The Information Content of Bond Liquidity: What Does It Reveal About the Business Cycle?*

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February 21, 2019

Abstract

We analyze the information content of bond liquidity associated with the future development of the economy in the United States. At the latest since the recent financial crisis the importance of liquidity, liquidity spirals, and finally the impact on the real economy has widely been discussed. In in- and out-of-sample analyses, we find bond liquidity to be an effective predictor for key macroeconomic variables. In further tests it turns out that the relation is mainly driven from crisis periods when liquidity deteriorates. To take advantage of this finding, we implement MS-MIDAS models and, indeed, liquidity augmented models outperform their benchmarks.

*We thank Jelena Eberbach, Martin Hain, and Karol Paludkiewicz for helpful suggestions and gratefully acknowledge financial support from the Deutsche Forschungsgemeinschaft (Grant No. UH 107/3−1).

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1 Introduction

The forward-looking nature of asset prices and its useful role in macroeconomic forecasting is well established in the literature. Earlier studies mainly focus on the predictive power of interest rates (Sims (1980), Bernanke and Blinder (1992)), term spreads (Estrella and Hardouvelis (1991)), and default spreads (Bernanke (1983), Friedman and Kuttner (1992)).

More recent theoretical literature emphasizes the consequences of liquidity for economic activity, e.g., due to liquidity spirals (Brunnermeier and Pedersen (2009)) or a reduction in financial sector's risk-bearing capacity (He and Krishnamurthy (2013)) but empirical evidence for liquidity's forecasting capability is still sparse. With the detrimental effect of deteriorating liquidity and its impact on the economy during the recent financial crisis, first empirical studies were conducted. Næs et al. (2011), for instance, are able to forecast changes in U.S. and Norwegian gross domestic product using different stock market liquidity measures. These results are confirmed for the United Kingdom and Germany by Apergis et al. (2015). In contrast, Chen et al. (forthcoming) focus on disentangling stock market liquidity and volatility and find information regarding the future economy contained in both variables and Chen et al. (2016) use stock market liquidity as early warning signal to successfully predict U.S. recessions.

While above studies provide clear evidence that market microstructure (illiquidity) can have macroeconomic implications, all studies invariably focus on stock market illiquidity.[1] But in contrast to centralized stock trading at exchanges, bonds are traded over-the-counter and thus the market microstructure and the degree of transparency differ substantially. In addition, the ownership concentration among bond holders (e.g., pension funds, insurance companies) and the main focus on a few issues (e.g., benchmark bonds) are characteristics of the bond market with effects on liquidity which are nonexistent in the stock market.

[1]Another strand of the literature which detects a relation between market microstructure and the economy deals with the signaling of investors' expectations about fundamental values through bond market order flows (Green (2004), Brandt and Kavajecz (2004), Pasquariello and Vega (2007)) and stock market order flows (Beber et al. (2011), Kaul (2017)).

Goyenko and Ukhov (2009) highlight also the importance of bond illiquidity in transmitting monetary policy shocks into the stock market, which indicates that some information is contained in bond liquidity first. Moreover, bond markets are the main (re-)financing source for governments and corporations and the backbone of the economy. The size of the market increased more than sevenfold in the last 30 years with an outstanding marketable debt of \$39.8 trillion (Q2 2017) from which \$14 trillion are federal debt securities.[2] Furthermore, a few theoretical models already examine the relation of firms' abilitiy to borrow and the impact on the economy and find higher refinancing costs leading to adverse consequences for the real economy (Bernanke et al. (1999), Jermann and Quadrini (2012)).

This paper therefore examines the information content of bond liquidity associated with the future economy. Using quarterly data ranging from Q1 1987 to Q4 2016, we investigate the relation between bond liquidity and several major macroeconomic variables to capture different facets of the business cycle. In the in-sample analysis, we find that bond liquidity clearly contains information about the future development of the economy. Since stock liquidity is included as control variable, the result is not driven by commonality between stock and bond market liquidity but by information solely contained in bond liquidity. The relation between liquidity and unemployment, private investment, and industrial production is highly significant and robust. In-sample results for gross domestic product are mixed. We further examine whether this relation holds out-of-sample, which is confirmed (for gross domestic product as well) with the characteristic that some liquidity augmented models outperform their benchmark mostly during recessions. Although predictions are of particular importance during such times and on average the augmented models are still superior, we further take advantage of this finding by estimating nonlinear models. It turns out that liquidity is, as expected from previous analyses, highly significant in the weak economic states and able to improve the models' performance.

Furthermore, the paper leads to substantial applications. The ability to predict changes

[2] Source: Securities Industry and Financial Markets Association (sifma), https://www.sifma.org/resources/research/us-bond-market-issuance-and-outstanding/, accessed on October 10, 2017.

in the business cycle is of crucial importance for several parties. First, it is highly relevant from an investor's perspective to adapt the portfolio to prevent serious losses and not to miss investment opportunities that may arise. Second, monetary authorities in particular need to consider all aspects which reveal substantial information about changes in the business cycle to implement a forward looking monetary policy and to evaluate the effectiveness of their decisions. Third, such information is also useful to value the profitability of companies' investment decisions and their strategic orientations.

The remaining paper is structured as follows: In Section 2 we explain the construction of the liquidity measure and introduce the data. Section 3 carries out in-sample analyses and causality tests to examine the information content of bond liquidity. In addition, out-of-sample analyses are performed in Section 4 and furthermore the prediction quality is studied during different economic times. In Section 5, nonlinearities are taken into account.

2 Bond Liquidity Measure and Data

2.1 Bond Liquidity Measure

Measuring liquidity of bonds is not as straightforward as it is the case for stock liquidity since most trades are settled over the counter and reliable historical data for common liquidity measures is not available for a long time period. We therefore use the liquidity measure developed by Hu et al. (2013) which relies solely on prices of traded bonds. It captures the dispersion of market observed U.S. Treasury yields around the theoretical yield curve implied by the Svensson (1994) model. The underlying intuition is as follows: During crisis times, prices move away from their fundamental value, which yields a higher price dispersion. Due to the scarcity of capital in such times, these arbitrage opportunities are not immediately exploited.

The measure is constructed as the root mean squared error between market observed and theoretical yields

$$\sqrt{\frac{1}{N_t}\sum_{i=1}^{N_t}\left[y_{t,i}-\hat{y}_{t,i}\right]^2},$$

where $y_{t,i}$ is the observed yield of bond i on date t, $\hat{y}_{t,i}$ the corresponding model-implied yield, and N_t the number of bonds available. Henceforth we refer to the variable as *Illiq*, since spikes are associated with deteriorating liquidity.

Hu et al. (2013) perform several analyses to demonstrate that the measure indeed captures liquidity and is not only driven by volatility.

2.2 Data

The main analysis is based on quarterly data ranging from Q1 1987 until Q4 2016. To capture different facets of the business cycle, we focus on the unemployment rate (*Unemp*), real gross domestic product (*GDP*), real gross private domestic fixed investment (*Inv*), and industrial production (*IP*).[3] All macroeconomic time series are chained dollar estimates (except *Unemp*), seasonally adjusted, and supplied from the Federal Reserve Bank of St. Louis (FRED).

The focus of the analysis is on bond liquidity (*Illiq*) described in Section 2.1 as explanatory variable. Based on U.S. Treasury data provided by Bloomberg, we extend the time series received from Hu et al. (2013) by two years (January 2015 until December 2016) to match the period of our investigation. We closely follow Hu et al. (2013) and include all exchange-listed plain vanilla treasury securities with a remaining maturity between one month and 10 years in the construction of the theoretical yield curve. For the computation of *Illiq*, the minimum time to maturity is increased to one year, due to known liquidity issues at the very short end (Kamara (1994)).

In addition, we also take a look at other financial variables which are identified in the

[3] Since *Unemp* and *IP* are available on a monthly frequency, we repeat all subsequent analyses on a monthly basis in Appendix A.

literature to be able to predict economic activity, namely term spread (*Term*), credit spread (*Credit*), volatility (*Vol*), market return (R^m), and stock liquidity based on Amihud (2002) (*Amihud*).[4] The first two variables are motivated by Fama and French (1989) and based on the bond market. *Term* is the yield spread between the 10-year and 1-year Treasury bond and *Credit* Moody's Seasoned Aaa Corporate Bond Yield in relation to the 10-year Treasury bond yield.[5] The data is received from the FRED. We use the excess return on the stock market from Fama and French (1993) and the historical 30-day volatility of the S&P500 is sourced from Bloomberg.[6] As an additional control variable, we also include the Amihud measure which reflects liquidity of the U.S. stock market to monitor whether bond liquidity contains superior information about economic activity. *Illiq* is significantly correlated with *Amihud* (0.42).

To achieve stationarity, we take log differences for all macroeconomic variables, *Amihud*, and *Credit*.

3 In-Sample Analysis

3.1 Methodology

The model for the in-sample analysis is:

$$y_t = \beta_1 y_{t-1} + \beta_2 Illiq_{t-1} + \beta_3' x_{t-1} + \epsilon_t, \tag{1}$$

with $y_t \in \{GDP_t,\ Unemp_t,\ Inv_t,\ IP_t\}$ and x_{t-1} a vector of control variables from Section 2.2. Control variables are added successively according to the scheme in Table 1. In the reported baseline model, we include only one lag of the dependent variable but rerun the analysis

[4]As additional proxy for U.S. stock market liquidity we also consider bid-ask spreads in the following section and results are qualitatively the same (available upon request).

[5]Alternatively, using Moody's Seasoned Baa Corporate Bond Yield in relation to the 10-year Treasury yield does not change the findings.

[6]90-day volatility does not alter the results.

with two and four lags in order to check the robustness of the results. To incorporate the possibility of autocorrelated and heteroskedastic residuals, Newey-West standard errors are reported.

All data is standardized to better understand the economic significance of each variable. A standardized coefficient indicates how many standard deviations the dependent variable changes as a result of a one standard deviation increase in the corresponding explanatory variable.

3.2 In-Sample Regression Results

Table 1 illustrates the results from the in-sample analysis.[7,8] The bond liquidity coefficient (column 2) is highly significant for *Unemp*, *Inv*, and *IP* regardless of the inclusion of control variables.[9] A one standard deviation increase in *Illiq* (which is a deterioration in liquidity) yields an increase of 0.322 standard deviations in *Unemp* and to a decrease of 0.219 and 0.220 standard deviations in *Inv* and *IP*, respectively. These values are not only statistically significant but also crucial from an economic perspective. The liquidity coefficient is significant in the first two specifications for *GDP* as well but becomes insignificant when Vol, R^m, and *Amihud* are additionally added as control variables. Nevertheless, bond liquidity contains predictive power for *GDP*, even though the in-sample properties of some control variables seem to be superior. However, the in-sample power of these variables does not necessarily have to hold in out-of-sample analyses, which we examine in Section 4.

To highlight the importance of liquidity, ΔR^2 (adjusted) is reported in the last column of

[7] In-sample results with *Illiq* based on the Hodrick-Prescott filter are in Appendix B.

[8] The bond liquidity results do not change when the Amihud and Hurvich (2004) adjustment is considered (results are available upon request) to avoid potential issues with the Stambaugh bias (see Stambaugh (1999) for details).

[9] Gilchrist and Zakrajšek (2012) decompose a credit spread index into a default component and a residual part which they label excess bond premium. The excess bond premium (Fig. 4 in Gilchrist and Zakrajšek (2012)) shares some commonality with *Illiq*, however, some spikes of the time series are neither related to *Illiq* nor to periods of financial turbulence. Although their indirect approach involves some caveats such as model assumptions, they show in an in-sample analysis that the excess bond premium is able to forecast the business cycle. We included the excess bond premium in an in-sample specification with *Illiq* and all other control variables from Section 2.2 and both liquidity-related variables remained statistically and economically significant (available upon request).

Table 1. It is the difference of the adjusted R^2 with *Illiq* in- and excluded in the regression of the respective model. The decline of ΔR^2 for models with more explanatory financial variables is not surprising since they share some information content with bond liquidity. Nevertheless, particularly for *Unemp* we find a large increase of 8.86 in the first specification (autoregressive model) and still a difference of 4.77 for the full model. *Inv* and *IP* increase at least between 2.00 and 7.82, depending on the model specification.

In addition, we find the lagged endogenous variable to be significant and positive in all cases which is a common finding for rather slow moving macroeconomic variables. Some control variables do have explanatory power as well but are always considerably lower in magnitude compared to bond liquidity. All significant signs are as expected. $Term$ is known to be high at troughs and therefore predicts periods of expansion (see, e.g., Fama and French (1989), Hamilton and Kim (2002)), along with a decrease in *Unemp* and an increase in *IP*. *Credit*, on the other hand, is high when investors are looking for safe havens and predicts recessions. This is in line with a positive coefficient of *Credit* for *Unemp*. Similar, high volatility is associated with periods of uncertainty which leads to negative signs for *GDP*, *Inv*, and *IP* and a positive sign for *Unemp* (although not significant). The coefficient for Amihud (R^m) is negative (positive) and significant for *Inv* and *IP* since stock liquidity - as bond liquidity - deteriorates during economic downturns and positive stock returns are related to stable times.

Table 1: **In-Sample Regression Results**

The table illustrates the estimated coefficients for the period from Q1 1987 until Q4 2016 based on the in-sample regression $y_t = \beta_1 y_{t-1} + \beta_2 Illiq_{t-1} + \beta_3' x_{t-1} + \epsilon_t$. One of the macroeconomic variables is contained in y_t. *Unemp* is unemployment, *GDP* is real gross domestic product, *Inv* is real gross private domestic fixed investment, and *IP* is industrial production. The focus is on coefficient β_2, which quantifies the impact of bond liquidity (*Illiq*) on the macroeconomic variable. The yield spread between the 10-year and 1-year Treasury bond (*Term*), Moody's Seasoned Aaa Corporate Bond Yield minus the 10-year Treasury bond yield (*Credit*), the excess return on the market based on Fama and French (1989) (R^m), the 30-day volatility of the S&P500 index (*Vol*), Amihud's (2002) stock liquidity measure (*Amihud*), and the lagged macroeconomic variable are included as control variables. The last column reports the difference in R^2 (adj) between the respective models with liquidity in- and excluded. ***,**,* indicate significance at the 1%, 5%, 10% levels, respectively.

	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3^{Term}$	$\hat{\beta}_3^{Credit}$	$\hat{\beta}_3^{Vol}$	$\hat{\beta}_3^{R^m}$	$\hat{\beta}_3^{Amihud}$	ΔR^2 (adj)
Unemp	0.444***	0.375***						8.36
	0.452***	0.372***	−0.115**	0.112*				8.38
	0.433***	0.323***	−0.113**	0.076	0.085	−0.043		4.98
	0.436***	0.322***	−0.113**	0.078	0.082	−0.044	−0.004	4.77
GDP	0.319***	−0.215*						3.26
	0.322***	−0.216*	0.021	0.011				3.33
	0.283***	−0.120	0.019	0.064	−0.164	0.054		0.15
	0.300***	−0.113	0.018	0.089	−0.165	0.028	−0.081	0.01
Inv	0.473***	−0.329***						6.94
	0.468***	−0.338***	0.100	−0.025				7.44
	0.452***	−0.235**	0.097*	0.061	−0.112	0.187***		2.52
	0.482***	−0.219*	0.091	0.098	−0.108	0.143**	−0.143**	2.00
IP	0.490***	−0.307**						6.17
	0.472***	−0.355***	0.158**	0.025				7.82
	0.448***	−0.247***	0.138**	0.096	−0.130	0.174***		2.88
	0.482***	−0.220***	0.128**	0.130	−0.128	0.133*	−0.138*	2.12

3.3 Causality Tests

In addition to the in-sample results from Table 1, we test for causality to find out whether the reverse relation might hold as well. The procedure by Toda and Yamamoto (1995) is robust with respect to poor results from unit root tests which are known to have low statistical power. It is based on an augmented vector autoregressive model (VAR)

$$y_t = \sum_{i=0}^{p} \Phi_{11,i} y_{t-i} + \sum_{j=p+1}^{d_{max}+p} \Phi_{11,j} y_{t-j} + \sum_{i=0}^{p} \Phi_{12,i} x_{t-i} + \sum_{j=p+1}^{d_{max}+p} \Phi_{12,j} x_{t-j} + \epsilon_t$$
$$x_t = \sum_{i=0}^{p} \Phi_{21,i} y_{t-i} + \sum_{j=p+1}^{d_{max}+p} \Phi_{21,j} y_{t-j} + \sum_{i=0}^{p} \Phi_{22,i} x_{t-i} + \sum_{j=p+1}^{d_{max}+p} \Phi_{22,j} x_{t-j} + u_t,$$

where the original lag length p (chosen in accordance with the Bayesian information criterion (BIC)) is extended by d_{max}, the highest order of integration of the original time series in levels. The hypothesis of non-causality is subsequently tested for the first p coefficients. For the augmented VAR which includes all macroeconomic variables and bond liquidity BIC suggests $p = 1$.[10]

Table 2 summarizes the results.[11] We begin with testing the null hypothesis that bond liquidity does not Granger-cause one of the macroeconomic variables. The first number of every column is the corresponding χ^2 value. The hypothesis can be rejected for each variable at the 1% level. This is in line with the findings in Section 3.2 and encourages our further analyses. The second number of every cell is the χ^2 value which results from testing the null hypothesis of no reverse causation. It can be rejected for *GDP* at the 10% level and for *IP* at the 1% level. Both variables appear to have at least some impact on bond liquidity as well. For *Unemp* and *Inv* we fail to reject the null hypothesis at every conventional level.

[10]Akaike information criterion (AIC) suggests a lag length of three. Nevertheless, the causality results do not alter for $p = 3$.

[11]Pairwise Toda and Yamamoto (1995) causality tests based on bivariate VARs lead to the same results.

Table 2: **Granger-Causality between Liquidity and Macroeconomic Variables**
The table shows Granger-causality results using the Toda and Yamamoto (1995) approach. In each column, the χ^2 value corresponding to H_0: bond liquidity (*Illiq*) does not Granger-cause the respective macroeconomic variable (first number) and the χ^2 value of reverse causality's test (H_0: macroeconomic variable does not Granger-cause bond liquidity) (second number) is reported. *Unemp* is unemployment, *GDP* is real gross domestic product, *Inv* is real gross private domestic fixed investment, and *IP* is industrial production. The sample period is from Q1 1987 until Q42016. ***,**,* indicate significance at the 1%, 5%, 10% levels, respectively.

	Unemp	GDP	Inv	IP
Illiq	15.1*** / 1.4	7.6*** / 3.5*	24.4*** / 1.2	9.2*** / 24.1***

4 Out-of-Sample Analysis

From Section 3 we conclude that bond liquidity contains information about the business cycle and is an effective in-sample predictor. Nevertheless, we cannot make any statement about its out-of-sample properties so far. In this section, we test whether bond liquidity is also useful in forecasting economic activities out-of-sample.

4.1 Methodology

In the out-of-sample analysis we compare the explanatory power of several financial variables with the respective models augmented with bond liquidity (Tables 3-6, Panel A) and the explanatory power of an autoregressive model in relation to its counterpart with bond liquidity and other financial variables included separately (Tables 3-6, Panel B).

An important issue for out-of-sample analyses is the timing of information to avoid look-ahead bias. The first estimate of *GDP* is published one month after the end of the previous quarter. A second and a final estimate based on more data is made available one and two additional months later, respectively. Since the goal of the paper is to forecast economic activity, we are only interested in the final and most accurate estimate. The same applies to *Inv*, which is a component of *GDP* and published in the same manner. On the other hand, *Unemp* and *IP* are available monthly and published in the following month.

The focus of the out-of-sample analyses is on the one quarter ahead forecast. At the end of each quarter t, we use current financial and lagged macroeconomic variables to forecast the corresponding macroeconomic variable in quarter $t+1$. Moreover, we also compute nowcasts, in which the present economic condition is predicted, which is of interest due to the publication lag. For nowcasts at the end of quarter t, estimates of *Unemp* and *IP* are already available for the first two months of the quarter. This is why we nowcast both variables (end of quarter) using the most recent available estimates as explanatory variables in the autoregressive models.

We study both recursive as well as rolling window estimates. There is no consensus which method yields more accurate forecasts. It is always a trade-off between a lower variance of the estimates and taking structural changes of the economy into consideration. To ensure precise estimates, we choose $R = 52$ quarters as a fixed width for the rolling window forecasts and as a training period for the first recursive estimate.[12]

There are basically two different approaches to evaluate the performance of out-of-sample forecasts: tests of equal mean squared prediction errors (MSE) and forecast encompassing tests. McCracken (2007) provides an F-type out-of-sample test of equal MSE

$$\begin{aligned} \textit{MSE-F} &= (T-R-\kappa+1)\frac{\sum_{t=R}^{T-\kappa}\hat{\epsilon}_{1,t+\kappa}^2-\sum_{t=R}^{T-\kappa}\hat{\epsilon}_{2,t+\kappa}^2}{\sum_{t=R}^{T-\kappa}\hat{\epsilon}_{2,t+\kappa}^2} \\ &= (T-R-\kappa+1)\frac{MSE_1-MSE_2}{MSE_2} \end{aligned} \tag{2}$$

and Clark and McCracken (2001) develop a forecast encompassing test for nested models

$$\textit{ENC-NEW} = (T-R-\kappa+1)\frac{\sum_{t=R}^{T-\kappa}(\hat{\epsilon}_{1,t+\kappa}^2-\hat{\epsilon}_{1,t+\kappa}\hat{\epsilon}_{2,t+\kappa})}{\sum_{t=R}^{T-\kappa}\hat{\epsilon}_{2,t+\kappa}^2}, \tag{3}$$

[12]Based on the findings of Shiller and Perron (1985), Rai (2015) stresses the necessity of long time series to measure the relation between macroeconomic and financial variables. Nevertheless, the length of the training period is of course arbitrary to a certain extent (e.g., Næs et al. (2011), Rai (2015), and Chen et al. (forthcoming) use 20, 60, and 120 quarters, respectively). We choose 52 quarters to ensures a stable estimation and still be able to take structural changes into account.

where $\hat{\epsilon}_{i,t+\kappa},\ i = 1,2$ are the prediction errors of the restricted and unrestricted models, T the total number of observations in the sample, and κ the forecast horizon. Since the limiting distribution of the tests is nonstandard, both papers compute bootstrapped critical values which are kindly provided by the Federal Reserve Bank of Kansas City.[13] Moreover, in Monte Carlo simulations, Clark and McCracken (2001) find that both test statistics have preferable finite-sample size properties but ENC-NEW has in addition higher power.[14]

A significant ENC-NEW test statistic implies that the restricted model does not encompass the unrestricted model which is augmented with bond liquidity, or, in other words, there is a linear combination of both models with an MSE less than the restricted model's MSE. However, the optimal weights are only known ex-post which is a drawback of forecast encompassing tests for practical purposes in general.

4.2 Out-of-Sample Regression Results

Tables 3-5 illustrate the results for *Unemp*, *Inv*, *IP*, and *GDP*, respectively. Generally speaking, we can confirm promising out-of-sample properties of bond liquidity for all macroeconomic variables.

Taking a closer look at *Unemp* (Table 3, Panel A), the fraction of the unrestricted and restricted models' MSEs are clearly below 1 for all specifications. The MSE-F tests in the following column confirm this statement from a statistical point of view. The forecast encompassing tests (ENC-NEW) are highly significant as well, for both the recursive and the rolling window approach. Although results for the nowcasts are already convincing, the finding is even more pronounced in the case of the one quarter ahead forecasts. Panel A leads to the conclusion that *Illiq* contains information associated with the future economy which is not included in one of the other financial variables. Panel B summarizes the results for the autoregressive models. The objective is to find out whether *Illiq* and the control

[13] `http://www.kansascityfed.org/publicat/other/criticalvalues_tec.xls`, accessed on June 12, 2016.

[14] Clark and McCracken (2001) also take other MSE and forecast encompassing tests into consideration in their Monte Carlo simulation and ENC-NEW emerges as the most powerful one.

variables contain information not included in lagged *Unemp*. It turns out that not every control variable is able to outperform the benchmark model. In particular the one quarter ahead forecast of *Term* does poorly, even though it is significant in the in-sample analysis. However, *Illiq* once again performs well: Only *Illiq* and *Vol* are able to outperform the nowcasts of the restricted model. Results for *Inv* and *IP* are similar (Table 4 and Table 5), with even more distinct improvements through *Illiq* in nowcasting.

For *GDP* (Table 6) results are mixed. First, in particular in Panel A, the rolling window approach seems to be superior, which indicates the existence of some structural changes in the relation of *GDP* and the financial variables during the complete sample. Second, the dominance of *Illiq* over the other financial variables in forecasting *GDP* is not that distinct. Nevertheless, according to ENC-NEW, the restricted financial model (which includes all financial variables) does not encompass its liquidity augmented counterpart in the case of nowcasting and the rolling window approach (Panel A). For the one quarter ahead forecasts of the same model, results are even stronger: Regardless of the forecasting approach and the test statistic, the model's forecasting quality is improved in a significant manner by adding *Illiq*. When the autoregressive model acts as a benchmark (Panel B), the *Illiq* augmented model is only able to make superior predictions when the rolling window approach is used. In general, only R^m improves forecasting accuracy independent of the parameter estimation scheme and the forecasting horizon in Panel B of Table 6.

Table 3: **Out-of-Sample Evaluation: Unemployment**

Panel A reports one quarter ahead unemployment (*Unemp*) forecasts and nowcasts for nested models, to compare the out-of-sample properties of bond liquidity (*Illiq*) in relation with other financial variables. *Term* is the yield spread between the 10-year and 1-year Treasury bond, *Credit* is Moody's Seasoned Aaa Corporate Bond Yield minus the 10-year Treasury bond yield, R^m is the excess return on the market based on Fama and French (1989), and *Vol* is the 30-day volatility of the S&P500 index. The training period for the first estimate lasts from Q2 1987 until Q2 2000. The subsequent testing period is from Q3 2000 until Q4 2016. To assess the significance of the results, MSE-F and ENC-NEW test statistics (equation (2) and (3)) are reported. A significant rejection of the null hypothesis of the MSE-F test implies lower forecast errors of the unrestricted model. A rejection of the null hypothesis of the ENC-NEW test leads to the conclusion that the restricted model does not encompass the unrestricted model. Panel B applies the same statistics to test whether one of the financial variables is able to beat the autoregressive benchmark. ***,**,* indicate significance at the 1%, 5%, 10% levels, respectively.

Panel A: Liquidity vs. Financial Variables								
	Unrestricted	Restricted	$\frac{MSE_U}{MSE_R}$		MSE-F		ENC-NEW	
			Rec.	Roll.	Rec.	Roll.	Rec.	Roll.
1-Q-Ahead	Illiq, Term	Term	0.465	0.377	76.049***	109.186***	60.771***	100.123***
	Illiq, R^m	R^m	0.501	0.435	65.802***	85.600***	50.867***	78.434***
	Illiq, Credit	Credit	0.475	0.395	72.932***	101.075***	57.479***	94.168***
	Illiq, Vol	Vol	0.673	0.657	32.129***	34.380***	23.569***	30.248***
	Illiq, All	All	0.675	0.685	31.798***	30.309***	23.820***	27.441***
Nowcast	Illiq, Term	Term	0.862	0.798	10.770***	16.909***	7.783***	13.731***
	Illiq, R^m	R^m	0.861	0.814	10.824***	15.312***	8.085***	14.223***
	Illiq, Credit	Credit	0.863	0.811	10.603***	15.603***	7.740***	13.738***
	Illiq, Vol	Vol	0.985	0.980	1.045*	1.350*	1.032	2.284**
	Illiq, All	All	0.976	0.969	1.682**	2.130**	1.329*	2.351**

Panel B: Financial Variables vs. Autoregressive Models								
	Unrestricted	Restricted	$\frac{MSE_U}{MSE_R}$		MSE-F		ENC-NEW	
			Rec.	Roll.	Rec.	Roll.	Rec.	Roll.
1-Q-Ahead	Illiq, Unemp	Unemp	0.567	0.446	50.371***	81.881***	36.719***	70.673***
	Term, Unemp	Unemp	1.011	1.000	−0.709	−0.032	−0.162	0.286
	R^m, Unemp	Unemp	0.933	0.916	4.773***	6.086***	3.535***	5.220***
	Credit, Unemp	Unemp	0.949	0.994	3.549**	0.381	2.343**	1.052
	Vol, Unemp	Unemp	0.696	0.636	28.877***	37.692***	22.246***	30.135***
Nowcast	Illiq, Unemp	Unemp	0.850	0.722	11.844***	25.818***	8.162***	21.441***
	Term, Unemp	Unemp	1.008	1.011	−0.545	−0.754	−0.012	0.418
	R^m, Unemp	Unemp	1.009	0.982	−0.597	1.251*	−0.188	0.941
	Credit, Unemp	Unemp	1.002	1.036	−0.124	−2.327	0.348	−0.575
	Vol, Unemp	Unemp	0.832	0.795	13.504***	17.248***	11.414***	15.740***

Table 4: **Out-of-Sample Evaluation: Real Gross Private Domestic Investment**
Panel A reports one quarter ahead private investment (*Inv*) forecasts and nowcasts for nested models, to compare the out-of-sample properties of bond liquidity (*Illiq*) in relation with other financial variables. *Term* is the yield spread between the 10-year and 1-year Treasury bond, *Credit* is Moody's Seasoned Aaa Corporate Bond Yield minus the 10-year Treasury bond yield, R^m is the excess return on the market based on Fama and French (1989), and *Vol* is the 30-day volatility of the S&P500 index. The training period for the first estimate lasts from Q2 1987 until Q2 2000. The subsequent testing period is from Q3 2000 until Q4 2016. To assess the significance of the results, MSE-F and ENC-NEW test statistics (equation (2) and (3)) are reported. A significant rejection of the null hypothesis of the MSE-F test implies lower forecast errors of the unrestricted model. A rejection of the null hypothesis of the ENC-NEW test leads to the conclusion that the restricted model does not encompass the unrestricted model. Panel B applies the same statistics to test whether one of the financial variables is able to beat the autoregressive benchmark. ***,**,* indicate significance at the 1%, 5%, 10% levels, respectively.

Panel A: Liquidity vs. Financial Variables								
	Unrestricted	Restricted	$\frac{MSE_U}{MSE_R}$		MSE-F		ENC-NEW	
			Rec.	Roll.	Rec.	Roll.	Rec.	Roll.
1-Q-Ahead	Illiq, Term	Term	0.650	0.555	35.576***	52.972***	31.106***	44.634***
	Illiq, R^m	R^m	0.688	0.594	29.986***	45.191***	25.313***	36.538***
	Illiq, Credit	Credit	0.665	0.570	33.298***	49.714***	28.595***	40.718***
	Illiq, Vol	Vol	0.797	0.736	16.803***	23.695***	14.722***	19.294***
	Illiq, All	All	0.778	0.701	18.829***	28.126***	16.389***	23.779***
Nowcast	Illiq, Term	Term	0.699	0.631	28.908***	39.223***	25.488***	29.642***
	Illiq, R^m	R^m	0.701	0.641	28.596***	37.606***	23.924***	27.176***
	Illiq, Credit	Credit	0.710	0.629	27.363***	39.533***	24.006***	29.124***
	Illiq, Vol	Vol	0.816	0.765	15.120***	20.529***	13.363***	14.752***
	Illiq, All	All	0.837	0.795	13.017***	17.281***	12.453***	12.607***
Panel B: Financial Variables vs. Autoregressive Models								
	Unrestricted	Restricted	$\frac{MSE_U}{MSE_R}$		MSE-F		ENC-NEW	
			Rec.	Roll.	Rec.	Roll.	Rec.	Roll.
1-Q-Ahead	Illiq, Inv	Inv	0.790	0.708	17.495***	27.281***	13.812***	20.287***
	Term, Inv	Inv	0.972	0.976	1.890**	1.590**	1.538*	1.237
	R^m, Inv	Inv	0.806	0.768	15.908***	19.897***	11.997***	15.108***
	Credit, Inv	Inv	0.944	0.936	3.908***	4.518***	2.425**	3.059**
	Vol, Inv	Inv	0.820	0.832	14.507***	13.348***	11.168***	10.960***
Nowcast	Illiq, Inv	Inv	0.811	0.780	15.653***	18.936***	13.987***	13.401***
	Term, Inv	Inv	0.997	1.002	0.202	−0.113	0.277	0.100
	R^m, Inv	Inv	0.972	0.948	1.921**	3.709***	1.804**	3.468**
	Credit, Inv	Inv	0.937	0.987	4.535***	0.872*	3.352**	1.180
	Vol, Inv	Inv	0.829	0.861	13.856***	10.793***	10.597***	8.948***

Table 5: **Out-of-Sample Evaluation: Industrial Production**
Panel A reports one quarter ahead industrial production (*IP*) forecasts and nowcasts for nested models, to compare the out-of-sample properties of bond liquidity (*Illiq*) in relation with other financial variables. *Term* is the yield spread between the 10-year and 1-year Treasury bond, *Credit* is Moody's Seasoned Aaa Corporate Bond Yield minus the 10-year Treasury bond yield, R^m is the excess return on the market based on Fama and French (1989), and *Vol* is the 30-day volatility of the S&P500 index. The training period for the first estimate lasts from Q2 1987 until Q2 2000. The subsequent testing period is from Q3 2000 until Q4 2016. To assess the significance of the results, MSE-F and ENC-NEW test statistics (equation (2) and (3)) are reported. A significant rejection of the null hypothesis of the MSE-F test implies lower forecast errors of the unrestricted model. A rejection of the null hypothesis of the ENC-NEW test leads to the conclusion that the restricted model does not encompass the unrestricted model. Panel B applies the same statistics to test whether one of the financial variables is able to beat the autoregressive benchmark. ***,**,* indicate significance at the 1%, 5%, 10% levels, respectively.

Panel A: Liquidity vs. Financial Variables

	Unrestricted	Restricted	$\frac{MSE_U}{MSE_R}$		MSE-F		ENC-NEW	
			Rec.	Roll.	Rec.	Roll.	Rec.	Roll.
1-Q-Ahead	Illiq, Term	Term	0.779	0.691	18.708***	29.449***	19.897***	35.880***
	Illiq, R^m	R^m	0.846	0.785	12.035***	18.053***	13.296***	24.697***
	Illiq, Credit	Credit	0.799	0.732	16.623***	24.213***	17.496***	30.437***
	Illiq, Vol	Vol	0.972	0.986	1.900**	0.937*	3.628***	6.032***
	Illiq, All	All	0.953	0.954	3.241**	3.189**	5.175***	8.516***
Nowcast	Illiq, Term	Term	0.816	0.747	15.080***	22.737***	16.412***	26.659***
	Illiq, R^m	R^m	0.830	0.791	13.730***	17.703***	14.703***	21.745***
	Illiq, Credit	Credit	0.826	0.751	14.112***	22.270***	15.138***	26.042***
	Illiq, Vol	Vol	0.975	0.976	1.687**	1.622**	3.071**	3.075**
	Illiq, All	All	0.988	1.013	0.795*	−0.858	2.648**	1.311

Panel B: Financial Variables vs. Autoregressive Models

	Unrestricted	Restricted	$\frac{MSE_U}{MSE_R}$		MSE-F		ENC-NEW	
			Rec.	Roll.	Rec.	Roll.	Rec.	Roll.
1-Q-Ahead	Illiq, IP	IP	0.868	0.821	10.018***	14.398***	9.598***	16.263***
	Term, IP	IP	0.988	0.990	0.778*	0.687*	1.394*	1.137
	R^m, IP	IP	0.783	0.784	18.333***	18.180***	14.958***	15.156***
	Credit, IP	IP	0.975	0.944	1.718**	3.946***	1.085*	2.856**
	Vol, IP	IP	0.771	0.774	19.571***	19.287***	16.652***	16.279***
Nowcast	Illiq, IP	IP	0.918	0.880	5.987***	9.159***	6.308***	10.201***
	Term, IP	IP	1.041	1.018	−2.666	−1.205	−0.521	0.008
	R^m, IP	IP	0.966	0.916	2.367**	6.150***	1.787**	5.061***
	Credit, IP	IP	1.001	0.972	−0.084	1.915**	0.074	1.880*
	Vol, IP	IP	0.776	0.764	19.347***	20.717***	17.960***	21.723***

Table 6: **Out-of-Sample Evaluation: Real Gross Domestic Product**

Panel A reports one quarter ahead gross domestic product (*GDP*) forecasts and nowcasts for nested models, to compare the out-of-sample properties of bond liquidity (*Illiq*) in relation with other financial variables. *Term* is the yield spread between the 10-year and 1-year Treasury bond, *Credit* is Moody's Seasoned Aaa Corporate Bond Yield minus the 10-year Treasury bond yield, R^m is the excess return on the market based on Fama and French (1989), and *Vol* is the 30-day volatility of the S&P500 index. The training period for the first estimate lasts from Q2 1987 until Q2 2000. The subsequent testing period is from Q3 2000 until Q4 2016. To assess the significance of the results, MSE-F and ENC-NEW test statistics (equation (2) and (3)) are reported. A significant rejection of the null hypothesis of the MSE-F test implies lower forecast errors of the unrestricted model. A rejection of the null hypothesis of the ENC-NEW test leads to the conclusion that the restricted model does not encompass the unrestricted model. Panel B applies the same statistics to test whether one of the financial variables is able to beat the autoregressive benchmark. ***,**,* indicate significance at the 1%, 5%, 10% levels, respectively.

Panel A: Liquidity vs. Financial Variables

	Unrestricted	Restricted	$\frac{MSE_U}{MSE_R}$ Rec.	$\frac{MSE_U}{MSE_R}$ Roll.	MSE-F Rec.	MSE-F Roll.	ENC-NEW Rec.	ENC-NEW Roll.
1-Q-Ahead	Illiq, Term	Term	0.989	0.843	0.751	12.333***	3.060**	13.262***
	Illiq, R^m	R^m	0.998	0.852	0.138	11.469***	1.957**	10.927***
	Illiq, Credit	Credit	0.994	0.839	0.370	12.659***	2.506**	12.422***
	Illiq, Vol	Vol	0.992	0.865	0.518	10.307***	1.060	7.823***
	Illiq, All	All	0.976	0.857	1.629**	11.054***	1.728**	8.622***
Nowcast	Illiq, Term	Term	0.992	0.863	0.546	10.660***	2.757**	10.469***
	Illiq, R^m	R^m	0.999	0.900	0.055	7.465***	1.939**	7.070***
	Illiq, Credit	Credit	0.993	0.875	0.461	9.532***	2.402**	8.655***
	Illiq, Vol	Vol	1.015	1.050	−1.018	−3.178	0.152	−0.072
	Illiq, All	All	0.994	0.996	0.416	0.256	1.059	1.384*

Panel B: Financial Variables vs. Autoregressive Models

	Unrestricted	Restricted	$\frac{MSE_U}{MSE_R}$ Rec.	$\frac{MSE_U}{MSE_R}$ Roll.	MSE-F Rec.	MSE-F Roll.	ENC-NEW Rec.	ENC-NEW Roll.
1-Q-Ahead	Illiq, GDP	GDP	1.053	0.950	−3.325	3.507***	−0.249	5.204***
	Term, GDP	GDP	1.013	1.020	−0.839	−1.271	−0.127	−0.505
	R^m, GDP	GDP	0.954	0.956	3.201**	3.069**	2.918**	3.216**
	Credit, GDP	GDP	0.982	1.024	1.236*	−1.521	0.922	−0.254
	Vol, GDP	GDP	1.036	1.080	−2.274	−4.863	0.418	0.112
Nowcast	Illiq, GDP	GDP	1.001	0.918	−0.049	5.988***	1.758**	6.578***
	Term, GDP	GDP	1.006	1.003	−0.419	−0.184	−0.130	−0.059
	R^m, GDP	GDP	0.948	0.903	3.648**	7.199***	2.794**	7.539***
	Credit, GDP	GDP	0.903	0.894	7.210***	7.974***	5.069***	6.769***
	Vol, GDP	GDP	0.848	0.758	11.990***	21.350***	8.802***	17.768***

4.2.1 Role of Economic Conditions

The aim of this section is to find out the relation between the quality of bond liquidity in forecasting the business cycle and the state of the economy. Similar to Welch and Goyal (2008) we calculate and plot the cumulative squared forecast error (CSFE) between the restricted and unrestricted model for the out-of-sample period from Q3 2000 until Q4 2016:

$$CSFE = \sum_{t=R}^{T-\kappa} \left(\hat{\epsilon}^2_{1,t+\kappa} - \hat{\epsilon}^2_{2,t+\kappa}\right). \tag{4}$$

For sake of brevity, the two most interesting model specifications and their respective liquidity augmented version are considered: i) with all financial variables and ii) the autoregressive model.

Figures 1-4 illustrate the results. Periods in which unrestricted models outperform their benchmarks are characterized by an upward sloping CSFE. National Bureau of Economic Research (NBER) based recession periods are shaded in gray. For *Unemp* and one quarter ahead forecasts the unrestricted model is at least as effective as the restricted model for the whole out-of-sample period. Additionally, it dominates the restricted model in particular from the beginning of the recent financial crisis on (Fig. 1a, 1b). The CSFE of the nowcasts is similar for the autoregressive model (Fig. 1d) but not that distinct for the financial model (Fig. 1c). Although the unrestricted model in Fig. 1c outperforms from 2008 on and the CSFE is clearly above zero at the end of the sample, the restricted model seems to have performed superior prior to 2008. Nevertheless, Figure 1 confirms the results from Table 3 that *Illiq* contains some information about future *Unemp*.

Figures 2-4 for *GDP*, *Inv*, and *IP* can be discussed together since they exhibit the same pattern: The unrestricted models augmented with *Illiq* outperform only (but very clearly) during the latest financial crisis. For all other periods of time their forecasting ability is either only as effective as the predictions of the restricted models or even worse. Since the CSFE at the end of the time period is larger than zero (except in the case of *GDP* and the one quarter forecast against the autoregressive model), the corresponding fractions of the MSEs in Tables 3-6 are smaller than one (statistically significant).

Based on the results in Tables 5-6, the liquidity augmented models outperform their restricted counterparts on average. Furthermore, the CSFE delivers important insights about the models' performance within the time period which is concealed when monitoring merely test statistics. As a result, the CSFE reveals the exceptional performance of the augmented models during economic downturns, a time when precise forecasts are of particular importance. Therefore, the utilization of liquidity augmented models is still advisable. Nevertheless, to take additional advantage of the findings from this section, we set up a nonlinear model in Section 5.

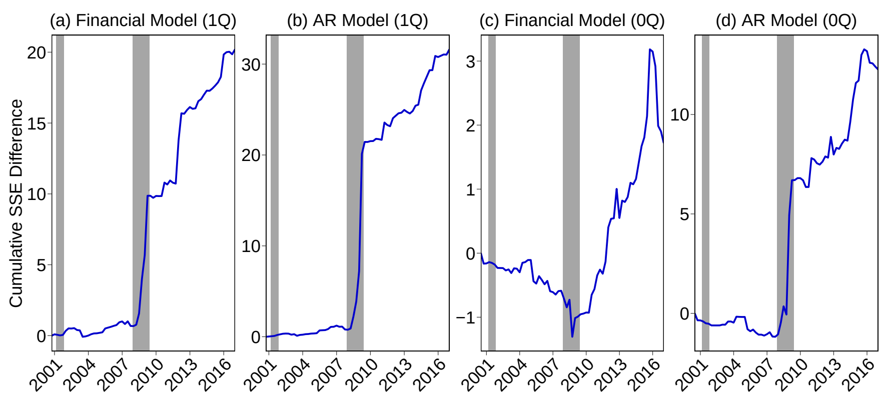

Figure 1: **Cumulative Squared Forecast Error: Unemployment**
The figures illustrate the cumulative squared forecast error (CSFE) from equation (4) in blue for the out-of-sample period from Q3 2000 until Q4 2016. CSFEs are based on unemployment (*Unemp*) forecasts. The figures labeled "Financial Model" include in the benchmark model the yield spread between the 10-year and 1-year Treasury bond (*Term*), Moody's Seasoned Aaa Corporate Bond Yield minus the 10-year Treasury bond yield (*Credit*), the excess return on the market based on Fama and French (1989) (R^m), and the 30-day volatility of the S&P500 index (*Vol*). In figures labeled "AR Model", lagged *Unemp* is the benchmark. The unrestricted models are augmented with bond liquidity (*Illiq*). Figure 1a and Figure 1b are based on one quarter ahead forecasts and Figure 1c and Figure 1d on nowcasts. NBER based recession periods are shaded in gray.

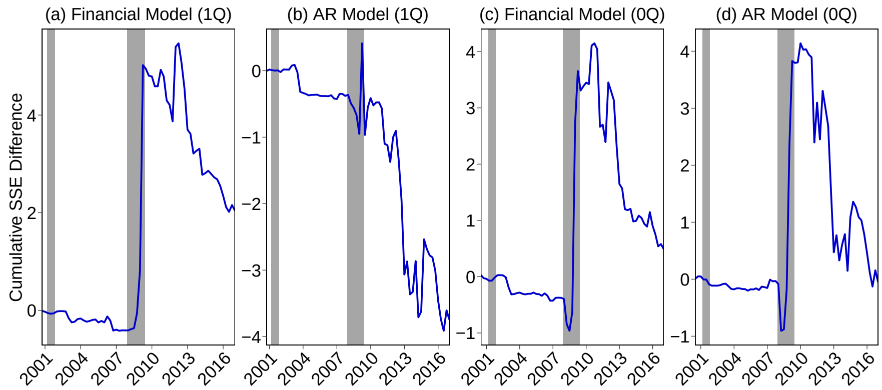

Figure 2: **Cumulative Squared Forecast Error: Real Gross Domestic Product**
The figures illustrate the cumulative squared forecast error (CSFE) from equation (4) in blue for the out-of-sample period from Q3 2000 until Q4 2016. CSFEs are based on gross domestic product (*GDP*) forecasts. The figures labeled "Financial Model" include in the benchmark model the yield spread between the 10-year and 1-year Treasury bond (*Term*), Moody's Seasoned Aaa Corporate Bond Yield minus the 10-year Treasury bond yield (*Credit*), the excess return on the market based on Fama and French (1989) (R^m), and the 30-day volatility of the S&P500 index (*Vol*). In figures labeled "AR Model", lagged *GDP* is the benchmark. The unrestricted models are augmented with bond liquidity (*Illiq*). Figure 2a and Figure 2b are based on one quarter ahead forecasts and Figure 2c and Figure 2d on nowcasts. NBER based recession periods are shaded in gray.

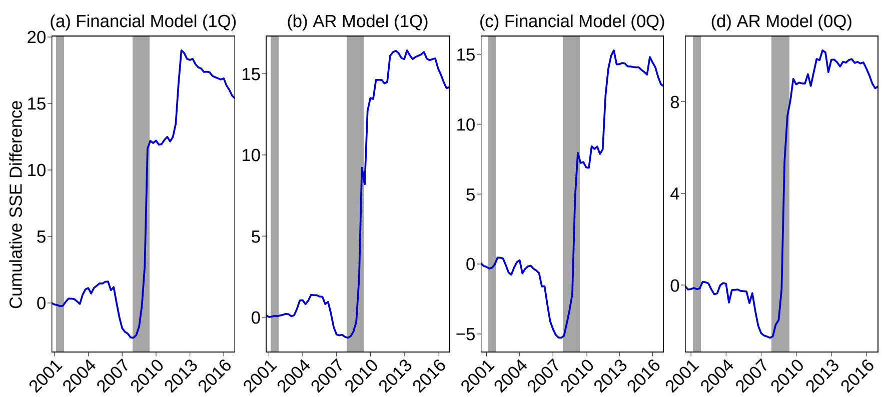

Figure 3: **Cumulative Squared Forecast Error: Real Gross Private Domestic Investment**
The figures illustrate the cumulative squared forecast error (CSFE) from equation (4) in blue for the out-of-sample period from Q3 2000 until Q4 2016. CSFEs are based on private investment (*Inv*) forecasts. The figures labeled "Financial Model" include in the benchmark model the yield spread between the 10-year and 1-year Treasury bond (*Term*), Moody's Seasoned Aaa Corporate Bond Yield minus the 10-year Treasury bond yield (*Credit*), the excess return on the market based on Fama and French (1989) (R^m), and the 30-day volatility of the S&P500 index (*Vol*). In figures labeled "AR Model", lagged *Inv* is the benchmark. The unrestricted models are augmented with bond liquidity (*Illiq*). Figure 3a and Figure 3b are based on one quarter ahead forecasts and Figure 3c and Figure 3d on nowcasts. NBER based recession periods are shaded in gray.

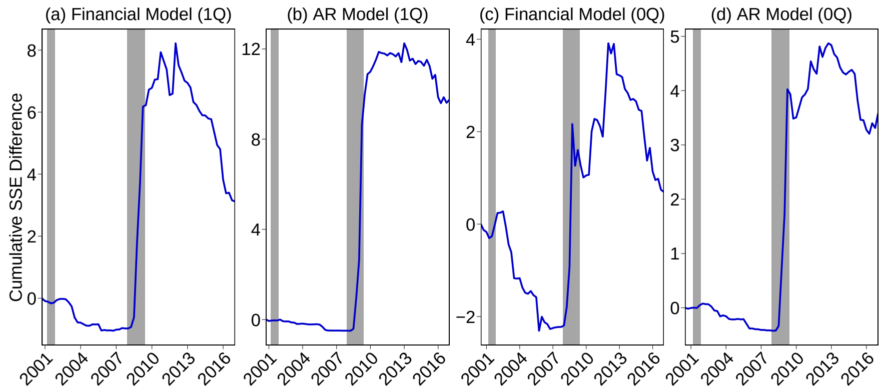

Figure 4: **Cumulative Squared Forecast Error: Industrial Production**
The figures illustrate the cumulative squared forecast error (CSFE) from equation (4) in blue for the out-of-sample period from Q3 2000 until Q4 2016. CSFEs are based on industrial production (*IP*) forecasts. The figures labeled "Financial Model" include in the benchmark model the yield spread between the 10-year and 1-year Treasury bond (*Term*), Moody's Seasoned Aaa Corporate Bond Yield minus the 10-year Treasury bond yield (*Credit*), the excess return on the market based on Fama and French (1989) (R^m), and the 30-day volatility of the S&P500 index (*Vol*). In figures labeled "AR Model", lagged *IP* is the benchmark. The unrestricted models are augmented with bond liquidity (*Illiq*). Figure 4a and Figure 4b are based on one quarter ahead forecasts and Figure 4c and Figure 4d on nowcasts. NBER based recession periods are shaded in gray.

5 Modelling Nonlinearities

Due to the findings from Section 4.2.1 about the beneficial predictions of liquidity during crisis times (for all macroeconomic variables), we now set up a nonlinear model to fully exploit this potential and to test whether *Illiq* is indeed of use in forecasting models when nonlinearities are taken into account. To take advantage of this issue and in addition incorporate financial variables which are available at a higher frequency, we implement a Markov-switching mixed-data sampling model (MS-MIDAS) which was introduced by Guérin and Marcellino (2013).

We focus on the model for *GDP* since it is monitored by many market participants as well as central banks and therefore attracts the most attention in the literature. This enables us the comparison of the specification and results with existing work. Nevertheless, to be able to draw a more general conclusion, we additionally fit models for *Unemp*, *Inv*, and *IP*.

5.1 Markov-Switching Mixed-Data Sampling Model Specifications

The Markov-switching (MS) model which takes nonlinearities into account is given by

$$y_t = \beta_0(s_t) + \beta_1(s_t)y_{t-1} + \beta_2(s_t)Illiq_{t-1} + \beta_3'(s_t)x_{t-1} + \epsilon_t(s_t), \tag{5}$$

where x_{t-1} is the vector of control variables from Section 3, namely *Term*, *Credit*, *Vol*, and R^m and $\epsilon_t(s_t) \sim \mathcal{N}(0, \sigma^2(s_t))$. The unobservable regime s_t follows an irreducible Markov process with M states, $s_t = \{1, \dots, M\}$, defined by the constant transition probabilities

$$p_{ij} = \mathbb{P}(s_{t+1} = j | s_t = i), \; i, j \in \{1, \dots, M\}. \tag{6}$$

The MIDAS model allows the incorporation of explanatory variables at a higher frequency than the dependent variable's time unit (e.g., a quarterly macroeconomic variable as regressand and monthly financial variables as regressors) and is defined by[15]

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 \sum_{j=1}^{K} b(j; \theta^{Illiq}) L^{\frac{(j-1)}{m}} Illiq_{t-1}^{(m)} + \beta_3' \sum_{j=1}^{K} b(j; \theta) L^{\frac{(j-1)}{m}} x_{t-1}^{(m)} + \epsilon_t, \tag{7}$$

with lag operator $L^{\frac{a}{m}} x_{t-1}^{(m)} = x_{t-1-\frac{a}{m}}^{(m)}$. m is the time unit of the vector of higher frequency variables $x_{t-1}^{(m)}$ and K the number of high frequency lags. The parametrization of $b(j; \theta)$ determines the weights of the lagged coefficients. The standard weighting scheme is the

[15] Clements and Galvão (2008) suggest the implementation of the autoregressive lag as common factor (AR-MIDAS). On the other hand, Andreou et al. (2012) point out that this can lead to misspecifications and propose the use of ADL-MIDAS models described by Andreou et al. (2013). Moreover, Guérin and Marcellino (2013) run a Monte Carlo experiment with the Markov-switching equivalent of both ADL-MIDAS and AR-MIDAS models and it turns out that ADL-MIDAS models outperform AR-MIDAS models in almost all cases. Therefore we use an ADL-MIDAS model.

exponential Almon lag[16] with two parameters

$$b(j;\theta) = \frac{e^{\theta_1 j + \theta_2 j^2}}{\sum_{j=1}^{K} e^{\theta_1 j + \theta_2 j^2}}. \tag{8}$$

The exponential Almon lag is usually chosen since it is highly flexible with very few parameters. An overview of other specifications is given in Ghysels et al. (2007).

Combining both models, we end up with an MS-MIDAS model similar to Guérin and Marcellino (2013)

$$\begin{aligned} y_t = \beta_0(s_t) + \beta_1(s_t) y_{t-1} + \beta_2(s_t) \sum_{j=1}^{K} b(j;\theta^{Illiq}) L^{\frac{(j-1)}{m}} Illiq_{t-1}^{(m)} \\ + \beta_3'(s_t) \sum_{j=1}^{K} b(j;\theta) L^{\frac{(j-1)}{m}} x_{t-1}^{(m)} + \epsilon_t(s_t). \end{aligned} \tag{9}$$

In the analysis with quarterly macroeconomic variables and monthly financial variables $m = 3$, and since it turns out that the model does not load on high frequency lags longer than six months ago, we set $K = 6$. In line with Guérin and Marcellino (2013) we do not allow the autoregressive parameter β_1 and the MIDAS parameters θ^{Illiq} and θ to change between regimes in order not to complicate the estimation any further. On the other hand, the coefficient β_2 and the parameter vector β_3 which both model the relation between the endogenous variable *GDP* and the variables of higher frequency (β_2 shows its relation to liquidity and β_3 to the control variables), are able to switch between regimes. The model deviates slightly in the number of regimes from the specification of Guérin and Marcellino (2013) and Bessec and Bouabdallah (2015) who also use MS-MIDAS models to predict output. Instead of three different states, AIC and BIC suggest only two regimes. In Figure 1 in the internet appendix of Guérin and Marcellino (2013), the smoothed probabilities of being in one of the three regimes are illustrated. The third regime, which they label "high expansionary regime", lasts mainly until the mid 1980s. A structural break (e.g., a reduction

[16] The exponential Almon lag was first introduced in Ghysels et al. (2007) and named based on the Almon lag in the distributed lag literature (e.g., Almon (1965))

in output volatility) during that time is also identified in Gordon (2005) and Arias et al. (2007), among others. Consequently, since our sample starts after the beginning of the Great Moderation[17], having only two regimes is also in accordance with the existing literature. The model is estimated using the Hamilton-filter (Hamilton (1989)).

In addition, we calculate two criteria to assess the quality of the regime classification. The quadratic probability score (QPS) based on Diebold and Rudebusch (1989) and the turning point indicator (TPI) based on Bessec and Bouabdallah (2015). The QPS is defined as

$$QPS = \frac{1}{T}\left[\mathbb{P}(s_t = 1|\mathcal{F}_T) - S_t\right]^2, \tag{10}$$

with $\mathbb{P}(s_t = 1|\mathcal{F}_T)$, the smoothed probabilities of being in state one, and a dummy variable S_t of the *true* regime proxied by NBER based recessions. QPS is bounded between 0 and 1 and a low QPS indicates that the model is able to classify each point in time to the correct regime. The TPI tests whether the model is able to detect a turning point with a lead or lag of one quarter. A threshold parameter α is introduced to assign each quarter to a regime. The TPI is calculated as

$$TPI(\alpha) = \frac{1}{n}\sum_{t=1}^{T} \max_{-1\leq h\leq 1}\left[\left(I_{\{\mathbb{P}(s_{t-h}=1|\mathcal{F}_T)>\alpha\}} - I_{\{\mathbb{P}(s_{t-h-1}=1|\mathcal{F}_T)>\alpha\}}\right)(S_t - S_{t-1})\right], \tag{11}$$

where n is the number of turning points within the sample. In contrast to the QPS, the TPI attaches more importance to the correct timing of a regime change but neglects probabilities below the threshold parameter.

[17]Stock and Watson (2002) determined the structural break date to be Q3 1983 and named the following period "Great Moderation".

5.2 Markov-Switching Mixed-Data Sampling Results

We first take a look at the probabilities of being in a specific regime followed by a discussion on QPS as well as TPI to confirm the quality of the model specification. Afterward, we deal with the estimates of the coefficients.

The smoothed probabilities of being in the 2nd regime are shaded in gray in Figure 5a. The recession lasting from July 1990 until March 1991 and the recent financial crisis are described very well. According to a 50% regime classification rule, the recession between March 2001 and November 2001 is identified correctly as well. Nevertheless, the model has some difficulties to explicitly determine the latter period as an economic downturn. This is similar in Chen et al. (2016) and not too surprising since the recession was to some extent different compared with others due to its extreme mildness and shortness (for an extensive comparison, see Kliesen (2003)). There is one spike in early 1992 in the probability function which is not identified as crisis by NBER. However, although officially the recession ended in March 1991, *GDP* growth remained weak. Henceforth we label the 2nd state "recession" due to the high degree of consensus between the MS-MIDAS implied probabilities and NBER based recession periods. On the other hand, the probability function of the first regime is close to one during periods of economic growth which is why we name it "expansion".

QPS and TPI confirm the intuition from Figure 5a. Panel A of Table 7 shows that the TPI equals one for $\alpha \in \{0.3, 0.5\}$. With a lead or lag of one quarter, every regime switch is predicted correctly. The low QPS of 0.04 confirms in addition the model's confidence about the regime and the correctness of its decision.

Table 7, Panel B and Panel C, summarize the parameter estimates of the model. Interestingly, there is no significant connection between one of the financial variables and *GDP* in the expansion state and only lagged *GDP* is significant at the 1% level. The estimated coefficients during recessions paint a completely different picture. In addition to lagged *GDP*, all financial variables are highly significant, except *Vol*. All signs are as expected (the expected relation between one of the dependent variables and the regressors is discussed in more detail in Section 3). This might be a reason for different findings in the literature related to the predictive power of financial variables, dependent on whether there is a crisis in the analyzed sample or not. The probability of staying in the expansion state in the following quarter is with 0.9337 larger than the probability of remaining in a recession which is 0.6131. This results in an expected duration of 15.1 and 2.6 quarters in the expansion and recession

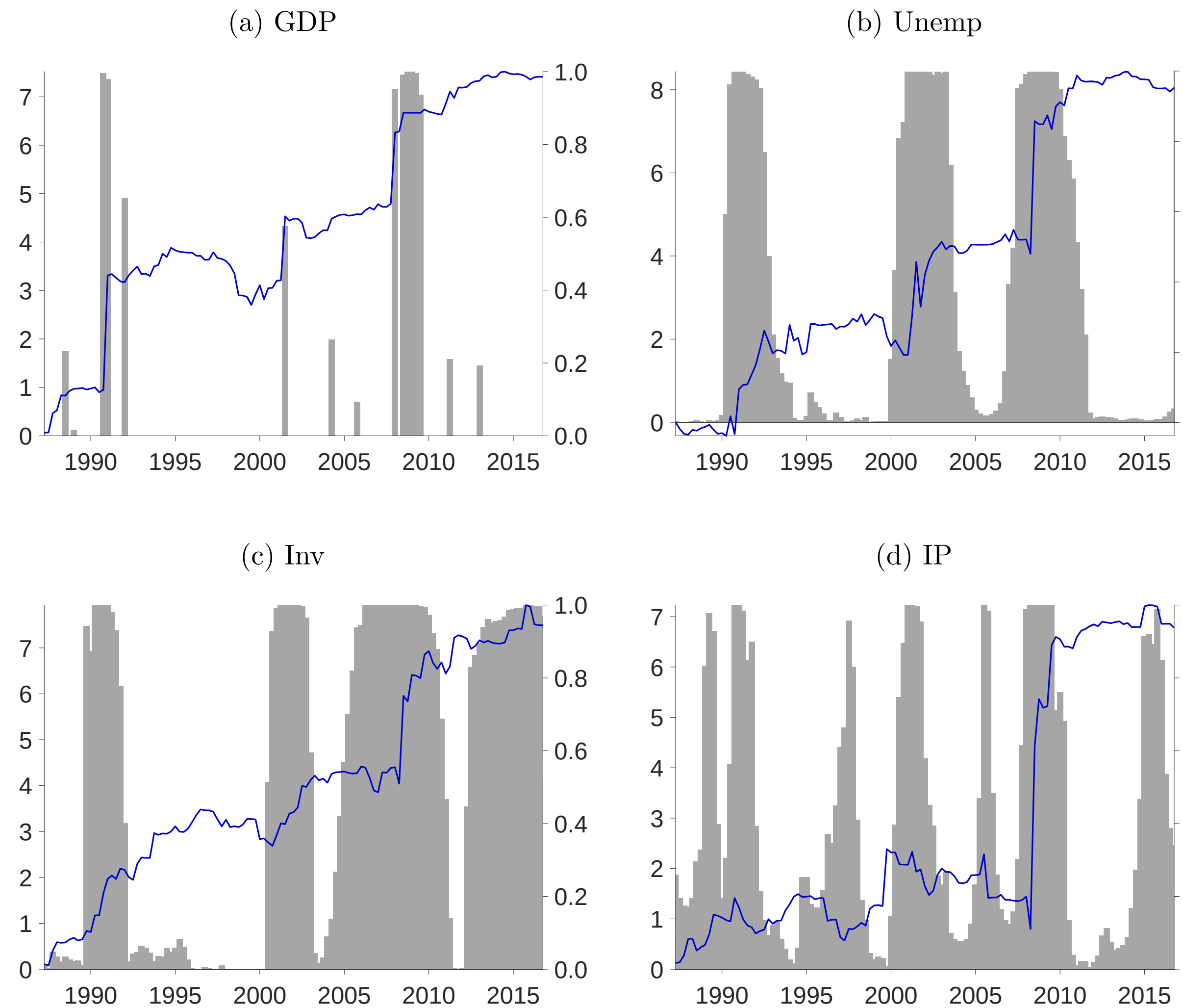

Figure 5: **MS-MIDAS Results**
The figures show the cumulative squared forecast error (CSFE) from equation (4) in blue (left axis) for gross domestic product (GDP), unemployment ($Unemp$), private investment (Inv), and industrial production (IP) based on the MS-MIDAS model specification in Section 5.1. The unrestricted model is augmented with bond liquidity ($Illiq$). Forecast errors are based on in-sample analyses from Q1 1987 until Q4 2016. MS-MIDAS implied recession probabilities (right axis) are shaded in gray.

Table 7: **MS-MIDAS Results: Real Gross Domestic Product**
Panel A illustrates the quadratic probability score (QPS) and the turning point indicator (TPI) from equation (10) and (11) to assess the quality of the model in separating both regimes. Panel B reports the estimates of the MS-MIDAS model (equation (9)) for gross domestic product (*GDP*). The focus is on coefficient β_2, which quantifies the impact of bond liquidity (*Illiq*) on *GDP*. In addition to *Illiq*, lagged *GDP*, the yield spread between the 10-year and 1-year Treasury bond (*Term*), Moody's Seasoned Aaa Corporate Bond Yield minus the 10-year Treasury bond yield (*Credit*), the excess return on the market based on Fama and French (1989) (R^m), and the 30-day volatility of the S&P500 index (*Vol*) are included in the model. State 1 is associated with economic growth. On the other hand, the 2nd state represents recession periods. ***,**,* indicate significance at the 1%, 5%, 10% levels, respectively. In Panel C, estimates of the parameter of the Almon lag (equation (8)) are shown. The sample period is from Q1 1987 until Q4 2016.

Panel A	
QPS	0.048
TPI (0.5%)	1.00
TPI (0.3%)	1.00

Panel B

			State 1 (Expansion)					
$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3^{Term}$	$\hat{\beta}_3^{Credit}$	$\hat{\beta}_3^{Vol}$	$\hat{\beta}_3^{R^m}$	$\hat{\sigma}_1$	$\hat{p}_{11}$
0.008	0.190***	0.043	0.031	0.022	–0.009	–0.066	0.90	0.933
			State 2 (Recession)					
$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3^{Term}$	$\hat{\beta}_3^{Credit}$	$\hat{\beta}_3^{Vol}$	$\hat{\beta}_3^{R^m}$	$\hat{\sigma}_2$	$\hat{p}_{22}$
0.003	0.190***	–0.543***	0.692***	–1.274***	–0.118	0.913***	0.18	0.613

Panel C

$\hat{\theta}_1^{Illiq}$	$\hat{\theta}_1^{Term}$	$\hat{\theta}_1^{Credit}$	$\hat{\theta}_1^{Vol}$	$\hat{\theta}_1^{R^m}$
0.742	6.520	–1.484	–1.567	–3.395
$\hat{\theta}_2^{Illiq}$	$\hat{\theta}_2^{Term}$	$\hat{\theta}_2^{Credit}$	$\hat{\theta}_2^{Vol}$	$\hat{\theta}_2^{R^m}$
–0.160	–0.337	0.003	0.076	0.281

regimes, respectively.[18] It is a common finding for business cycles that periods of economic growth last longer. The estimates of θ (Almon lag) from equation (8) are given in Panel C. They determine the shapes of the weighting functions of the lags of higher frequency. Small parameter imply more weight on the first few lags which is the case for *Credit*, *Vol*, and R^m. The weights for *Illiq* are almost equally distributed among the first four lags and *Term*

[18]This is in line with the mean duration of expansion and contraction in the sample.

loads highly on the last one. Taken together, the model is consistent with reality and the expectation from Figure 6 about the importance of bond liquidity during weak economic times is confirmed for *GDP*.

To illustrate the superior performance of liquidity, Figure 5a additionally plots in blue the CSFE from equation (4) of the MS-MIDAS model augmented with *Illiq* against the MS-MIDAS model with *Illiq* excluded. Again, an upward sloping CSFE indicates periods of dominance of the liquidity augmented model while periods with a downward sloping CSFE argue in favor of the restricted model. While during stable economic times prediction errors of both models are roughly the same, during all three crises the CSFE is clearly upward sloping.

Figures 5b-5d plot the smoothed probabilities of the 2nd regime for the remaining macroeconomic variables *Unemp*, *Inv*, and *IP*. Compared with Figure 5a, the second regime is in all cases clearly more persistent. This is consistent with the literature as well as our expectations, since *GDP* is a highly aggregated time series. In the case of *Unemp*, an extensive literature exists on the so called "jobless recovery". A phenomenon observable in the United States since the recession of the early 1990s which describes the recovery of output after a through without the origination of jobs. Reasons are, for example, job polarization and permanent job losses due to structural changes (e.g., Groshen and Potter (2003), Schmitt-Grohé and Uribe (2012), and Jaimovich and Siu (2015)). The probability function of *Inv* is similar compared with *Unemp*. To better understand the figure, it is advantageous to consider both components of *Inv*, residential and nonresidential investment, separately. As Kydland et al. (2016) demonstrate, residential investment precedes and nonresidential investment follows fluctuations in output. In addition, residential investment usually regains faster than nonresidential investment (Leamer (2007)). This is the reason why the first two spikes of the probability function in Figure 5c last longer compared with NBER based recession periods. However, in the case of the Great Recession, residential investment behaved differently. While nonresidential investment reached its pre-crisis level around Q3 2012, residential investment has not yet recovered (an in-depth analysis of this issue can be found in Rognlie et al. (forthcoming)). Moreover, *Inv* declined during two consecutive quarters in Q4 2015 and Q1 2016. Taken these factors together explains the characteristics of the last two spikes. The smoothed probability function of *IP* (which consists of manufacturing, mining, and electric and gas utilities) is a bit more volatile but closely related to events which took place in the United States and had an immediate impact on firms' productivity and thus on industrial production. In addition to the spikes which coincide with NBER based recessions, the increase in 1996 is due to the blizzard which hit the U.S. East Coast in January.[19] The peak around 1998 is related to strikes at General Motors. *IP* in total declined 1.1% and 0.6% in June and July 1998, respectively. With motor vehicles and parts excluded from *IP*, the change in June would have been only -0.4% and 0% in July.[20] In September 2005 a large drop of 1.8% can be monitored due to the hurricanes Katrina and Rita.[21] With the exception of one month, *IP* decreased in every month in 2015. Several things came together here. A strong dollar and economic weakness abroad led to a drop in manufacturing. Utility declined due to warm weather and mining (including oil and gas well drilling) suffered from low prices.[22] Again, the regime classifications of the models seem reasonable.

Table 8 contains the parameter estimates.[23] The intercept is highly significant in the first regime for all variables. The regime is associated with, on average, low *Unemp* as well as high *Inv* and *IP*. Furthermore, for some dependent variables (in particular for *Unemp*)

[19]Board of Governors of the Federal Reserve System (U.S.), G.17 Industrial Production and Capacity Utilization (February 16, 1996). `https://fraser.stlouisfed.org/title/77#63650`, accessed on October 17, 2017.

[20]Board of Governors of the Federal Reserve System (U.S.), G.17 Industrial Production and Capacity Utilization (August 14, 1998). `https://fraser.stlouisfed.org/title/77#555195`, accessed on October 17, 2017.

[21]Board of Governors of the Federal Reserve System (U.S.), G.17 Industrial Production and Capacity Utilization (October 14, 2005). `https://fraser.stlouisfed.org/title/77#555256`, accessed on October 17, 2017.

[22]Mutikani, L. (2015). U.S. industrial output hurt by weakness in manufacturing, mining. *Reuters*. Retrieved from `http://www.reuters.com/article/us-usa-economy-industrialoutput/u-s-industrial-output-hurt-by-weakness-in-manufacturing-mining-idUSKBN0OV1OY20150615`, accessed on October 17, 2017.

[23]We do not report QPS and TPI in Table 8 as it is unclear how to proxy the *true* regime for *Unemp*, *Inv*, and *IP*. Due to reasons discussed above, NBER based recessions are not suitable.

a couple of parameters (including *Illiq*) are slightly significant with the expected sign. In contrast, when *GDP* was the dependent variable, we did not find any significant parameter in this regime beside lagged *GDP*. *IP*'s expected duration of the 1st regime is with 7.46 quarters the shortest (14.71 quarters and 28.57 quarters for *Inv* and *Unemp*, respectively). In the second regime, which represents adverse macroeconomic conditions, the importance of *Illiq* appears again. The coefficients are large in magnitude and *Illiq* is a highly significant predictor for all three macroeconomic variables. *Term* and R^m have at least predictive power for two out of three dependent variables.

CSFEs in Figures 5b-5d for *Unemp*, *Inv*, and *IP* are similar to the CSFE of *GDP* in Figure 5a. Within the 2nd regime, the *Illiq* augmented models outperform their respective benchmarks. Periods with a high probability of being in the 1st regime are rather characterized by constant CSFEs.

Table 8: **MS-MIDAS Results: Remaining Macroeconomic Variables**

Panel A reports the estimates of the MS-MIDAS model (equation (9)) for unemployment (*Unemp*), privat investment (*Inv*), and industrial production (*IP*). The focus is on coefficient β_2, which quantifies the impact of bond liquidity (*Illiq*) on one of the macroeconomic variables. In addition to *Illiq*, the lagged macroeconomic variable, the yield spread between the 10-year and 1-year Treasury bond (*Term*), Moody's Seasoned Aaa Corporate Bond Yield minus the 10-year Treasury bond yield (*Credit*), the excess return on the market based on Fama and French (1989) (R^m), and the 30-day volatility of the S&P500 index (*Vol*) are included in the model. State 1 is associated with growth. On the other hand, the 2nd state represents periods of turmoil. ***,**,* indicate significance at the 1%, 5%, 10% levels, respectively. In Panel B, estimates of the parameter of the Almon lag (equation (8)) are shown. The sample period is from Q1 1987 until Q4 2016.

Panel A

					State 1				
	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3^{Term}$	$\hat{\beta}_3^{Credit}$	$\hat{\beta}_3^{Vol}$	$\hat{\beta}_3^{R^m}$	$\hat{\sigma}_1$	$\hat{p}_{11}$
Unemp	−0.417***	−0.107	0.157*	−0.135**	0.339**	−0.181*	0.036	0.44	0.965
Inv	0.610***	−0.014	−0.184	−0.060	−0.038	0.000	−0.062	0.53	0.932
IP	0.246***	0.154*	0.180	0.072	0.029	−0.131**	0.016	0.43	0.866
					State 2				
	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3^{Term}$	$\hat{\beta}_3^{Credit}$	$\hat{\beta}_3^{Vol}$	$\hat{\beta}_3^{R^m}$	$\hat{\sigma}_2$	$\hat{p}_{22}$
Unemp	0.430***	−0.107	0.512***	−0.251**	−0.040	0.175	−0.272*	0.61	0.910
Inv	−0.432***	−0.014	−0.433***	0.267***	−0.027	−0.415***	0.126	0.49	0.931
IP	−0.091	0.154*	−0.388***	0.141	−0.001	0.068	1.584**	0.85	0.825

Panel B

	$\hat{\theta}_1^{Illiq}$	$\hat{\theta}_1^{Term}$	$\hat{\theta}_1^{Credit}$	$\hat{\theta}_1^{Vol}$	$\hat{\theta}_1^{R^m}$
Unemp	−18.778	44.821	−0.357	10.754	21.803
Inv	6.960	15.717	−3.689	0.024	−12.914
IP	−1.002	−5.185	3.243	18.027	−0.102
	$\hat{\theta}_2^{Illiq}$	$\hat{\theta}_2^{Term}$	$\hat{\theta}_2^{Credit}$	$\hat{\theta}_2^{Vol}$	$\hat{\theta}_2^{R^m}$
Unemp	−0.604	1.618	0.088	5.088	−2.725
Inv	2.497	−0.191	−1.609	2.015	0.792
IP	1.196	0.288	−0.356	−2.867	−0.021

5.2.1 Nonlinear Out-of-Sample Results

To strengthen the reliability of our nonlinear results, out-of-sample forecasts are desirable. Since the number of parameters more than doubles compared to the linear specification in Section 4.2, the training period has to be extended. Moreover, both regimes have to occur during the training period sufficiently long, such that all parameters can be identified. In addition, the subsequent testing period should include both regimes as well so that the model has the chance to take advantage of its nonlinearity. We exemplary test the quality of the model's predictions for *Unemp* since we are able to divide the sample in such a way that both criteria are met. Due to the reasons discussed in Section 5.2, periods with increasing *Unemp* are more persistent and the impact of the early 1990s as well as the early 2000s recessions are long-lasting enough to estimate the parameter of the 2nd regime. Therefore, in case of the MS-MIDAS model, we chose $R = 75$ quarters as training period for the first recursive estimate for two reasons. First, with $R = 75$ the training period lasts from the beginning until Q4 2005 and thus covers both recessions mentioned above. Second, the testing period starts before the first indication of the Great Recession and gives the model the opportunity to predict it at an early stage. Moreover, the testing period covers in addition to the crisis also the solid period afterward. Thus, both regimes appear during the testing period.[24]

In Figure 6 the prediction errors of the *Illiq* augmented MS-MIDAS model are compared with an MS-MIDAS model which does not include *Illiq*. The almost monotonic increase of the CSFE makes clear the importance of *Illiq* in a nonlinear model. Out-of-sample results are considerably improved by including *Illiq*, in particular during periods of high unemployment.

[24]Data standardization is based on values of the training data to avoid any look-ahead bias.

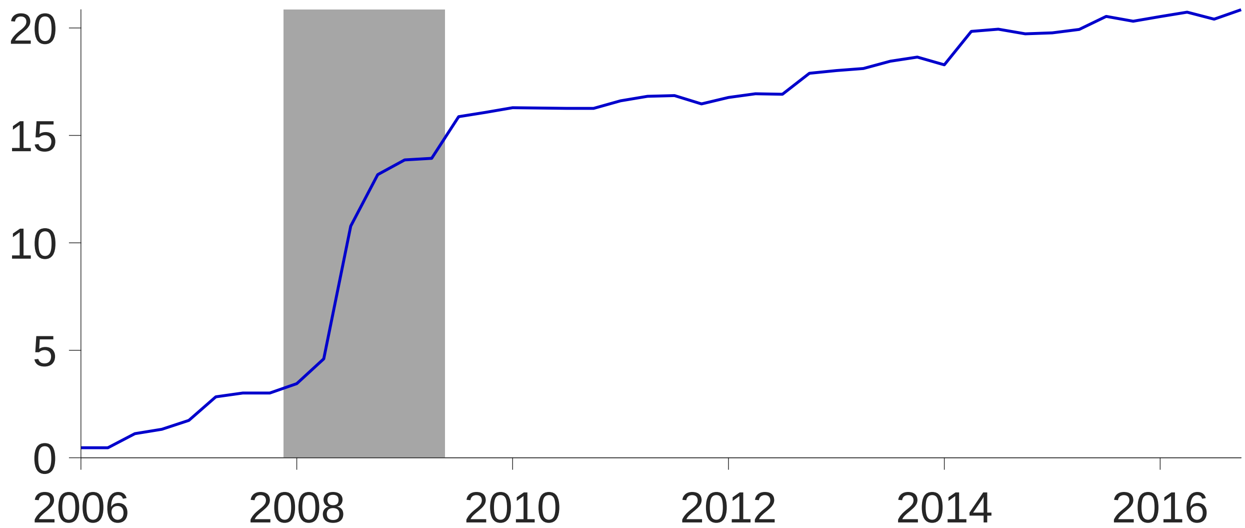

Figure 6: **Out-of-Sample MS-MIDAS Result: Unemployment**
The figure shows the cumulative squared forecast error (CSFE) from equation (4) in blue for the out-of-sample period from Q1 2006 until Q4 2016. The CSFE is based on unemployment (*Unemp*) forecasts of the MS-MIDAS model specified in Section 5.1. The unrestricted model is augmented with bond liquidity (*Illiq*). NBER based recession periods are shaded in gray.

6 Conclusion

In this paper we analyze the information content of bond liquidity associated with the business cycle. To capture different facets of the economy, we focus on gross domestic product, unemployment, private investment, and industrial production. It turns out that liquidity is a precise predictor with accurate in-sample and out-of-sample estimates, in particular during economic downturns. Although other variables which are already known in the literature to be able to predict the development of the economy have an impact on some of the dependent variables, only bond liquidity is consistently significant in all models.

There is still room left for further research in this area. Closely related with our study, it is necessary to validate the performance of all liquidity augmented MS-MIDAS models (or other models which take nonlinearities into account) in out-of-sample analyses. Therefore, long time series are required which include crises during the training period, such that a reliable estimation of the coefficients can be ensured in every regime. Fortunately, *Unemp* satisfies both conditions and we successfully carried out out-of-sample predictions in Section 5.2.1. Nevertheless, in particular for *GDP*, a similar analysis is of great interest and value. Furthermore, we focus on short term predictions. The ability of long-term forecasts is also an interesting research question with useful applications which still has to be analyzed. More generally, the ability of bond liquidity in predicting future business cycles can be studied for other countries or in an international setting.

Appendices

A Analyses Based on Monthly Frequency

Unemp and *IP* are available on a monthly frequency and converted into quarterly frequency throughout the paper. In this section, we review whether the results hold on a monthly basis as well.

A.1 Linear Framework

The design of the analyses is comparable to Sections 3-4, with the sole difference of one month instead of one quarter predictions. The results of the in-sample analysis are in Table A.1 and very similar to those in Table 1. The magnitude and the significance of the lagged endogenous variable is slightly reduced but *Illiq* is still highly significant and of about the same size. In addition to *Illiq*, *Term* is still a significant predictor for *IP*. As one can see in the last column of Table A.1, the explanatory power of *Illiq* is remarkable and even larger compared with results from the quarterly analysis in Table 1.

Outcomes from the out-of-sample analysis with a training period of $R = 120$ months are summarized in Tables A.2-A.3. Again, the findings of the quarterly analyses do not change. On the contrary, differences between nowcasts of liquidity augmented models and their respective benchmarks are even more pronounced on a monthly frequency. However, the

Table A.1: **In-Sample Regression Results (Monthly)**
The table illustrates the estimated coefficients for the period from March 1987 until December 2016 based on the in-sample regression $y_t = \beta_1 y_{t-1} + \beta_2 Illiq_{t-1} + \beta_3' x_{t-1} + \epsilon_t$ on a monthly frequency. One of the macroeconomic variables is contained in y_t. *Unemp* is unemployment, *GDP* is real gross domestic product, *Inv* is real gross private domestic fixed investment, and *IP* is industrial production. The focus is on coefficient β_2, which quantifies the impact of bond liquidity (*Illiq*) on the macroeconomic variable. The yield spread between the 10-year and 1-year Treasury bond (*Term*), Moody's Seasoned Aaa Corporate Bond Yield minus the 10-year Treasury bond yield (*Credit*), the excess return on the market based on Fama and French (1989) (R^m), the 30-day volatility of the S&P500 index (*Vol*), Amihud's (2002) stock liquidity measure (*Amihud*), and the lagged macroeconomic variable are included as control variables. The last column reports the difference in R^2 (adj) between the respective models with liquidity in- and excluded. ***,**,* indicate significance at the 1%, 5%, 10% levels, respectively.

	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3^{Term}$	$\hat{\beta}_3^{Credit}$	$\hat{\beta}_3^{Vol}$	$\hat{\beta}_3^{R^m}$	$\hat{\beta}_3^{Amihud}$	ΔR^2 (adj)
Unemp	−0.118**	0.381***						12.9
	−0.123**	0.395***	−0.076	0.012				13.5
	−0.123**	0.352***	−0.078	−0.003	0.066	−0.025		6.8
	−0.112*	0.352***	−0.077	−0.004	0.059	−0.033	0.006	6.8
IP	0.142**	−0.314***						8.9
	0.134**	−0.329***	0.092**	−0.049				9.4
	0.132**	−0.289***	0.094**	−0.035	−0.067	−0.003		4.5
	0.134**	−0.290***	0.091**	−0.044	−0.076	−0.004	0.087	4.5

predictive power of most other financial variables has deteriorated. In Panel B of both tables, only *Illiq* and *Vol* bear additional predictive information beyond the autoregressive lag. The corresponding CSFEs (equation (4)) for *Unemp* and *IP* are illustrated in Figures A.1-A.2. For *Unemp*, the CSFE follows a similar pattern as in Figure 1 and is clearly upward sloping from the beginning of the Great Recession on. For *IP* results are identical with the quarterly findings as well. The augmented model shines only during recessions with an otherwise constant or even decreasing CSFE. To summarize in short, the findings from the quarterly analysis are representative for the monthly frequency as well.

Table A.2: **Out-of-Sample Evaluation: Unemployment (Monthly)**
Panel A reports one month ahead unemployment (*Unemp*) forecasts and nowcasts for nested models, to compare the out-of-sample properties of bond liquidity (*Illiq*) in relation with other financial variables. *Term* is the yield spread between the 10-year and 1-year Treasury bond, *Credit* is Moody's Seasoned Aaa Corporate Bond Yield minus the 10-year Treasury bond yield, R^m is the excess return on the market based on Fama and French (1989), and *Vol* is the 30-day volatility of the S&P500 index. The training period for the first estimate lasts from April 1987 until April 1997. The subsequent testing period is from May 1997 until December 2016. To assess the significance of the results, MSE-F and ENC-NEW test statistics (equation (2) and (3)) are reported. A significant rejection of the null hypothesis of the MSE-F test implies lower forecast errors of the unrestricted model. A rejection of the null hypothesis of the ENC-NEW test leads to the conclusion that the restricted model does not encompass the unrestricted model. Panel B applies the same statistics to test whether one of the financial variables is able to beat the autoregressive benchmark. ***,**,* indicate significance at the 1%, 5%, 10% levels, respectively.

	Unrestricted	Restricted	$\frac{MSE_U}{MSE_R}$		MSE-F		ENC-NEW	
			Rec.	Roll.	Rec.	Roll.	Rec.	Roll.
Panel A: Liquidity vs. Financial Variables								
1-Q-Ahead	Illiq, Term	Term	0.836	0.825	46.330***	49.927***	35.998***	46.628***
	Illiq, R^m	R^m	0.845	0.832	43.413***	47.630***	32.544***	44.690***
	Illiq, Credit	Credit	0.842	0.834	44.393***	47.048***	33.879***	44.965***
	Illiq, Vol	Vol	0.917	0.956	21.326***	10.757***	15.519***	11.238***
	Illiq, All	All	0.915	0.954	21.993***	11.307***	16.242***	12.177***
Nowcast	Illiq, Term	Term	0.852	0.840	41.008***	45.125***	30.468***	38.239***
	Illiq, R^m	R^m	0.855	0.849	40.111***	42.215***	29.559***	37.054***
	Illiq, Credit	Credit	0.858	0.846	39.109***	43.136***	28.488***	37.665***
	Illiq, Vol	Vol	0.919	0.943	20.892***	14.347***	14.669***	14.576***
	Illiq, All	All	0.914	0.941	22.312***	14.841***	15.983***	14.649***
Panel B: Financial Variables vs. Autoregressive Models								
	Unrestricted	Restricted	$\frac{MSE_U}{MSE_R}$		MSE-F		ENC-NEW	
			Rec.	Roll.	Rec.	Roll.	Rec.	Roll.
1-Q-Ahead	Illiq, Unemp	Unemp	0.875	0.874	33.634***	34.168***	24.837***	30.907***
	Term, Unemp	Unemp	1.013	1.012	−3.109	−2.766	−1.134	−1.158
	R^m, Unemp	Unemp	0.998	1.006	0.365	−1.360	1.265*	1.173
	Credit, Unemp	Unemp	1.002	0.998	−0.558	0.511	−0.258	0.571
	Vol, Unemp	Unemp	0.937	0.910	15.785***	23.235***	10.348***	22.048***
Nowcast	Illiq, Unemp	Unemp	0.833	0.834	47.586***	47.305***	34.590***	40.679***
	Term, Unemp	Unemp	1.011	1.008	−2.662	−1.772	−1.067	−0.478
	R^m, Unemp	Unemp	1.009	1.011	−2.175	−2.593	−0.870	−0.573
	Credit, Unemp	Unemp	1.006	1.012	−1.452	−2.895	−0.284	−1.173
	Vol, Unemp	Unemp	0.930	0.908	17.906***	24.111***	11.679***	20.088***

Table A.3: **Out-Of-Sample Evaluation: Industrial Production (Monthly)**
Panel A reports one month ahead industrial production (*IP*) forecasts and nowcasts for nested models, to compare the out-of-sample properties of bond liquidity (*Illiq*) in relation with other financial variables. *Term* is the yield spread between the 10-year and 1-year Treasury bond, *Credit* is Moody's Seasoned Aaa Corporate Bond Yield minus the 10-year Treasury bond yield, R^m is the excess return on the market based on Fama and French (1989), and *Vol* is the 30-day volatility of the S&P500 index. The training period for the first estimate lasts from April 1987 until April 1997. The subsequent testing period is from May 1997 until December 2016. To assess the significance of the results, MSE-F and ENC-NEW test statistics (equation (2) and (3)) are reported. A significant rejection of the null hypothesis of the MSE-F test implies lower forecast errors of the unrestricted model. A rejection of the null hypothesis of the ENC-NEW test leads to the conclusion that the restricted model does not encompass the unrestricted model. Panel B applies the same statistics to test whether one of the financial variables is able to beat the autoregressive benchmark. ***,**,* indicate significance at the 1%, 5%, 10% levels, respectively.

Panel A: Liquidity vs. Financial Variables

	Unrestricted	Restricted	$\frac{MSE_U}{MSE_R}$		MSE-F		ENC-NEW	
			Rec.	Roll.	Rec.	Roll.	Rec.	Roll.
1-Q-Ahead	Illiq, Term	Term	0.850	0.825	41.561***	50.211***	41.582***	55.501***
	Illiq, R^m	R^m	0.863	0.846	37.470***	42.864***	36.467***	48.133***
	Illiq, Credit	Credit	0.864	0.842	37.141***	44.156***	36.137***	48.968***
	Illiq, Vol	Vol	0.933	0.950	16.997***	12.396***	18.018***	19.320***
	Illiq, All	All	0.924	0.942	19.436***	14.469***	21.412***	22.333***
Nowcast	Illiq, Term	Term	0.925	0.934	19.204***	16.799***	19.655***	25.068***
	Illiq, R^m	R^m	0.927	0.946	18.540***	13.403***	18.534***	22.666***
	Illiq, Credit	Credit	0.932	0.946	17.179***	13.611***	17.166***	22.015***
	Illiq, Vol	Vol	0.973	1.006	6.655***	–1.314	8.162***	4.642***
	Illiq, All	All	0.967	0.996	8.107***	0.872*	9.691***	6.315***

Panel B: Financial Variables vs. Autoregressive Models

	Unrestricted	Restricted	$\frac{MSE_U}{MSE_R}$		MSE-F		ENC-NEW	
			Rec.	Roll.	Rec.	Roll.	Rec.	Roll.
1-Q-Ahead	Illiq, IP	IP	0.934	0.936	16.662***	16.108***	18.727***	25.260***
	Term, IP	IP	1.008	1.007	–1.807	–1.628	–0.196	–0.496
	R^m, IP	IP	1.007	1.011	–1.549	–2.558	–0.618	–0.729
	Credit, IP	IP	1.002	1.007	–0.503	–1.672	0.024	–0.367
	Vol, IP	IP	0.959	0.962	9.982***	9.338***	7.044***	11.812***
Nowcast	Illiq, IP	IP	0.975	0.993	6.077***	1.688**	8.573***	12.001***
	Term, IP	IP	1.017	1.012	–3.874	–2.888	–0.968	–1.111
	R^m, IP	IP	1.015	1.017	–3.608	–3.978	–0.581	–1.050
	Credit, IP	IP	1.004	1.011	–0.931	–2.602	–0.450	–1.141
	Vol, IP	IP	0.998	1.012	0.520	–2.787	1.763**	6.676***

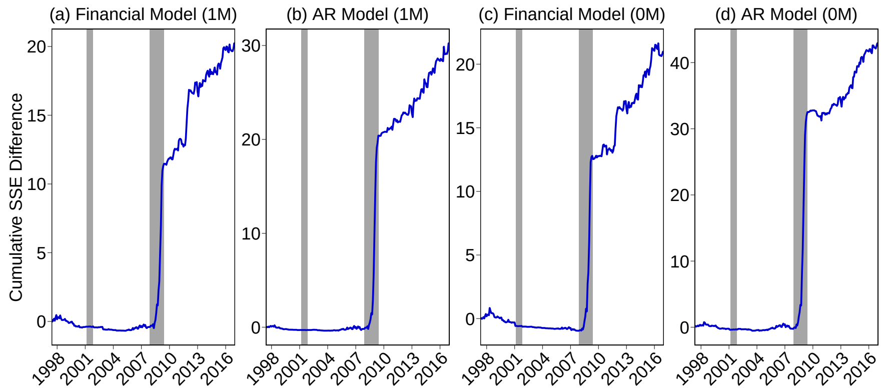

Figure A.1: **Cumulative Squared Forecast Error: Unemployment (Monthly)**
The figures illustrate the cumulative squared forecast error (CSFE) from equation (4) in blue for the out-of-sample period from May 1997 until December 2016. CSFEs are based on unemployment (*Unemp*) forecasts. The figures labeled "Financial Model" include in the benchmark model the yield spread between the 10-year and 1-year Treasury bond (*Term*), Moody's Seasoned Aaa Corporate Bond Yield minus the 10-year Treasury bond yield (*Credit*), the excess return on the market based on Fama and French (1989) (R^m), and the 30-day volatility of the S&P500 index (*Vol*). In figures labeled "AR Model", lagged *Unemp* is the benchmark. The unrestricted models are augmented with bond liquidity (*Illiq*). Figure A.1a and Figure A.1b are based on one month ahead forecasts and Figure A.1c and Figure A.1d on nowcasts. NBER based recession periods are shaded in gray.

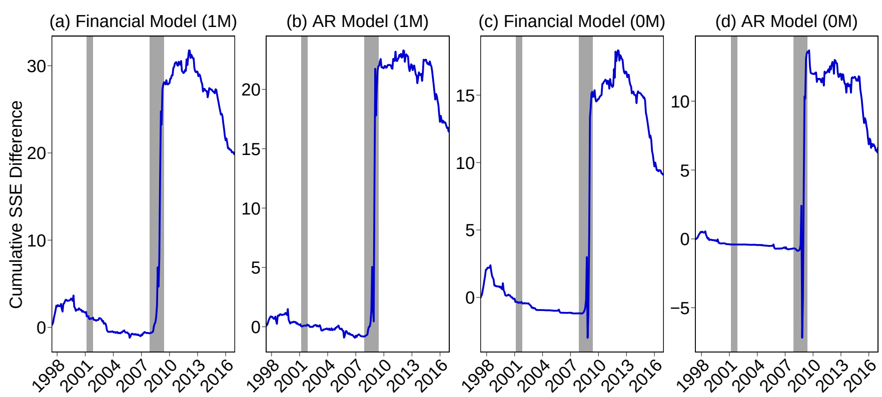

Figure A.2: **Cumulative Squared Forecast Error: Industrial Production (Monthly)**
The figures illustrate the cumulative squared forecast error (CSFE) from equation (4) in blue for the out-of-sample period from May 1997 until December 2016. CSFEs are based on industrial production (*IP*) forecasts. The figures labeled "Financial Model" include in the benchmark model the yield spread between the 10-year and 1-year Treasury bond (*Term*), Moody's Seasoned Aaa Corporate Bond Yield minus the 10-year Treasury bond yield (*Credit*), the excess return on the market based on Fama and French (1989) (R^m), and the 30-day volatility of the S&P500 index (*Vol*). In figures labeled "AR Model", lagged *IP* is the benchmark. The unrestricted models are augmented with bond liquidity (*Illiq*). Figure A.2a and Figure A.2b are based on one month ahead forecasts and Figure A.2c and Figure A.2d on nowcasts. NBER based recession periods are shaded in gray.

A.2 Markov-Switching Mixed-Data Sampling Models

As in Section 5, we proceed with the implementation of MS-MIDAS models using monthly data. Since all variables have the same frequency now, we end up with

$$\begin{aligned} y_t = \beta_0(s_t) + \beta_1(s_t) \sum_{j=1}^{K} b(j;\theta^y) L^{(j-1)} y_{t-1} + \beta_2(s_t) \sum_{j=1}^{K} b(j;\theta^{Illiq}) L^{(j-1)} Illiq_{t-1} \\ + \beta_3'(s_t) \sum_{j=1}^{K} b(j;\theta) L^{(j-1)} x_{t-1} + \epsilon_t(s_t). \end{aligned} \tag{A.1}$$

All variables and specifications are described in Section 5.1.

Table A.4 illustrates the estimated coefficients. Altogether, the magnitude of *Illiq* is slightly smaller compared with Table 8, but nevertheless highly significant. On a monthly frequency, the lagged regressand gains in importance and is the only variable significant in the 1st regime. This is somewhat different compared with the results in Table 8 where some financial variables had predictive power as well.

Figures A.3a and A.3b are similar to Figures 5b and 5d regarding probability functions as well as CSFEs. Since *IP* is even more volatile on a monthly frequency, this is also reflected in the probability function. Smaller events with an impact on monthly industrial production are not averaged out as it is the case in the quarterly aggregate where only incidents with either an extreme or a more persistent impact are visible. Nevertheless, both CSFEs are upward sloping in periods with a high probability of being in the 2nd regime.

Table A.4: **MS-MIDAS Results (Monthly): Unemployment and Industrial Production**

Panel A reports the estimates of the MS-MIDAS model (equation (9)) for unemployment (*Unemp*), privat investment (*Inv*), and industrial production (*IP*). The focus is on coefficient β_2, which quantifies the impact of bond liquidity (*Illiq*) on one of the macroeconomic variables. In addition to *Illiq*, the lagged macroeconomic variable, the yield spread between the 10-year and 1-year Treasury bond (*Term*), Moody's Seasoned Aaa Corporate Bond Yield minus the 10-year Treasury bond yield (*Credit*), the excess return on the market based on Fama and French (1989) (R^m), and the 30-day volatility of the S&P500 index (*Vol*) are included in the model. State 1 is associated with growth. On the other hand, the 2nd state represents periods of turmoil. ***,**,* indicate significance at the 1%, 5%, 10% levels, respectively. In Panel B, estimates of the parameter of the Almon lag (equation (8)) are shown. The sample period is from March 1987 until December 2016.

Panel A

	State 1								
	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3^{Term}$	$\hat{\beta}_3^{Credit}$	$\hat{\beta}_3^{Vol}$	$\hat{\beta}_3^{R^m}$	$\hat{\sigma}_1$	$\hat{p}_{11}$
Unemp	–0.119	0.258**	0.050	–0.070	0.132	0.045	0.044	0.91	0.983
IP	–0.002	0.514***	0.002	–0.006	–0.001	–0.001	0.002	1.06	0.712

	State 2								
	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3^{Term}$	$\hat{\beta}_3^{Credit}$	$\hat{\beta}_3^{Vol}$	$\hat{\beta}_3^{R^m}$	$\hat{\sigma}_2$	$\hat{p}_{22}$
Unemp	0.244*	0.258**	0.226**	–0.364***	0.037	0.131	–0.269	0.68	0.955
IP	–0.014	0.514***	–0.331***	0.168**	–0.695***	–0.038	0.856***	0.52	0.774

Panel B

	$\hat{\theta}_1^{Illiq}$	$\hat{\theta}_1^{Term}$	$\hat{\theta}_1^{Credit}$	$\hat{\theta}_1^{Vol}$	$\hat{\theta}_1^{R^m}$	$\hat{\theta}_1^{y}$
Unemp	–12.440	7.740	1.342	–0.175	10.817	2.9159
IP	–0.187	–0.053	–0.422	0.732	–0.032	0.484

	$\hat{\theta}_2^{Illiq}$	$\hat{\theta}_2^{Term}$	$\hat{\theta}_2^{Credit}$	$\hat{\theta}_2^{Vol}$	$\hat{\theta}_2^{R^m}$	$\hat{\theta}_2^{y}$
Unemp	–0.191	–0.074	–0.278	0.029	1.988	0.256
IP	0.112	0.024	–0.003	0.018	0.018	0.052

(a) Unemp (b) IP

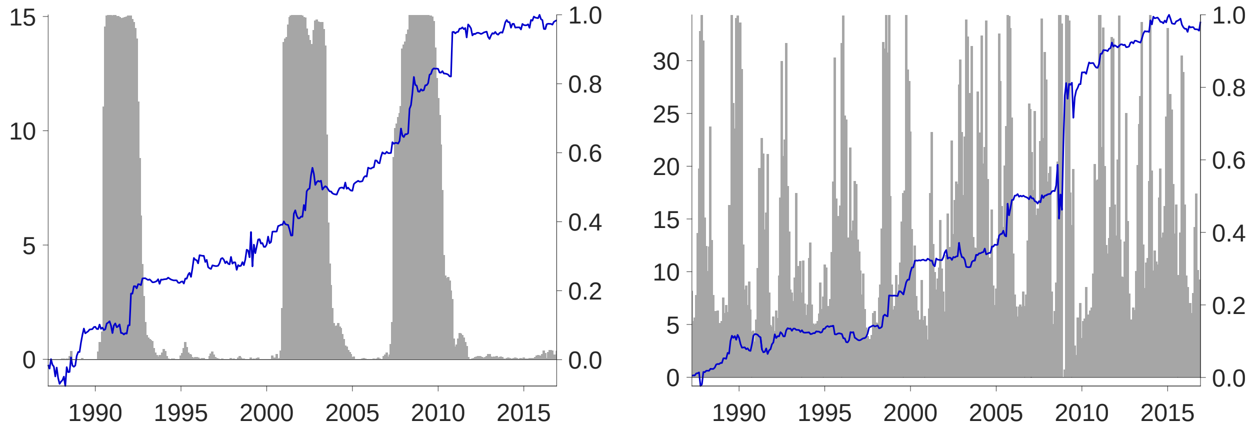

Figure A.3: **MS-MIDAS Results (Monthly)**
The figures show the cumulative squared forecast error (CSFE) from equation (4) in blue (left axis) for unemployment (*Unemp*) and industrial production (*IP*) based on the MS-MIDAS model (equation (A.1)). The unrestricted model is augmented with bond liquidity (*Illiq*). Forecast errors are based on in-sample analyses from March 1987 until December 2016. MS-MIDAS implied recession probabilities (right axis) are shaded in gray.

B Filtered Liquidity Measure (Hodrick-Prescott Filter)

Although the variables are stationary according to unit root tests, the power of such tests is known to be low. In addition to the causality tests in Section 2 which are already robust with respect to non stationary data, we also repeat the in-sample analysis using *Illiq* based on the Hodrick-Prescott filter. The Hodrick-Prescott filter separates the trend and the cyclical component of a time series. Table B.1 yields the same conclusions as Table 3 which strengthens our confidence in the results.

Table B.1: **In-Sample Regression Results (HP-Filter)**
The table illustrates the estimated coefficients for the period from Q1 1987 until Q4 2016 based on the in-sample regression $y_t = \beta_1 y_{t-1} + \beta_2 Illiq_{t-1} + \beta_3' x_{t-1} + \epsilon_t$. One of the macroeconomic variables is contained in y_t. *Unemp* is unemployment, *GDP* is real gross domestic product, *Inv* is real gross private domestic fixed investment, and *IP* is industrial production. The focus is on coefficient β_2, which quantifies the impact of bond liquidity (*Illiq*) based on the Hodrick-Prescott filter on the macroeconomic variable. The yield spread between the 10-year and 1-year Treasury bond (*Term*), Moody's Seasoned Aaa Corporate Bond Yield minus the 10-year Treasury bond yield (*Credit*), the excess return on the market based on Fama and French (1989) (R^m), the 30-day volatility of the S&P500 index (*Vol*), Amihud's (2002) stock liquidity measure (*Amihud*), and the lagged macroeconomic variable are included as control variables. The last column reports the difference in R^2 (adj) between the respective models with liquidity in- and excluded. ***,**,* indicate significance at the 1%, 5%, 10% levels, respectively.

	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3^{Term}$	$\hat{\beta}_3^{Credit}$	$\hat{\beta}_3^{Vol}$	$\hat{\beta}_3^{R^m}$	$\hat{\beta}_3^{Amihud}$	ΔR^2 (adj)
Unemp	0.517***	0.291***						5.58
	0.517***	0.306***	−0.137***	0.114**				6.27
	0.492***	0.248***	−0.131***	0.074	0.097	−0.046		2.96
	0.495***	0.252***	−0.134***	0.074	0.088	−0.044	0.007	3.04
GDP	0.305***	−0.226*						3.52
	0.306***	−0.231*	0.037	0.007				3.69
	0.274***	−0.136	0.029	0.060	−0.156	0.053		0.33
	0.294***	−0.120	0.027	0.085	−0.161	0.028	−0.078	0.07
Inv	0.508***	−0.294**						5.96
	0.497***	−0.316***	0.121*	−0.024				6.90
	0.477***	−0.208**	0.110**	0.062	−0.115	0.187***		1.93
	0.514***	−0.182**	0.104*	0.103	−0.112	0.142**	−0.150*	1.35
IP	0.336***	−0.316***						7.09
	0.307***	−0.346***	0.142**	−0.115				8.54
	0.314***	−0.252**	0.131**	−0.028	−0.045	0.246***		2.96
	0.342***	−0.239**	0.125**	0.002	−0.031	0.210**	−0.132*	2.62

Out-of-sample analyses with the filtered bond liquidity measure suffer from look-ahead bias and are therefore not suitable.

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