[\hat{u}^2_{r,t+1} - \hat{u}_{r,t+1}\cdot\hat{u}_{u,t+1}\right]}{MSFE_u} \tag{10}$$

where P is the number of out-of-sample forecasts, h is the forecast horizon, $\hat{u}_{r,t+1}$ denotes the out-of-sample forecast errors for the restricted model and $MSFE_u$ is the mean squared forecast error for the unrestricted model.

The other test for nested models that we consider is the MSE–F test proposed by McCracken (2007). This is an F-style test for equal MSFE between the restricted and unrestricted models. The test statistic is given by the following:

$$\mathrm{MSE}-\mathrm{F}=(P-h+1)\frac{MSFE_r-MSFE_u}{MSFE_u} \tag{11}$$

where $MSFE_u$ is the mean squared forecast error of the unrestricted model. Both these test statistics have a nonstandard asymptotic distribution, so we use the bootstrapped critical values provided by Clark and McCracken (2001) and McCracken (2007). Table IV presents the results of the out-of-sample forecasting tests.

The DM tests of non-nested models allows us to test whether there is any significant out-of-sample forecasting gain by using our uncertainty measure based on liquidity and volatility measures versus a liquidity measure based upon multiple liquidity measures or the raw liquidity measures themselves. While the previous tests have shown that there is a connection between our uncertainty measure and macroeconomic variables, the DM tests conclude that the expected MSFE of forecasts based on UNC, LIQ, and the quarterly mean of the Amihud measure is equal. The nested model tests show that there is definitely a benefit to including either UNC or LIQ as an additional regressor into an AR(1) forecasting model. So, while our uncertainty measure is certainly useful in predicting changes to real GDP growth and displays a strong correlation with several macroeconomic variables, it doesn't appear to significantly outperform LIQ or Amihud when estimating forecasts of real GDP growth.

4. Conclusion

With the recent financial crisis, during which there was a noticeable link between the economic downturn and a reduction in liquidity, there has been a lot of research focusing on measuring liquidity and linking it to the overall state of the economy. Næs *et al.* (2011) show that a link between liquidity and GDP growth has existed in past

	Non-nested tests (forecasting GDP growth)		
		Model 2	
Model 1	UNC	LIQ	Amihud
LIQ	−0.38		
Amihud	0.38	0.49	
Roll	1.62*	1.75*	1.55*
	Nested Tests (AR(1))		
Unrestricted Model	Restricted Model	ENC-NEW	MSE-F
UNC, dGDP	dGDP	41.07**	5.09**
LIQ, dGDP	dGDP	37.57**	6.67**

Notes: Quarterly measures of what we term "uncertainty" (UNC) are derived from liquidity and volatility measures calculated from daily CRSP data. The sample includes 5,281 NYSE stocks from January 1947 to December 2012. The macroeconomic series span 1947Q1 to 2012Q4 and were obtained from the FRED as provided by the Federal Reserve Bank of St. Louis. This table includes tests between nested and non-nested models. The Diebold–Mariano (1995) test statistic was used to compare non-nested models, while the ENC–NEW of Clark and McCracken (2001) and the MSE–F of McCracken (2007) were used for the nested model comparisons. The non-nested models always include the lagged GDP growth as well as one of the measures of either uncertainty or liquidity. The null hypothesis for the DM test is that of equal MSFE with a one-sided alternative that Model 2 has a lower MSFE than Model 1.5 and 10% significance are denoted with a ** and * respectively

Table IV. Out-of-sample real GDP growth forecast performance recessions and that it isn't limited to this most recent crisis. In this paper, we use the uncertainty measure of Carlston (2012), which is based on multiple measures of stock liquidity and volatility.

The construction of this quarterly "uncertainty" measure relies on daily measures of liquidity and volatility and is based on the work of Korajczyk and Sadka (2008), who analyze several liquidity measures. It relies on various liquidity and volatility measures across 5281 NYSE firms from January 1947 to December 2012. A latent factor model is estimated across the collection of all liquidity and volatility measures, and from these factors, we obtain a measure of the commonality of liquidity and volatility, which we call "uncertainty". Shocks to the measure of uncertainty have a correlation of 0.65 to changes in the uncertainty measure of Jurado *et al.* (2015). Then, we explore a possible link between real economic variables and this uncertainty measure. We find that the uncertainty measure exhibits both in-sample and out-of-sample predictive ability for real GDP growth. Furthermore, when examining the average shock to uncertainty with the average quarterly real GDP growth around NBER recession dates, we find evidence that they track each other. Additional statistical tests show that our uncertainty measure Granger causes real GDP growth in addition to other macroeconomic variables, including industrial production and real consumption. Out-of-sample forecasting tests show that while our uncertainty measure adds predictive power to a simple forecast based on an AR(1) model for GDP growth, Diebold and Mariano (1995) tests indicate that there is no significant improvement in forecasts based on our uncertainty measure from those based solely on liquidity measures. We conclude that while the common measure of liquidity and volatility risk correlates with the real economy, when forecasting economics variables there is no statistical difference between the accuracy of forecasts based on our uncertainty measure and those based solely on liquidity measures.

Notes

1. The estimates from Baker *et al.* (2016) were obtained from www.PolicyUncertainty.com and those of Jurado *et al.* (2015) were obtained from www.sydneyludvigson.com/data-and-appendixes/
2. Real GDP is taken from the GDPC96 series, which is the real GDP taken to three decimals, in billions of chained 2005 dollars, and seasonally adjusted.
3. Harris (1990), suggests using $\hat{s} = -2\sqrt{Scov}$ when $Scov < 0$, but this would result in a negative spread, which would imply a negative transaction cost.
4. Similar results were found when using a simple GARCH(1, 1) model or a GJR-GARCH(1, 1, 1) model.
5. To illustrate, consider the variance estimate $\mathrm{RV}_{\mathrm{i,t}}$. Let $RV_t^{99\%}$ be the 99th percentile of all RV estimates for the quarter t. If $RV_{j,t} > RV_t^{99\%}$, then $\mathrm{RV}_{j,t}$ is set equal to $RV_t^{99\%}$. Similarly, any quarterly measure that is less than $RV_t^{1\%}$ will be set equal to the 1st first percentile.
6. The BIC chose VAR systems with one lag for each test.

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