Bank Rollover Risk and Liquidity Supply Regimes*

Eric Jondeau,[a] Benoit Mojon,[b] and Jean-Guillaume Sahuc[c]
[a]Swiss Finance Institute and HEC Lausanne
[b]Bank for International Settlements
[c]Banque de France and University Paris-Nanterre

The maturity mismatch between their short-term financing and long-term lending exposes banks to the risk of rolling over their funding. Such a rollover risk is sufficient on its own to cause a panic at the bank level and have ripple effects on the banking system as a whole. We propose a new indicator that helps central banks monitor rollover risk and thus design liquidity support operations when needed. Building on forward rates, our rollover risk indicator (RRI) captures the way banks price the risk of not being able to obtain funding at the horizon of specific interest rate derivatives. We show that our RRI has a better predictive power for economic growth and bank lending than usual bank credit spreads. In addition, our indicator helps to contrast three liquidity regimes (crisis, moderate, and abundant), which coincide with the levels of excess liquidity supplied by central banks.

JEL Codes: E44, E58, G1, G21.

---

*We thank Hendrik Bessembinder, Stijn Claessens, Benoît Coeuré, Ian Dew-Becker, Simon Gilchrist, Pete Klenow, Cyril Monnet, Andreas Schrimpf, Vladyslav Sushko, Egon Zakrajsek, and the participants of several conferences for their useful comments and suggestions. We hope that the daily measures of the forward funding spread for USD, EUR, JPY, and GBP, posted on our websites and updated periodically, will provide useful benchmark indicators to applied economists. Declarations of interest: none. The views expressed in this paper are those of the authors and should under no circumstances be interpreted to reflect those of the Bank for International Settlements, the Banque de France, or the Eurosystem. E. Jondeau: Swiss Finance Institute and Faculty of Business and Economics (HEC Lausanne), University of Lausanne, Extranef 232, CH-1015 Lausanne, Switzerland (e-mail: eric.jondeau@unil.ch). B. Mojon: Bank for International Settlements, Centralbahnplatz 2, 4051 Basel, Switzerland (e-mail: benoit.mojon@bis.org). J.-G. Sahuc: Banque de France, 31 rue Croix des Petits Champs, 75049 Paris, France, and University of Paris-Nanterre (e-mail: jean-guillaume.sahuc@banque-france.fr).

1. Introduction

The maturity mismatch between short-term funding and long-term lending exposes banks to *rollover risk*. Rollover risk refers to the risk of rolling over a maturing financial debt obligation. In good times, such a risk is relatively weak because short-term debt displays high liquidity and low risk. In bad times, when bank assets are more volatile and may dry up, short-term debt generates significant rollover risk and affects future investment incentives (Diamond and Rajan 2001; Acharya, Gale, and Yorulmazer 2011; Diamond and He 2014; Morris and Shin 2016). Rollover risk is sufficient on its own to cause a panic at the bank level and have ripple effects on the banking system as a whole (Kacperczyk and Schnabl 2010; Gorton and Metrick 2012; Covitz, Liang, and Suarez 2013; Filipović and Trolle 2013; Copeland, Martin, and Walker 2014; Gallitschke, Seifried, and Seifried 2017; Bernanke 2018). In such adverse scenarios, central banks may decide to supply public liquidity when private liquidity vanishes, following the Thornton (1802)-Bagehot (1873) principle. By providing liquidity to institutions in large amounts, they can match the panic-driven demands for liquidity and avoid disruptions to payments and credit intermediation, allowing continuity in the supply of bank credit.[1] Measuring and monitoring rollover risk in real time is thus fundamental for central banks to design operations for liquidity support.

In this paper, we propose a new daily indicator of rollover risk for large banks, which is based on forward interest rates.[2] Future

[1]See among others, Holmström and Tirole (1998), Rochet and Vives (2004), Brunnermeier (2009), Freixas, Martin, and Skeie (2011), Brunnermeier and Sannikov (2014), Calomiris, Flandreau, and Laeven (2016), and Bernanke (2018). For instance, Bernanke (2018) shows that the depth of the 2007–09 financial crisis is mainly due to the supply side of the credit market and, specifically, to the liquidity drought in the money market. In other words, preventing liquidity from drying up in the market may have reduced the depth of the recession and the accumulation of the public debt needed to stabilize the economy through fiscal policy.

[2]Several authors show that forward rates contain information about future yields and excess bond returns (Fama and Bliss 1987; Stambaugh 1988; Cochrane and Piazzesi 2005). Recently, Engstrom and Sharpe (2019) use the difference between the six-quarter-ahead forward rate on U.S. Treasuries and the current three-month Treasury-bill rate, which they call the "near-term forward spread." Benzoni, Chyruk, and Kelley (2018) find that a change in the yield curve slope due

liquidity planning for financial institutions must take into account the possibility of losing market access, and market participants have to form expectations on how rollover costs will evolve over time. The pricing of this risk depends on banks' perception of the future economic situation and expected monetary policy decisions, among others. The interest rates at which forward contracts are negotiated (i.e., based on the agreement between two counterparties to exchange, at a settlement date in the future, two payment obligations based on two interest rates) provide a means of gauging banks' short-term interest rate expectations. Consequently, using forward rates allows us to capture the way banks price rollover risk at the horizon of specific interest rate contracts. Our so-called rollover risk indicator (RRI) may be especially useful during periods when central banks saturate markets with liquidity and serves as a good signal of the change in the stance of monetary policy. The RRI can be computed for different starting forward dates, different maturities, and different frequencies of payments (tenors). It has several desirable properties: (i) it is available at a daily frequency for the dollar, the euro, and most of the major currencies;[3] (ii) it is obtained from interbank market instruments and therefore reflects the funding cost of large banks; and (iii) it relies on widely traded interest contracts and hence accurately measures the market price of funding.

We provide evidence that the RRI helps forecast macroeconomic developments in the euro area and the United States. Over the sample from 2005 to 2019, the RRI has significant predictive content for economic activity, better than those obtained from bank credit risk measures (credit default swap and bank bond spreads).[4] This result indicates that (i) the expectations of market participants regarding the future cost of funding matters a lot for the business cycle and (ii) the information content of this indicator reflects the attitude

to a monetary policy easing, measured by the current real interest rate level and its expected path, is associated with an increase in the probability of a future recession within the next year. Nakamura and Steinsson (2018) and Hansen, McMahon, and Tong (2019) also use forward rates on long-term government bonds.

[3]Daily time series of the forward funding spreads are available for the dollar, the euro, the yen, and the British pound at https://SyRis.ch/risk-management/.

[4]Before 2007, the RRI was essentially equal to zero, as the difference in tenor was not considered material by financial institutions.

of banks towards credit supply and this attitude depends on their expected cost of funding. This might be particularly relevant when central banks supply large amounts of liquidity and the market shifts its attention to the persistence of such policies. The RRI performs well at predicting bank lending, which suggests that reducing bank funding costs can help banks feed credit markets. Interestingly, our findings highlight a funding channel of the business cycle. The supply of credit by financial intermediaries depends on the cost of funding both in the United States (where market finance dominates) and in the euro area (where banks dominate the financial system). In turn, credit supply is correlated with future economic fluctuations (Bernanke 2018).

We illustrate the usefulness of the RRI to contrast liquidity regimes in the euro area and the United States, which coincide with the levels of excess liquidity supplied by central banks. Indeed, any policy that aims at reducing uncertainty regarding the availability of future lender-of-last-resort funding for banks (e.g., by lengthening the maturity of bank debt) is expected to play a crucial role in decreasing funding costs, reducing fire-sale externalities, mitigating the markup that borrowers with urgent liquidity needs pay for immediate funding, and ultimately increasing financial intermediation by banks (He and Xiong 2012; Stein 2012; Segura and Suarez 2017; Jasova Mendicino, and Supera 2021; Bechtel, Ranaldo, and Wrampelmeyer 2023). Since the 2007–09 financial crisis, three liquidity regimes can be identified: (i) a *crisis* regime, associated with a lack of liquidity in the financial system and a strong connection between the rollover risk measured by the RRI and the credit risk measured by the credit default swap (CDS) spread, (ii) a regime of *abundant liquidity*, associated with massive central bank injections of liquidity with no uncertainty over the cost of liquidity and therefore a disconnect between liquidity/rollover and credit risks, and (iii) a regime of *moderate liquidity*, characterized by uncertainty over the expected cost of liquidity but little correlation between liquidity/rollover and credit risks. In the euro area, the crisis period lasted until the end of 2012 with the announcement of the Outright Monetary Transactions program. Since then, the liquidity provided by the European Central Bank (ECB) has been abundant. Fluctuations in credit risk, which resumed in 2015, were not reflected in the RRI. In the United States, the crisis regime corresponds to the period 2007–12, including both the 2007–09 financial crisis and the European sovereign debt crisis. The period 2013–15 is associated with the abundant liquidity regime, during which the Federal Reserve provided a massive amount of liquidity through its QE3 program. From December 2015 to the end of 2020, when our sample ends, the U.S. economy has been in a moderate liquidity regime, in which rollover risk is independent of credit risk. Hence, when COVID-19 hit financial markets in March 2020, the euro area and the United States were characterized by a different liquidity regime. The euro area still stood in an abundant liquidity regime while the United States was in a moderate liquidity regime. Not surprisingly, the pandemic triggered much larger spikes in the RRI in the United States than in the euro area, as would be expected given the very different prevailing liquidity conditions.[5]

The remainder of the paper is organized as follows. In Section 2, we define the rollover risk indicators and explain how to construct them using interbank market data. In Section 3, we evaluate the ability of these indicators and some other well-established indicators of bank liquidity and credit risk to predict future real activity and bank lending. In Section 4, we analyze the link between the RRI and central bank liquidity regimes in the euro area and the United States since 2008. The final section concludes the paper.

2. Rollover Risk Indicator

This section precisely describes the concept and the construction of the RRI and presents the underlying interbank data used to measure it.

2.1 Definition

Rollover risk can be illustrated by considering the two following strategies. On the one hand, bank A borrows at the three-month interbank offered rate (IBOR). At maturity, the bank repays the notional plus the fixed rate. On the other hand, bank B borrows

[5]It is consistent with Copeland, Duffie, and Yang (2021), who show that only with a substantial amount of reserves do the large dealer banks avoid intraday liquidity stress and provide liquidity efficiently to wholesale funding markets.

cash on a daily basis at the overnight federal funds rate for three months and simultaneously enters into an overnight index swap (OIS), receiving the floating rate (the overnight effective federal funds rate) and paying the fixed rate (the OIS three-month rate). In both cases, the interest rate for the three-month funding is set in advance, and therefore no interest rate risk is involved. However, in a stressed market, banks A and B would face different situations. For bank A, the funding is guaranteed, as the contract runs until the end of the three months. Bank B, in contrast, may be unable to roll its funding if it cannot find a counterpart and therefore may become illiquid and have to accept higher prices to access funding liquidity. This situation may happen in the event of a market freeze (funding liquidity risk) or if the lender demands a higher credit spread (credit risk). Because bank B may suffer from such rollover risk, it pays a lower interest rate than bank A. Therefore, the funding based on a three-month IBOR contract commands a higher interest rate, which generates the observed tenor spread between the IBOR and the OIS rate. Because liquidity and credit risks are negligible for OIS contracts, the rollover risk corresponds to the risk of the three-month floating leg.

More generally, rollover risk depends on the tenor of the floating leg. The tenor of a financial contract refers to the frequency with which coupon payments are exchanged. For instance, for a one-year swap with a 3-month tenor, bank A will pay the fixed rate every 3 months for 12 months, whereas bank B will pay the floating 3-month rate. The tenor therefore specifies the maturity of the floating rate and the frequency of the cash flows. Most contracts on interbank markets are linked to the IBOR of a specific tenor (typically, 1, 3, 6, or 12 months). For a given bank, interest rate instruments with the same maturity but different underlying tenors are characterized by different liquidity or credit risk premiums, reflecting the different views and interests of the market counterparts.

Before the financial crisis, rollover risk was close to nil and was therefore neglected. During the financial crisis, there was a disconnection of the IBOR from the OIS rate with the same maturity, such that this spread is now considered an indicator of market stress or panic. It is usually interpreted as reflecting rollover risk, which combines funding liquidity risk and credit risk.

A limitation of IBOR-OIS spread is that it measures the current funding cost but does not inform on the expected rollover risk. In contrast, forward rates allow us to extract such market participants' expectations from the yield curve. We define the three-month rollover risk indicator (RRI), starting in three months for the three-month tenor as follows:

$$RRI^{(3m)}_{3m,3m} = F^{(3m)}_{3m,3m} - F^{(ois)}_{3m,3m}, \tag{1}$$

where the forward rate $F^{(3m)}_{3m,3m}$ is computed from the three-month tenor curve and the forward rate $F^{(ois)}_{3m,3m}$ is computed from the OIS curve. As rollover risk is negligible for the OIS curve, the RRI measures the rollover risk originating from the three-month tenor curve.

For some starting dates, maturities, and tenors, the forward rates can be obtained directly from market data when the relevant forward rate agreements (FRAs) or interest rate swaps (IRS) are quoted. This is the case, for instance, of the $RRI^{(3m)}_{3m,3m}$ introduced above. However, in general, as not all starting dates, maturities, and tenors are available on interbank markets, one needs to construct a complete yield curve for each tenor to compute the RRI. We briefly describe this approach in the next section.

2.2 Data and Construction

Our rollover risk indicator measures the expected cost of funding of large banks. It is constructed using interbank data, i.e., deposits, forward rate agreements (FRAs), overnight index swaps (OIS), and interest rate swaps (IRS). For major currencies, these instruments correspond to very wide markets and exhibit extremely large turnover. As the BIS triennial report reveals (Bank for International Settlements 2019), as of the first half of 2019 the notional amount outstanding for all currencies represents USD 89 trillion on the FRA market and 389.3 trillion on the swap market (including both OIS and IRS). Gross market values are equal to USD 232 billion and 7,793 billion, respectively.[6] Daily turnover also posts impressive numbers. On a net-net basis, as of April 2019, the daily turnover

[6]For comparability, all foreign exchange contracts had a notional amount outstanding of USD 98.7 trillion and a gross market value of 2,229 billion.

on the FRA and swap segments amounts to USD 1,902 billion and 4,146 billion, respectively. EUR and USD instruments are by far the largest segments of the market: overall, they represent respectively 22 percent and 54 percent of all interest rate contracts in terms of gross market values and 52 percent and 22 percent of total turnover.

We collected from Bloomberg quotes for all EUR and USD interest rate instruments on the interbank markets. These instruments include bank deposits (unsecured euro overnight index average (EONIA) and federal funds) and FRA, OIS, IRS, and basis swaps for all available tenors. To compute the forward yield curve of a given tenor in a given month, we rely on the literature dealing with the multicurve environment that followed the 2007–09 financial crisis (see, among others, Henrard 2007, 2010; Ametrano and Bianchetti 2009; Bianchetti 2009; and Mercurio 2009, 2010). Two types of yield curves are constructed: a *discounting curve*, which is used to compute the present value of future cash flows, and several *forwarding curves*, which are used to compute the future cash flows corresponding to a given tenor. The discounting curve is based on OIS contracts with different maturities (and sufficient liquidity). It can be interpreted as the curve corresponding to the absence of liquidity and credit risks.[7] The forwarding curves, also called funding curves, correspond to different tenors (from 1 to 12 months). For instance, the three-month funding curve in the United Sates is based on the three-month IBOR, a sequence of three-month FRA, and a sequence of IRS with a three-month tenor.

The discounting and forwarding curves are constructed using a standard optimization procedure. The estimation of the yield curve

[7]OIS discounting is relevant in the absence of counterparty risk or in the case of derivatives that are collateralized on a daily basis (Mercurio 2009, 2010). Most derivatives traded over the counter have ISDA (International Swaps and Derivatives Association) master agreements. These agreements usually include a credit support annex (CSA) that specifies the protections from which the derivatives benefit. Typical CSAs involve daily collateralization, which means that margin calls can take place on a daily basis. Alternatively, in the case of a contract with a general counterparty or without collateral, a discounting curve based on IBOR may be more relevant because it reflects the risk of the interbank sector as a whole (Ametrano and Bianchetti 2009; Bianchetti 2009). Hull and White (2013) provide theoretical arguments that, in all cases, OIS discounting should be preferred. We follow this advice and use the OIS curve as the unique discounting curve. The credit risk in an OIS is the risk of a possible default by one of the counterparties on an overnight loan and is usually viewed as negligible.

of a given tenor produces a sequence of three-month forward rates that minimize the difference between theoretical and market prices of the available instruments, while maintaining sufficient smoothing of the yield curve.

Our collected data start in January 1999 and end in December 2020. Between 1999 and 2004, the number of instruments available for each tenor is not sufficient to compute a yield curve. As a consequence, we construct tenor yield curves at a daily frequency from January 2005 onward for the United States and the euro area. As put forward by several papers (Ametrano and Bianchetti 2009; Bianchetti 2009; Mercurio 2009), tenor spreads were negligible before 2007. Between 2005 and July 2007, the average $RRI^{(3m)}_{3m,3m}$ is equal to 2.5 basis points (bp) in the United States and 3.2 bp in the euro area, while the average $RRI^{(6m)}_{6m,6m}$ is equal to –1.4 bp in the United States and 0.7 bp in the euro area.

The estimated yield curves fit the observed prices very well.[8] Indeed, between 2005 and 2009, the relative error in reproducing observed prices is on average equal to 3 bp and 1.7 bp for the three-month curve in the United States and the euro area, respectively (1.2 bp and 0.8 bp for the six-month curve). After 2009, the relative error is on average below 10.5 bp in the United States and below 0.25 bp in the euro area for both tenor curves.[9] Tenor yield curves are available at a daily frequency from January 2005 onward for the euro area and the United States, although we start our analysis in January 2007. Data are available upon request and are updated regularly.

In summary, the RRI is based on highly liquid instruments and cover a very large spectrum of maturities. The construction of the tenor yield curves is easily performed at a daily frequency, for the one-, three-, and six-month tenors. In addition, the resulting curves

[8]See Appendix A for additional details on the instruments used for the construction of yield curves and results on the quality of the fit.

[9]These numbers are below those reported by Goldberg (2020) for the U.S. Treasury curve. The relative error of the monthly Treasury yields between September 1990 and May 2017 is measured at 3.4 bp on average. He also finds a peak in 2008–09 during the subprime crisis. The fact that the relative error is lower for interbank curves than it is for U.S. Treasury curves is not surprising because interbank instruments are far more traded, leaving lower arbitrage opportunities.

closely match observed prices, so that the RRI reflects true market conditions accurately and timely.

3. Predictive Content of the RRI

In this section, we investigate whether macroeconomic and banking variables are mainly driven by rollover or credit risks by comparing the predictive ability of the RRI with that of widely used indicators of bank credit risks.

3.1 Bank Credit Risk Indicators

We consider two indicators of bank credit risks: the credit default swap spread and the bank bond credit spread. The first measure relies on banks' CDS contracts. As they directly measure the risk of default of banks, these contracts are a standard way to measure the extent of a bank's credit risk. One limitation of the approach is that CDS contracts are usually written on individual institutions and the aggregation over banks may introduce some biases because of the interdependence between banks. As an index representative of banks' CDS spreads, we use data from ICE Credit Market Analysis (CMA), which collects quotes from the largest and most active credit investors in the over-the-counter (OTC) market. These indices are based on five-year maturity senior unsecured debt, as these contracts are usually considered the most liquid. The data start in January 2004.[10]

The second measure relies on bonds issued by banks and is calculated as the difference between the corporate yield of a given maturity and the corresponding government bond yield with similar maturity. This approach was initiated by Gilchrist and Zakrajšek (2012a) (GZ) for U.S. data and Gilchrist and Mojon (2018) (GM) for European data. The challenge of this approach is related to the structure of the bond market for banks because it may suffer from some lack of liquidity, at least for some financial intermediaries.

[10]Mayordomo, Ignacio Peña, and Schwartz (2014) compare several databases collecting CDS prices. They report that CMA quotes lead the price discovery process. We also estimate predictive regressions with Thomson Reuters indices, starting in December 2007, and reach very similar conclusions.

Indeed, total debt securities represent a relatively small fraction of total bank financing.[11] The GZ index is constructed as follows. For a given month t and a given firm i, the market price of the outstanding bond security k is used to compute its yield $y_{i,t}[k]$. Then, the individual credit spread is computed by subtracting the yield of a Treasury security of the same maturity $y_{f,t}[k]$, so that the credit spread is written as $S_{i,t}[k] = y_{i,t}[k] - y_{f,t}[k]$. Finally, the index is the (unweighted) average over maturities and over firms of the individual credit spreads: $S_t^{GZ} = \frac{1}{N_t}\sum_i \sum_k S_{i,t}[k]$, where N_t is the number of bond/firm observations in month t. For the GM index in the euro area, the individual credit spread is calculated by subtracting the German bund zero-coupon interest rate of a similar maturity. The GM credit risk indicator is then calculated as the (weighted) average of the individual credit spreads, where weights correspond to the ratio of the market value of the security relative to the total market value of all bonds in the sample.[12]

Figure 1 displays the monthly evolution of the 3-month RRI (3-month tenor) (denoted by $RRI^{(3m)}_{3m,3m}$) and 12-month RRI (6-month tenor) ($RRI^{(6m)}_{12m,12m}$), the CDS spread, and the GM and GZ spreads for the euro area and the United States between 2005 and 2020. We observe some substantial differences between the indicators across the two zones.

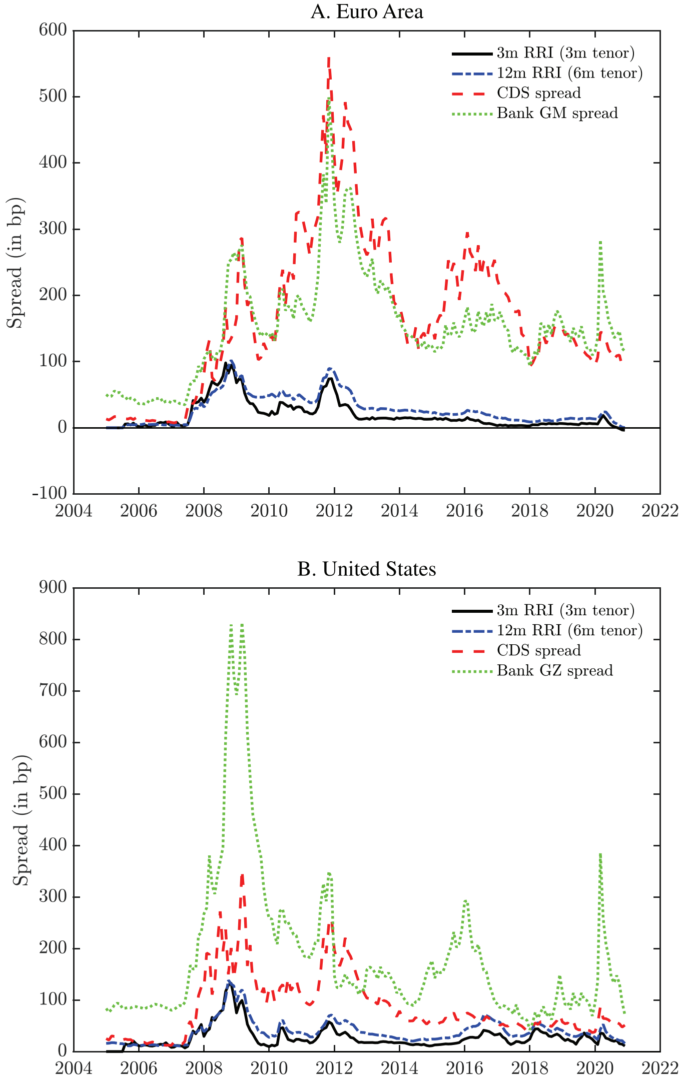
In the euro area (panel A), the CDS and GM spreads have similar levels and temporal evolutions: both indicators sharply increase during the 2008–09 crisis (to a maximum of 300 bp in March 2009), and they experience an even more pronounced increase in 2011–12 during the sovereign debt crisis (from 200 bp to a maximum of 500 bp in November–December 2011). We note that the CDS spread also jumps at the end of 2015, with a peak in February

---

[11] Long-term debt securities represent on average less than 2 percent of commercial banks' total liabilities in the United States.

[12] The GZ spread for banks covers the period from January 1985 to December 2012 and has not been updated since, while the spread for non-financial firms covers the period from January 1973 to November 2019 (Gilchrist and Zakrajšek 2012a). We have estimated the linear relation between the two indicators between 2005 and 2012 and used this relation to update the bank spread between 2013 and 2019. We investigated other approaches and obtained similar results.

Figure 1. Rollover and Credit Risk Indicators



Note: Panel A displays the bank credit risk indicators for the euro area: the 3-month and 12-month RRI, the CDS spread, and the GM spread (Gilchrist and Mojon 2018). Panel B displays the bank credit risk indicators for the United States: the 3-month and 12-month RRI, the CDS spread, and the bank GZ spread (Gilchrist and Zakrajšek 2012b). The sample periods run from January 2005 to December 2020.

2016, while the GM spread barely increases. Both tenor spreads also increase substantially during the subprime crisis (with a maximum of 100 bp for the 3- and 12-month RRIs). The impact of the sovereign debt crisis is similar, as the spreads reach 75 bp and 90 bp, respectively. In the recent period, the evolution is smoothed, and the tenor spreads do not exceed 25 bp. In contrast to the United States, the correlation between the RRI and the credit spreads is relatively low. The correlation is below 50 percent with the CDS spread and below 70 percent with the GM spread. As expected, the correlation between the CDS and GM spreads is much higher, approximately 90 percent.

In the United States (panel B), the four indicators exhibit a peak during the financial crisis but with different timings. The 3- and 12-month RRIs reach their maximum values in October 2008 just before the GZ spread (November), while the CDS spread peaks in March 2009. The four indicators also substantially increase in November–December 2011 with very similar timings. We note, however, that the CDS spread is almost as high as the maximum attained in 2008–09. Finally, there is a surge in the GZ spread in January 2016 that is not associated with significant movement in the other spreads. Note that the 3- and 12-month RRIs display similar correlation patterns. They have high correlation with the GZ spread (77 percent and 79 percent, respectively) and relatively lower correlation with the CDS spread (65 percent and 70 percent, respectively). All this evidence suggests that the indicators may capture different phenomenons.

In summary, in the euro area, the series are likely to exhibit different predictive properties because of their different temporal evolution. In contrast, in the United States, the similarity between the series suggests that predictive ability should be more similar across indicators.[13]

[13]We also considered the indicator of broker-dealers liquidity supply constructed by Goldberg (2020). This measure is based on broker-dealers trading positions in Treasury bonds and the deviations of Treasury yields from a fitted yield curve. We have tested the ability of this indicator to predict real activity and bank lending variables for the United States. The results based on this indicator are reported in Appendix B.

3.2 Methodology

We now adopt the following methodology to measure the ability of liquidity and credit spreads to predict real economic activity (Gilchrist and Zakrajšek 2012a, Gilchrist and Mojon 2018, and Goldberg 2020). Let $\Delta^h y_{t+h} = \log(Y_{t+h}/Y_t)$ measure the h-quarter-ahead percent change in the variable of interest Y_t. The predictive equation is written as

$$\Delta^h y_{t+h} = \alpha_h + \beta_h S_t + \gamma_h \Delta^h y_t + \delta_{1,h} r_t + \delta_{2,h} term_t + \epsilon_{t+h}, \quad (2)$$

where S_t is the spread indicator and ϵ_{t+h} is an error term. As control variables, we include the lag of the variable of interest, as observed at date t; the real short-term interest rate (r_t); and the term premium ($term_t$).[14]

As for risk indicators, we consider various measures of rollover risk, the CDS spread, and the GZ/GM spread. Regarding funding spreads, we investigate the role of their tenor and maturity in determining their predictive ability. We report results for RRIs with one-, three-, and six-month tenors, for different starting dates and maturities. Specifically, we test 3-, 6-, and 12-month RRIs with x-month tenor, denoted by $RRI^{(xm)}_{(3m,3m)}$, $RRI^{(xm)}_{(6m,6m)}$, and $RRI^{(xm)}_{(12m,12m)}$. We also consider alternative combinations of starting dates and maturities such as a 12-month forward spread starting in 6 months ($RRI^{(xm)}_{(6m,12m)}$) or a 12-month forward spread starting in 24 months ($RRI^{(xm)}_{(24m,12m)}$), to investigate the importance of the forward-looking component. We do not report all of the results for the sake of space and focus on results based on 3-month $RRI^{(xm)}_{(3m,3m)}$ and 12-month forward rates $RRI^{(xm)}_{(12m,12m)}$. All results are available upon request.

We consider four real activity variables (real GDP, real consumption, real investment, and the unemployment rate) and four measures of bank lending (total bank lending, consumer loans, real estate

[14] The real interest rate is measured as the short-term rate (federal funds rate in the United States, EONIA rate in the euro area) minus the 12-month inflation rate. The term spread is measured as the difference in yields on 10-year AAA sovereign bonds minus the short-term interest rate (federal funds or EONIA rates).

loans, and commercial and industrial loans). The results related to real activity are reported in Tables 1 and 2 for the euro area and the United States, respectively. The results related to bank lending are reported in Tables 3 and 4. In all tables, we focus on two- and four-quarter predictability. We do not report estimates of γ_h, $\delta_{1,h}$, and $\delta_{2,h}$ to save space.[15]

We perform our analysis from January 2005 to December 2019. This period covers a single business cycle, the origin of which was clearly in the financial sector. We do not include data prior to 2005 because tenor spreads were negligible before 2007 and could not be computed from multiple yield curves before 2004. We do not include data for 2020 to avoid the regressions being polluted by the extreme shock associated with the COVID-19 pandemic, which caused an unprecedented drop in real activity. This (relatively) short sample prevents us from performing a rolling-window analysis or estimates based on subsamples to evaluate the specific role played by some episodes, such as the 2007–09 financial crisis.

3.3 Predicting Real Activity

3.3.1 GDP Growth

We begin with the ability of the spread indicators to predict real GDP growth. As Table 1 (panel A) reveals, the RRI is the best predictor of euro-area GDP growth. For instance, the adjusted R^2 values are equal to 73 percent and 70 percent for the two- and four-quarter horizons, respectively, for the three-month RRI (three-month tenor). The spreads based on other starting dates and other tenors exhibit similar results, with negative and highly significant coefficients (all p-values are below 0.1 percent). On average, an increase of 10 bp in the three-month RRI predicts a decrease in GDP of 0.5 percent and 0.9 percent in the subsequent quarters. Credit spreads have much lower predictive performance. For the GM spread, the adjusted R^2 is approximately equal to 38 percent and 27 percent, for the two- and four-quarter horizons, respectively, also with highly significant

[15] Appendix B reports all results, with one-, two-, and four-quarter horizons, all parameter estimates (including γ_h, $\delta_{1,h}$, and $\delta_{2,h}$), and Goldberg (2020) indicators of liquidity supply and demand for U.S. broker-dealers.

Table 1. Predicting Euro-Area Real Activity Variables Using the RRI and Credit Spreads

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			**12-Month RRI** $\left(RRI^{(xm)}_{12m,12m}\right)$			**CDS Spread**	**GM Spread**
	1m	**3m**	**6m**	**1m**	**3m**	**6m**		
A. Real GDP Growth								
Variables in $t-2$								
Variable	–8.421	–5.109	–3.042	–9.949	–6.353	–5.067	–0.414	–1.007
(t-stat)	(4.027)	(5.061)	(6.188)	(5.745)	(5.261)	(4.614)	(2.029)	(2.865)
Adj. R^2	0.0674	**0.726**	0.623	0.679	0.712	0.676	0.303	0.378
Variables in $t-4$								
Variable	–14.994	–9.084	–5.341	–16.539	–11.330	–9.125	–1.016	–2.088
(t-stat)	(5.721)	(7.863)	(5.526)	(5.471)	(7.664)	(6.676)	(2.069)	(4.259)
Adj. R^2	0.658	**0.703**	0.555	0.605	0.683	0.619	0.150	0.268
B. Real Consumption Growth								
Variables in $t-2$								
Variable	–2.874	–1.873	–0.883	–2.633	–2.319	–1.808	–0.171	–0.239
(t-stat)	(4.181)	(6.972)	(3.386)	(3.418)	(6.743)	(6.389)	(1.769)	(1.768)
Adj. R^2	0.680	**0.714**	0.634	0.630	0.705	0.684	0.572	0.556
Variables in $t-4$								
Variable	–6.633	–4.165	–2.167	–6.294	–5.186	–4.174	–0.414	–0.708
(t-stat)	(5.082)	(5.794)	(3.564)	(3.406)	(5.357)	(5.427)	(1.556)	(2.147)
Adj. R^2	0.545	**0.586**	0.464	0.458	0.576	0.542	0.313	0.311

(*continued*)

Table 1. (Continued)

	3-Month RRI $\left(\boldsymbol{RRI}^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(\boldsymbol{RRI}^{(xm)}_{12m,12m}\right)$			CDS Spread	GM Spread
	1m	**3m**	**6m**	**1m**	**3m**	**6m**		
C. Real Investment Growth								
Variables in $t-2$								
Variable	–19.083	–11.877	–7.430	–22.151	–14.830	–12.354	–1.203	–2.721
(t-stat)	(4.777)	(7.231)	(8.585)	(7.214)	(7.833)	(7.378)	(2.728)	(4.194)
Adj. R^2	0.533	**0.592**	0.561	0.547	0.575	0.569	0.190	0.315
Variables in $t-4$								
Variable	–34.784	–21.674	–12.763	–38.535	–27.418	–22.346	–2.797	–5.046
(t-stat)	(6.135)	(8.900)	(6.549)	(6.376)	(9.086)	(8.293)	(2.658)	(5.113)
Adj. R^2	0.631	**0.701**	0.577	0.589	0.691	0.647	0.214	0.321
D. Unemployment Rate Change								
Variables in $t-2$								
Variable	2.627	1.612	0.979	2.977	2.021	1.610	0.111	0.278
(t-stat)	(6.548)	(7.145)	(10.465)	(8.497)	(7.246)	(5.687)	(1.822)	(2.716)
Adj. R^2	0.831	**0.841**	0.805	0.832	0.838	0.810	0.589	0.628
Variables in $t-4$								
Variable	6.168	3.724	2.109	6.622	4.694	3.726	0.390	0.753
(t-stat)	(10.153)	(13.622)	(8.564)	(7.612)	(11.652)	(9.580)	(2.138)	(4.422)
Adj. R^2	0.785	**0.800**	0.665	0.730	0.789	0.716	0.317	0.400

Note: This table reports predictive regressions for euro-area real activity variables. Predictive horizons are two and four quarters. Presented are the parameter estimates, Newey-West adjusted t-statistics in parentheses, and adjusted R^2 values. The sample period runs from January 2005 to December 2019.

Table 2. Predicting U.S. Real Activity Variables Using the RRI and Credit Spreads

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$			CDS Spread	GZ Spread
	1m	**3m**	**6m**	**1m**	**3m**	**6m**		
A. Real GDP Growth								
Variables in $t-2$								
Variable	–4.907	–4.023	–2.597	–5.942	–4.531	–3.355	–0.969	–0.427
(t-stat)	(4.770)	(3.451)	(4.388)	(3.785)	(3.117)	(2.914)	(2.257)	(2.167)
Adj. R^2	0.519	0.502	0.412	**0.523**	0.461	0.377	0.276	0.208
Variables in $t-4$								
Variable	–6.706	–5.760	–4.269	–8.819	–7.083	–5.694	–2.329	–1.099
(t-stat)	(4.329)	(4.209)	(4.043)	(4.587)	(3.976)	(3.605)	(2.580)	(4.239)
Adj. R^2	0.426	0.443	0.440	**0.481**	0.453	0.387	0.428	0.319
B. Real Consumption Growth								
Variables in $t-2$								
Variable	–2.010	–1.665	–1.102	–2.995	–2.153	–1.531	–0.750	–0.068
(t-stat)	(3.791)	(4.010)	(3.062)	(4.573)	(4.071)	(3.941)	(3.576)	(0.605)
Adj. R^2	0.557	0.557	0.542	**0.591**	0.566	0.540	0.575	0.473
Variables in $t-4$								
Variable	–4.109	–3.661	–2.732	–6.077	–4.928	–3.917	–2.138	–0.337
(t-stat)	(3.715)	(4.325)	(3.414)	(4.281)	(4.300)	(4.340)	(4.265)	(1.913)
Adj. R^2	0.503	0.517	0.523	0.557	0.547	0.511	**0.613**	0.394

(*continued*)

Table 2. (Continued)

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$			CDS Spread	GZ Spread
	1m	**3m**	**6m**	**1m**	**3m**	**6m**		
C. Real Investment Growth								
Variables in $t-2$								
Variable	–15.654	–12.178	–8.245	–17.831	–13.406	–10.142	–2.343	–1.929
(t-stat)	(4.275)	(2.783)	(3.032)	(2.997)	(2.400)	(2.072)	(1.591)	(1.770)
Adj. R^2	**0.691**	0.634	0.578	0.649	0.585	0.526	0.413	0.470
Variables in $t-4$								
Variable	–23.489	–18.088	–12.078	–27.543	–20.566	–14.891	–5.238	–2.967
(t-stat)	(4.939)	(3.551)	(3.757)	(3.650)	(2.917)	(2.332)	(1.700)	(3.135)
Adj. R^2	**0.597**	0.558	0.522	0.577	0.526	0.457	0.433	0.435
D. Unemployment Rate Change								
Variables in $t-2$								
Variable	2.531	2.083	1.474	3.033	2.369	1.879	0.382	0.417
(t-stat)	(7.307)	(4.187)	(5.548)	(4.539)	(3.300)	(2.727)	(1.683)	(2.790)
Adj. R^2	**0.821**	0.787	0.764	0.800	0.751	0.703	0.574	0.670
Variables in $t-4$								
Variable	4.825	3.922	2.713	5.907	4.646	3.693	1.105	0.681
(t-stat)	(6.801)	(5.188)	(6.051)	(5.313)	(4.244)	(3.661)	(1.816)	(4.356)
Adj. R^2	**0.702**	0.683	0.664	0.697	0.655	0.591	0.471	0.545

Note: This table reports predictive regressions for U.S. real activity variables. Predictive horizons are two and four quarters. Presented are the parameter estimates, Newey-West adjusted t-statistics in parentheses, and adjusted R^2 values. The sample period runs from January 2005 to December 2019.

Table 3. Predicting Euro-Area Bank Lending Variables Using the RRI and Credit Spreads

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			**12-Month RRI** $\left(RRI^{(xm)}_{12m,12m}\right)$			**CDS Spread**	**GM Spread**
	1m	**3m**	**6m**	**1m**	**3m**	**6m**		
A. Bank Credit Growth								
Variables in $t-2$								
Variable	–6.348	–3.566	–2.045	–6.929	–4.515	–3.604	–0.755	–1.17
(t-stat)	(5.864)	(6.459)	(4.936)	(7.469)	(6.951)	(5.193)	(3.741)	(3.113)
Adj. R^2	**0.845**	0.839	0.822	0.843	0.839	0.831	0.802	0.825
Variables in $t-4$								
Variable	–19.168	–11.199	–6.268	–20.592	–14.279	–11.32	–2.244	–3.282
(t-stat)	(5.662)	(7.938)	(6.030)	(8.018)	(9.247)	(7.318)	(4.319)	(3.412)
Adj. R^2	0.833	0.844	0.803	0.828	**0.848**	0.836	0.761	0.791
B. Consumer Loan Growth								
Variables in $t-2$								
Variable	–5.009	–3.055	–1.692	–5.015	–3.759	–3.154	–0.746	–1.143
(t-stat)	(4.387)	(5.610)	(4.158)	(4.666)	(5.847)	(5.095)	(2.953)	(3.539)
Adj. R^2	0.682	**0.693**	0.670	0.666	0.688	0.685	0.673	0.687
Variables in $t-4$								
Variable	–14.219	–8.388	–4.669	–14.517	–10.541	–8.533	–1.547	–2.634
(t-stat)	(7.496)	(9.119)	(6.394)	(7.516)	(9.884)	(8.187)	(2.884)	(4.667)
Adj. R^2	0.778	**0.789**	0.738	0.745	0.786	0.767	0.667	0.719

(*continued*)

Table 3. (Continued)

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$			CDS Spread	GM Spread
	1m	**3m**	**6m**	**1m**	**3m**	**6m**		
C. Real Estate Loan Growth								
Variables in $t-2$								
Variable	–3.644	–2.009	–1.053	–3.847	–2.586	–2.079	–0.366	–0.535
(t-stat)	(4.057)	(3.668)	(2.608)	(4.200)	(3.498)	(2.63)	(2.121)	(1.99)
Adj. R^2	**0.732**	0.726	0.706	0.724	0.727	0.719	0.696	0.696
Variables in $t-4$								
Variable	–9.978	–5.476	–2.854	–9.857	–6.946	–5.613	–1.255	–1.638
(t-stat)	(5.519)	(5.070)	(3.622)	(4.493)	(4.564)	(3.816)	(2.856)	(3.400)
Adj. R^2	**0.713**	0.697	0.648	0.677	0.696	0.679	0.651	0.641
D. C&I Loan Growth								
Variables in $t-2$								
Variable	–9.010	–5.019	–3.271	–10.042	–6.374	–5.187	–0.909	–1.712
(t-stat)	(6.533)	(7.506)	(9.637)	(9.162)	(8.339)	(8.836)	(4.155)	(4.306)
Adj. R^2	0.889	0.886	**0.903**	0.898	0.888	0.890	0.846	0.901
Variables in $t-4$								
Variable	–27.828	–16.771	–10.284	–30.724	–21.346	–17.192	–2.757	–4.833
(t-stat)	(5.920)	(10.505)	(10.413)	(10.118)	(11.908)	(12.015)	(4.369)	(4.466)
Adj. R^2	0.830	0.860	0.875	0.850	0.866	**0.876**	0.755	0.840

Note: This table reports predictive regressions for euro-area bank lending variables. Predictive horizons are two and four quarters. Presented are the parameter estimates, Newey-West adjusted t-statistics in parentheses, and adjusted R^2 values. "C&I loan" means commercial and industrial loan. The sample period runs from January 2005 to December 2019.

Table 4. Predicting U.S. Bank Lending Variables Using the RRI and Credit Spreads

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$			CDS Spread	GZ Spread
	1m	**3m**	**6m**	**1m**	**3m**	**6m**		
A. Bank Credit Growth								
Variables in $t-2$								
Variable	–2.623	–2.832	–2.474	–3.735	–3.775	–3.704	–1.129	–0.532
(t-stat)	(1.781)	(2.323)	(3.646)	(2.117)	(2.867)	(3.734)	(1.866)	(3.262)
Adj. R^2	0.353	0.405	0.483	0.380	0.431	**0.493**	0.385	0.434
Variables in $t-4$								
Variable	–9.237	–8.063	–6.054	–11.675	–10.089	–9.055	–2.789	–1.343
(t-stat)	(6.022)	(6.749)	(9.907)	(6.028)	(7.279)	(11.004)	(2.627)	(5.803)
Adj. R^2	0.614	0.682	0.766	0.658	0.714	**0.792**	0.561	0.671
B. Consumer Loan Growth								
Variables in $t-2$								
Variable	–0.740	–2.055	–2.534	–1.791	–2.898	–3.342	–0.556	–0.734
(t-stat)	(0.284)	(1.125)	(3.592)	(0.629)	(1.590)	(2.799)	(0.839)	(4.138)
Adj. R^2	0.404	0.419	0.458	0.408	0.429	0.459	0.412	**0.489**
Variables in $t-4$								
Variable	–4.821	–6.112	–5.323	–7.255	–7.683	–8.293	–1.847	–1.802
(t-stat)	(1.446)	(2.441)	(3.128)	(1.994)	(2.625)	(3.586)	(1.559)	(4.062)
Adj. R^2	0.513	0.546	0.572	0.528	0.555	0.602	0.526	**0.650**

(*continued*)

Table 4. (Continued)

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$			CDS Spread	GZ Spread
	1m	**3m**	**6m**	**1m**	**3m**	**6m**		
C. Real Estate Loan Growth								
Variables in $t-2$								
Variable	–0.282	–1.066	–1.397	–1.410	–1.998	–2.208	–0.822	–0.265
(t-stat)	(0.147)	(0.662)	(1.511)	(0.585)	(1.090)	(1.567)	(1.604)	(1.235)
Adj. R^2	0.529	0.536	0.558	0.534	0.547	**0.563**	0.552	0.544
Variables in $t-4$								
Variable	–4.558	–4.978	–4.539	–7.143	–7.010	–7.144	–2.226	–1.186
(t-stat)	(1.973)	(2.605)	(3.552)	(2.411)	(3.124)	(4.246)	(2.414)	(4.567)
Adj. R^2	0.674	0.701	0.747	0.696	0.722	**0.764**	0.702	0.742
D. C&I Loan Growth								
Variables in $t-2$								
Variable	–12.384	–10.483	–7.926	–14.488	–12.263	–10.590	–3.432	–2.101
(t-stat)	(5.344)	(4.645)	(6.827)	(4.165)	(4.014)	(4.488)	(1.863)	(8.747)
Adj. R^2	0.694	0.735	0.809	0.697	0.727	0.757	0.633	**0.847**
Variables in $t-4$								
Variable	–34.528	–28.842	–20.605	–40.960	–33.598	–28.601	–8.539	–5.379
(t-stat)	(10.627)	(7.673)	(10.069)	(7.078)	(6.256)	(7.221)	(1.809)	(15.428)
Adj. R^2	0.589	0.668	0.750	0.613	0.657	0.718	0.408	**0.812**

Note: This table reports predictive regressions for U.S. bank lending variables. Predictive horizons are two and four quarters. Presented are the parameter estimates, Newey-West adjusted t-statistics in parentheses, and adjusted R^2 values. "C&I loan" means commercial and industrial loan. The sample period runs from January 2005 to December 2019.

parameters. For CDS spreads, the adjusted R^2 values are below these values. The better prediction generated by the RRI is due to the ability of this indicator to anticipate the magnitude of the recession during the subprime crisis. Tenor spreads predict a more severe recession in 2008–09 than in 2012. In contrast, the CDS and GM spreads predict a more severe recession in 2012.

We obtain similar results for U.S. GDP growth (Table 2, panel A). The 12-month forward spreads (1-month tenor) have the highest predictive power for GDP growth. The adjusted R^2 values are equal to 52 percent and 48 percent, for the two- and four-quarter horizons, respectively. On average, an increase of 10 bp in the RRI predicts a decrease of 0.6 percent and 0.9 percent in GDP growth in the subsequent quarters. The parameters are all highly significant. Their magnitude increases with the forecast horizon and decreases with the tenor. Credit spreads also have relatively high adjusted R^2 values, but they remain below 28 percent for the two-quarter horizon and below 43 percent for the four-quarter horizons.

3.3.2 Consumption Growth

We now consider the ability of spread indicators to predict real consumption growth. The results reported in panel B indicate that the three-month RRI (three-month tenor) strongly outperforms the other indicators for all horizons in the euro area. For instance, for the four-quarter horizon, the adjusted R^2 is as high as 59 percent, whereas it is below 32 percent for credit spreads.

In the United States, the 12-month RRI (1-month tenor) produces the best forecast for the two-quarter horizon, with an adjusted R^2 equal to 59 percent, whereas the adjusted R^2 of the CDS spread is equal to 57.5 percent. For the four-quarter horizon, the adjusted R^2 values are equal to 56 percent and 61 percent, respectively.

3.3.3 Investment Growth

Panel C reports that in terms of predicting euro-area investment growth, the gain of using the RRI is as large for investment as for consumption. The adjusted R^2 values of the three-month RRI (three-month tenor) are equal to 59 percent and 70 percent for the two- and four-quarter horizons but only 31 percent and 32 percent for the GM spread. The results with the CDS spread are even worse (adjusted R^2 close to 20 percent). A 10 bp increase in the three-month RRI (three-month tenor) predicts, on average, a decline in investment of 1.2 percent and 2.2 percent in the subsequent quarters.

For U.S. investment growth, the three-month RRI (one-month tenor) dominates the other indicators for all horizons: the adjusted R^2 values are close to 70 percent and 60 percent for the two- and four-quarter horizons, respectively. Credit spreads produce R^2 values that are close to 40–45 percent. It is worth emphasizing that the 3-month RRI performs well for investment growth, whereas the 12-month RRI dominates for consumption growth. This result suggests that expectations play a different role for these two variables. Investment seems to be more reactive to the most recent information, while consumption is based on more forward-looking expectations.

3.3.4 Unemployment Rate

For the unemployment rate (panel D), the predictive ability of the RRI is again very strong. In the euro area, the predictive ability of the three-month RRI (three-month tenor) is considerable, with adjusted R^2 values equal to 84 percent and 80 percent for the two- and four-quarter horizons. The adjusted R^2 values are below 63 percent for the credit spreads.

For the two- and four-quarter horizons, the three-month RRI (one-month tenor) produces adjusted R^2 values equal to 82 percent and 70 percent for the United States. The performance is lower for credit risk indicators. The GZ spread and the CDS spread generate R^2 values that are 15 and 20 percentage points below the R^2 values of the RRI, respectively.

In summary, these results indicate that the expected bank RRI brings additional information that helps predict real activity in the euro area and the United States. In general, the tenor of the RRI is longer for the euro area than for the United States (three months versus one month). This result is probably partly driven by the way expectations are formed in the two areas. In particular, the dynamics of the monetary policy in the euro area during the sovereign debt crisis may have affected the expectations process.

3.4 Predicting Bank Lending

Tables 3 and 4 present the results of the predictive regressions for bank lending in the euro area and the United States, respectively. We investigated several specifications of the RRI and found that predicting lending relies on relatively long expectations. In the euro area, the best predictions are obtained with the 3-month RRI for the two-quarter horizon and the 12-month RRI for the four-quarter horizon. The adjusted R^2 is as high as 84 percent for both horizons. Credit spreads also perform well, with adjusted R^2 values close to 80 percent.

In the United States, predictions are often improved when we consider a more distant starting date (such as the 12-month RRI) and a longer tenor (such as 6 months). We note that, in general, R^2 values are relatively high because of the persistence in the predicted variable. The 12-month RRI (with a 6-month tenor) has by the highest predictive ability for bank lending. The adjusted R^2 is as high as 49 percent and 79 percent for the two- and four-quarter horizons. In comparison, credit spreads generate R^2 values close to 40–60 percent for these horizons.

We now decompose bank lending into its main components: consumer loans, real estate loans, and commercial and industrial loans. For the euro area, the three-month RRI produces the best performance for consumer loans, real estate loans, and commercial and industrial loans, although predictions provided by the GM spread are in general in a similar range of values. In all cases, the adjusted R^2 values obtained with the RRI are remarkably high, between 65 percent and 80 percent. For commercial and industrial loans, the GM spread is still slightly dominated by the RRI.

In the United States, we find that spread indicators usually exhibit good predictive performance. For consumer loans, the adjusted R^2 is the highest for the GZ spread. For real estate loans, the 12-month RRI has the highest performance. For commercial and industrial loans, the GZ spread again dominates. For the RRI, the adjusted R^2 values are close to 80 percent for the two-quarter horizon and 75 percent for the four-quarter horizon. It is remarkable that RRIs and the GZ indicators have similar predictive ability, despite being built on different types of information.

In summary, (i) real activity variables rely on relatively short expectations, so short-horizon RRIs perform quite well, while CDS and GZ/GM spreads usually fail at predicting real activity; (ii) bank lending variables rely on relatively long expectations, so long-horizon RRIs perform better in the United States. The main advantage of the RRIs is that they allow us to adapt the predictor to the length of the expectations needed. Short horizons (typically the 3-month RRI) are sufficient for real activity variables; long horizons (typically the 12-month RRI) are useful for bank lending variables.

4. Rollover Risk Indicator and Liquidity Regimes

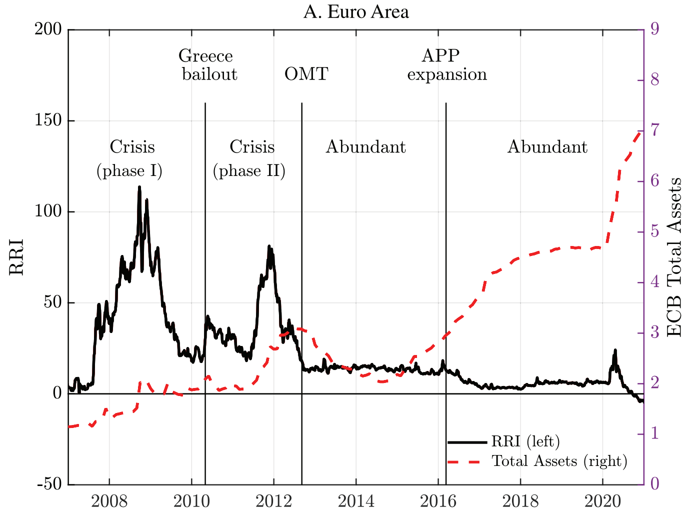
The evolution of the rollover risk indicator helps to contrast three liquidity regimes for central banks: (i) a *crisis* regime, associated with a lack of liquidity in the financial system and a strong connection between liquidity risk and credit risk, (ii) a regime of *abundant liquidity*, associated with massive central bank injections of liquidity, flat forward funding spreads, and a disconnect between liquidity and credit risk, and (iii) a regime of *moderate liquidity*, characterized by uncertainty over the cost of liquidity that is however unrelated to credit risk. Figure 2 displays the three-month RRI and the size of the central bank balance sheet, for the euro area and the United States, respectively. The latter provides an indication of changes in the supply of central bank liquidity. To cross-check what the RRI reveals about liquidity regimes, the CDS spread (as an indicator of banks' credit risk) and the uncertainty over short-term interest rates (measured as the sum of disagreement among forecasters and the perceived variability of future aggregate shocks; see Istrefi and Mouabbi 2018) are displayed in Figure 3. In addition, Figures 4 and 5 provide more detailed dynamics of the RRI for the euro area and the United States, respectively.

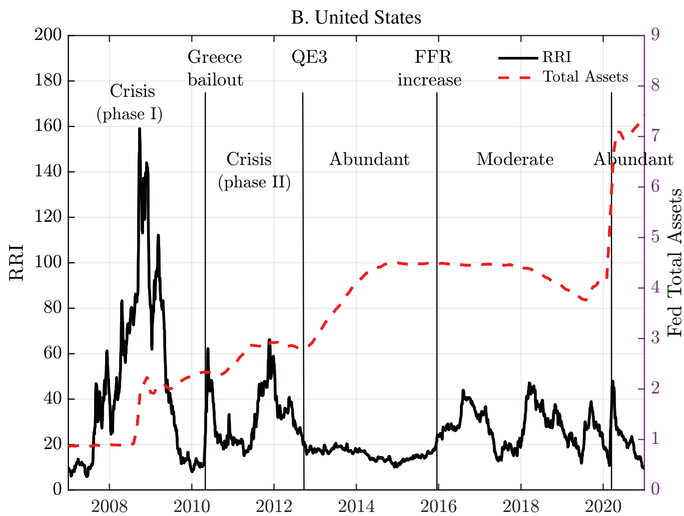
4.1 The Euro Area

4.1.1 Crisis Regime—Phase I: The Interbank Crisis (Summer 2007–May 2010)

The RRI was negligible, below 5 bp, until mid-2007 (panel A of Figure 4). In the fall of 2007, the RRI increased to approximately 50 bp. In September 2008, it jumped again, although it did not exceed 120 bp.

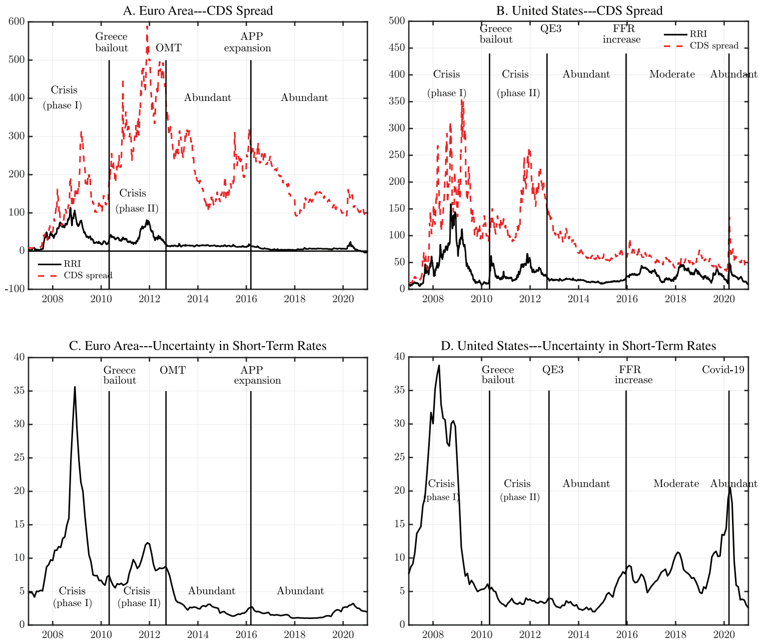
Figure 2. Rollover Risk Indicator and Central Bank's Total Assets





Note: Panel A displays the three-month rollover risk indicator (in bp) and the ECB total assets (in EUR trillion). Panel B displays the three-month rollover risk indicator (in bp) and the Federal Reserve total assets (in USD trillion). The RRI series are smoothed using a five-day moving average. The sample periods run from January 2005 to December 2020.

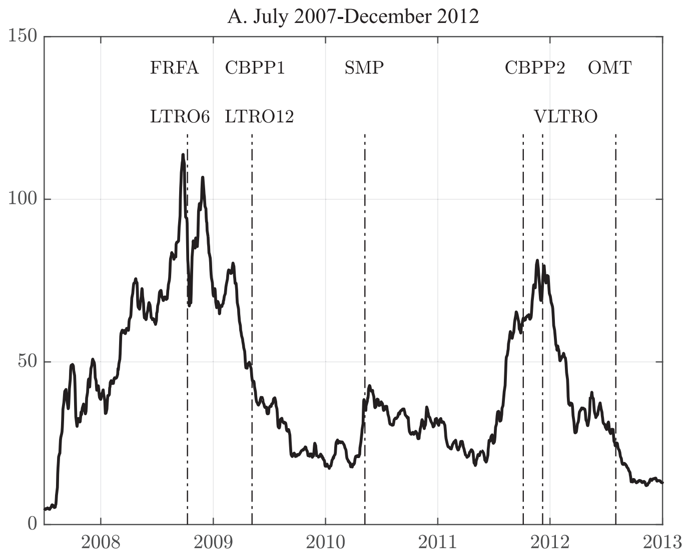
Figure 3. Bank CDS Spreads and Uncertainty in Short-Term Interest Rates

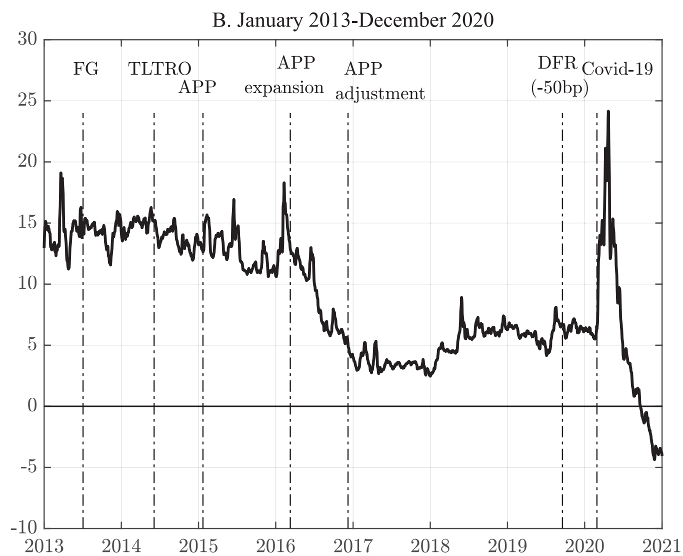


Note: Panels A and B display the bank CDS spread and the rollover risk indicator ($RRI^{(3m)}_{(3m,3m)}$) (in bp) for the euro area and the United States, respectively. The RRI and credit spread series are smoothed using a five-day moving average. Panels C and D display the uncertainty in three-month interest rates in three months, as measured as the sum of disagreement among forecasters and the perceived variability of future aggregate shocks for the euro area and the United States, respectively. See Istrefi and Mouabbi (2018). The sample periods run from January 2007 to December 2020.

We observe that (i) the ECB took measures at a time when bank rollover costs were high and (ii) their effects were quite immediate. The ECB's reaction was first to carry out its main refinancing operations through a fixed-rate tender procedure with full allotment (FRFA) in October 2008, so that all demand for liquidity would be satisfied as long as adequate collateral was available. The introduction of the FRFA credit operations built up excess liquidity in the banking system. The RRI almost instantaneously fell in reaction to this measure. In a second round, the ECB sought to satisfy

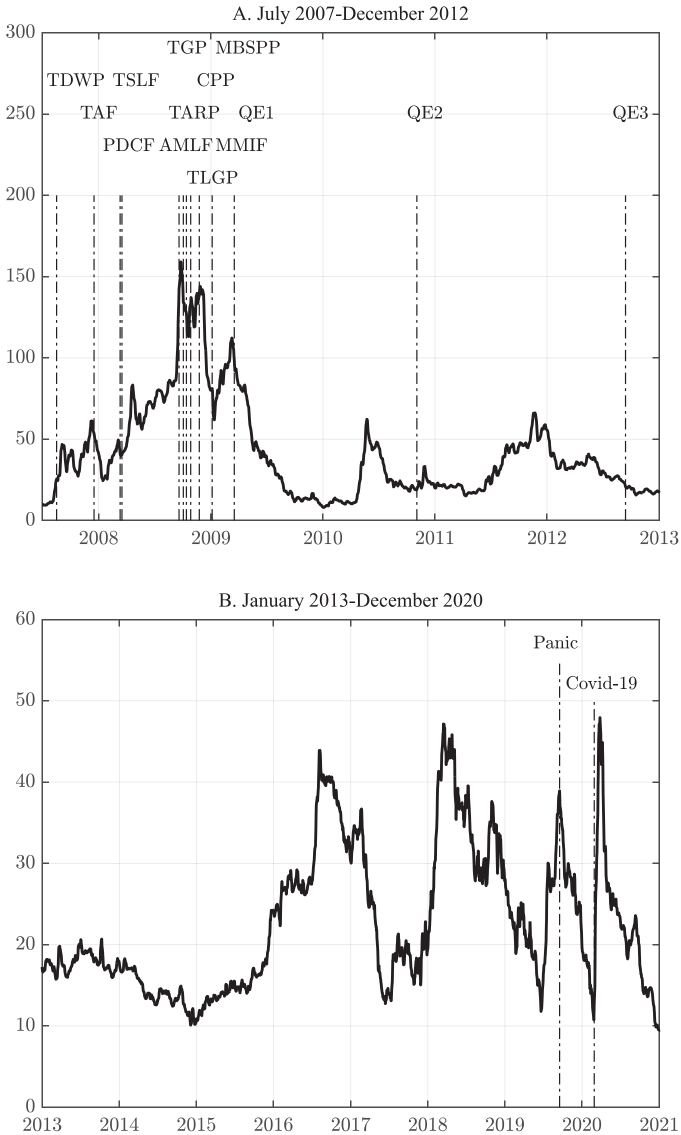
Figure 4. Rollover Risk Indicator for the Euro Area—Subsamples





Note: The figure displays the rollover risk indicator ($RRI^{(3m)}_{(3m,3m)}$) (in bp) for the euro area for two subsamples. The series are smoothed using a five-day moving average.

Figure 5. Rollover Risk Indicator for the United States—Subsamples



Note: The figure displays the rollover risk indicator ($RRI^{(3m)}_{(3m,3m)}$) (in bp) for the euro area for two subsamples. The series are smoothed using a five-day moving average.

the increased demand for liquidity by adjusting both the timing and the maturity of open market operations: 3- and 6-month full allotment long-term refinancing operations (LTROs) were implemented in November 2008 (EUR 300 billion) plus 12-month LTROs in June 2009 (EUR 442 billion). Providing banks with large amounts of liquidity for one year at a favorable rate allowed them to build up liquidity buffers. The combination of these unconventional responses had a beneficial impact on rollover risk, as the RRI decreased to 60 bp at the beginning of 2009.

This suggests that extended-maturity LTROs are an efficient tool to reduce bank borrowing costs by limiting rollover risk on maturing debt. By increasing the duration of their refinancing operations, the ECB reduces the credit risk premium of troubled banks by relaxing the constraint of bank equity holders associated with the frequently accruing rollover costs (Nyborg 2017).

4.1.2 Crisis Regime—Phase II: The Sovereign Debt Crisis (2010–12)

In reaction to the sovereign debt crisis, the ECB expanded its monetary outright portfolio in May 2010 through secondary market purchases of sovereign bonds under a new Securities Markets Program (SMP). The SMP was effective at mitigating upward pressures on the interbank market: the RRI remained relatively low, close to 20 bp, suggesting that there was no lack of liquidity in the euro market at that time (panel A of Figure 4). However, this program did not stop the rise in sovereign spreads. By July 2011, when markets started to question the status of Italian and Spanish sovereign debts, financial tensions intensified again and the crisis turned into a twin sovereign debt and banking crisis. Concerns about the solvency of large European banks increased, as testified by the jump in banks' CDS spreads in the second half of 2011. In August 2011, the RRI increased in parallel, from 25 to 60 bp at the end of the month, and then stabilized.

At the end of 2011, the ECB intervened substantially, using several measures designed to address funding risk: two LTROs of 12 and 13 months announced on October 2011, the second Covered Bond Purchase Program (CBPP2), and the announcement in December 2011 of two 36-month very long-term refinancing operations (VLTROs) to give banks funding certainty and help them sustain credit lines to the private sector. The ECB's balance sheet thus increased from approximately EUR 2 trillion in mid-2011 to almost EUR 3 trillion in mid-2012. The new sets of LTROs, by providing full-allotment liquidity and financing at a fixed policy rate and at a longer maturity, served as indirect bailout for weaker banks and sovereigns in the euro area. In this context, many euro-area banks have converted most of their short-term secured funding into long-term debt, by using swap operations. VLTROs induced an increase in the overall maturity of banks' liabilities, reducing their maturity mismatch and ultimately their rollover risk. Consequently, the RRI started to fall as soon as the monetary policy measures were announced, and it reached a first plateau at 30 bp in April despite still-elevated bank CDS rates.[16]

The speech by Mario Draghi on July 26, 2012, in which he stated that the ECB was ready to do "whatever it takes to preserve the euro" and the announcement shortly after of the Outright Monetary Transactions (OMT) program (with the option for governments to request the purchase of short-term sovereign bonds in secondary markets in unlimited amounts, under strict conditions) put the ECB in the position of lender of last resort for sovereigns. In turn, the rollover risk of banks stabilized: by end-2012, the RRI was close to 15 bp.

4.1.3 Abundant Liquidity (2013–February 2020)

After the OMT announcement, the euro area entered a persistent regime with very little uncertainty over the expected funding cost of banks. Remarkably, liquidity risk was low but the CDS spreads were still high. However, the combined effects of the FRFA of the ECB and the off-balance-sheet option character of the OMT kept the RRI flat at a low level (panel B of Figure 4).

[16] A substantial literature has evaluated these measures, in most cases finding that the programs worked as intended. For instance, Pelizzon et al. (2016) show that LTROs weakened the sensitivity to the credit risk of market-makers' liquidity provision, highlighting the importance of funding liquidity measures as determinants of market liquidity. Carpinelli and Crosignani (2017) show that banks more affected by the liquidity drought used central bank liquidity to restore credit supply, while less-affected banks increased their holdings of high-yield government bonds.

Given the low inflation and the persistence of low real growth in the area, the ECB adopted additional conventional and unconventional measures. The deposit facility rate was put into negative territory in June 2014, and the Asset Purchase Program (APP) was launched in 2015 (EUR 60 billion per month). In March 2016, the ECB took several measures to add further monetary stimulus (Hartmann and Smets 2018): The APP was expanded to EUR 80 billion in monthly purchases, a Corporate Sector Purchase Program (CSPP) was launched, and Targeted Longer-Term Refinancing Operations (TLTRO-II) were announced with a maturity of four years. This new package of measures allowed funding spreads to decrease considerably. The RRI declined from an already low 15 bp to 5 bp.

The liquidity injected into the financial system increased rapidly by EUR 2.5 trillion between 2015 and 2019, and the interest rate uncertainty fell below 2 percent, notably under the influence of the commitment to the future path of interest rates (forward guidance) implemented from July 2013.

4.2 The United States

4.2.1 Crisis Regime—Phase I: The U.S. Financial Crisis (Summer 2007–May 2010)

The first signs of stress on interbank liquidity appeared in the summer of 2007 with an increase in the RRI to approximately 50 bp (see panel A of Figure 5). The Federal Reserve introduced the Term Discount Window Program (TDWP) in August 2007, a temporary program that offered discount window funds with maturities beyond overnight and created the Term Auction Facility (TAF) in December 2007. As argued by Berger et al. (2014), these facilities increased aggregate lending, enhancing lending by expanding banks and slowing the decline in credit supplied by contracting banks.

However, these measures were not sufficient in view of the severity of the crisis. The usual redistribution mechanisms for liquidity within the financial system were too much altered. By mid-September 2008, the RRI jumped to a level close to 150 bp. The Federal Reserve started to provide liquidity directly to market participants through several programs and facilities: the Temporary Guarantee Program for money market funds (TGP) and the

Asset-Backed Commercial Paper and Money Market Liquidity Facility (AMLF) in September 2008; the Troubled Asset Relief Program (TARP) and the Capital Purchase Program (CPP), which were intended to provide capital injections for financial institutions in October 2008; the Money Market Investor Funding Facility (MMIFF) and the Term Asset-Backed Securities Loan Facility (TALF) in November 2008. In March 2009, the Federal Reserve decided to purchase up to USD 300 billion of longer-term Treasury securities (a program called quantitative easing, QE1) and to increase the purchase of agency debt.

Overall, the Federal Reserve injected approximately USD 1.3 trillion in liquidity between the summer of 2007 and the end of QE1 in May 2010. All these monetary policy actions seem to have dramatically reduced the cost of bank rollover: in early 2010, the RRI returned to its pre-crisis levels (approximately 10 bp).

4.2.2 Crisis Regime—Phase II: Between QE2 and QE3 (2010–12)

The period 2010–12 corresponds to the sovereign debt crisis in the euro area. The global integration of liquidity markets for large banks was clearly manifested during the second phase of the crisis. The Merkel-Sarkozy decision in October 2010 to impose losses on the private-sector lenders to the Greek Republic perturbed money markets in both euros and dollars. U.S. banks and money market funds held large positions in securities issued by European banks or had direct exposure to banks with direct exposure to Europe.

Financial tensions started to increase in spring 2010, as market participants started to question whether Greece, and possibly other highly indebted European countries, would be pushed to default and perhaps out of the euro area. The RRI increased by 20 bp (see panel A of Figure 5). The Federal Reserve started a second round of quantitative easing (QE2) in November 2010, buying USD 580 billion of Treasury securities by July 2011. Both spreads decreased to a level close to 20 bp, suggesting that liquidity was sufficiently abundant in the U.S. market. However, after stopping QE2 and facing a broadening of the sovereign debt crisis to Italian and Spanish sovereign debt, the RRI increased to 35 bp, suggesting that market participants expected the stress on money markets to resume.

4.2.3 Abundant Liquidity during QE3 (2013–15)

In September 2012, the Federal Reserve decided to launch an open-ended bond-purchasing program for agency mortgage-backed securities (QE3). The period of this program was characterized by additional increases in the supply of liquidity by the Federal Reserve. As shown in panel B of Figure 2, the Federal Reserve's balance sheet increased by USD 1.7 trillion to reach approximately 4.5 trillion in December 2015, a level five times larger than that before the crisis. The RRI stabilized at approximately 25 bp. A highly likely consequence of this larger scale of excess liquidity was that the rollover costs of large U.S. banks (panel B of Figure 5) were flat. During this period, bank CDS spreads decreased from above 150 bp to 60 bp and short-term interest rate uncertainty was extremely low (below 5 percent). Interestingly, the taper tantrum that hit global financial markets in Q2 and Q3 of 2013 had no effect on the expected cost of bank rollover.

In October 2014, the Federal Reserve announced the end of large-scale asset purchases. With QE ending, the Federal Reserve laid out its exit strategy: monetary policy normalization would consist of gradually raising its target range for the federal funds rate to more normal levels and gradually reducing the Federal Reserve's securities holdings. In reaction, the uncertainty associated with the interest rate increased.

4.2.4 Normalization of Federal Reserve Monetary Policy (2016–October 2019)

In December 2015, the Federal Reserve raised the target range for the federal funds rate for the first time since December 2008, and continued to increase it until January 2019 (panel B of Figure 5). It also began to gradually reduce its securities holdings from January 2018. The Federal Reserve's balance sheet was reduced to a level of USD 3.8 trillion in the summer of 2019 (panel B of Figure 2).

On September 16, 2019, there was an incident on the interbank market: the market rate spiked because cash-rich banks preferred keeping excess liquidity on their books to lending on the market to smooth a short episode of higher demand from other market players.

The Federal Reserve had to inject a massive amount of liquidity (over USD 50 billion) into the repo market the next day. The RRI had been rising in the few days before the panic. It almost instantaneously reverted on September 17 to a declining trend, suggesting that the event was due to a purely temporary lack of liquidity. Within a week after the incident, the Federal Reserve stepped up its liquidity supply to offer at least USD 75 billion in overnight repo funding and between 135 and 170 billion in term funding. Furthermore, additional monthly purchases of up to USD 60 billion of Treasury bills were announced, increasing its balance sheet again.

4.3 The COVID-19 Pandemic

The World Health Organization raised the risk of COVID-19 going global from high to very high on February 28, 2020. By that time, the United States was in a regime of moderate liquidity while the euro area was in a regime of abundant liquidity. Given these initial conditions, the pandemic could be expected to hit the bank RRI in very different proportions on the two sides of the Atlantic. And this is what happened (see panels B in Figures 4 and 5).

In the euro area, the spike in the RRI has been moderate, reaching approximately 24 bp as of end of April, before falling back to 0 bp in September 2020. In the United States, the RRI jumped to 50 bp. In addition, the rise in the RRI has been correlated with those of measures of bank credit risk (spreads on bank corporate bonds and CDSs on bank debt), a worrying feature already observed during the crisis environment that characterized U.S. money markets between 2007 and the beginning of QE3 in September 2012.

The ECB expanded its provision of liquidity in quantity and through various channels. The March 18 and April 30, 2020 announcements by the ECB of (i) a new temporary Pandemic Emergency Purchase Program (PEPP) that will have an additional envelope of EUR 750 billion until the end of 2020 and (ii) a new series of seven additional longer-term refinancing operations, called pandemic emergency longer-term refinancing operations (PELTROs) confirms (i) the continuation of the abundant regime and (ii) the desire of lengthening bank debt maturity and reducing rollover risk. In addition, the ECB decided to increase the initial EUR 750 billion envelope for the PEPP by EUR 600 billion on June 4, 2020 and by EUR

500 billion on December 10, 2020 for a new total of EUR 1,850 billion.

The Federal Reserve responded swiftly too. It announced several extraordinary measures to increase liquidity on U.S. money markets between March 12 and April 9, 2020 including (i) an injection of up to USD 1.5 trillion in the repo market; (ii) the purchase of at least USD 500 billion of Treasury securities and at least USD 200 billion of mortgage-backed securities; (iii) encouraging banks to use the discount window and intraday credit from the Federal Reserve; (iv) the establishment of the Primary Dealer Credit Facility (PDCF), the Commercial Paper Funding Facility (CPFF), and the Money Market Mutual Fund Liquidity Facility (MMFLF). Beyond the size of these operations, the Federal Reserve has made liquidity available through differentiated instruments to target various forms of funding stress.[17]

These multiple measures provided the U.S. money market with abundant liquidity conditions, and the RRI fell sharply to reach 25 bp at the end of May 2020 and 10 bp in December 2020. To some extent, this multiplicity of support channels echoes the ECB experience. In periods of stress, it is important to combine a large envelope of excess liquidity and multiple channels that target market participants confronted with specific forms of liquidity shortage.

4.4 Statistical Approach

We complement the narrative approach with a statistical approach based on a simple Markov-switching model. The objective is to estimate a model with regime-dependent means and volatilities and analyze whether the detected regimes do correspond to our narrative. The RRI is assumed to be driven by the following process:

$$RRI_{t+1} = \mu(\mathcal{S}_{t+1}) + \varepsilon_{t+1}, \tag{3}$$

where $\mu(\mathcal{S}_{t+1})$ is the vector of expected returns, conditional on state $\mathcal{S}_{t+1}$. The vector of unexpected returns is defined as

[17]See, among others, Gilchrist et al. (2020), Falato, Goldstein, and Hortaçsu (2021), Haddad, Moreira, and Muir (2021), and Chodorow-Reich et al. (2022) for analysis about the effects of Federal Reserve actions on markets and the economy in 2020.

$\varepsilon_{t+1} = \sigma(\mathcal{S}_{t+1})z_{t+1}$, where $\sigma(\mathcal{S}_{t+1})$ denotes the volatility of unexpected returns and z_{t+1} is a sequence of iid innovations with distribution $N(0, 1)$.

States are defined by the Markov chain $\{\mathcal{S}_t\}$ with k regimes and transition matrix

$$P = \begin{pmatrix} p_{11} & \cdots & p_{1k} \\ \vdots & \ddots & \vdots \\ p_{k1} & \cdots & p_{kk} \end{pmatrix},$$

where the transition probabilities are $p_{ij} = \Pr(\mathcal{S}_t = j|\mathcal{S}_{t-1} = i)$, $i, j \in \{1, \ldots, k\}$. We assume that expected returns $\mu(\mathcal{S}_{t+1}) = \mu_{(k)}$ and volatility $\sigma(\mathcal{S}_{t+1}) = \sigma_{(k)}$ are constant within states if $\mathcal{S}_{t+1} = k$.

We estimate a three-state model using standard likelihood maximization over the period from January 2007 to December 2020.[18] Table 5 reports the parameter estimates. In the euro area, the RRI varies between the high regime ($\mu_{(3)} = 68$ bp, $\sigma_{(3)} = 2.3$) and the intermediate regime ($\mu_{(2)} = 30$ bp, $\sigma_{(2)} = 0.53$) until September 2012. As for the United States, the high regime corresponds to the periods from February 2008 to May 2009 and from August 2011 to February 2012. After 2012, the RRI remains in the low regime ($\mu_{(1)} = 9$ bp, $\sigma_{(1)} = 0.25$) until the end of the sample, with an exception in April 2020 during the COVID-19 pandemic. Figure 6 shows the evolution of the expected levels across regimes.

For the United States, we observe a sequence of regime switches, from the high RRI regime ($\mu_{(3)} = 83$ bp, $\sigma_{(3)} = 7.8$) to the low RRI regime ($\mu_{(1)} = 16$ bp, $\sigma_{(1)} = 0.15$), reflecting the hectic evolution of market rates during this period. The high regime occurs from April 2008 to May 2009 (subprime crisis) and again from November to December 2011 (sovereign debt crisis). Then, there is one clear detection of the low RRI regime corresponding to period from September 2012 to December 2015, with an average RRI equal to 16 bp. From December 2015 onward, we observe that the RRI is mainly in the intermediate regime ($\mu_{(2)} = 33$ bp, $\sigma_{(2)} = 0.55$), which corresponds to our moderate liquidity regime.

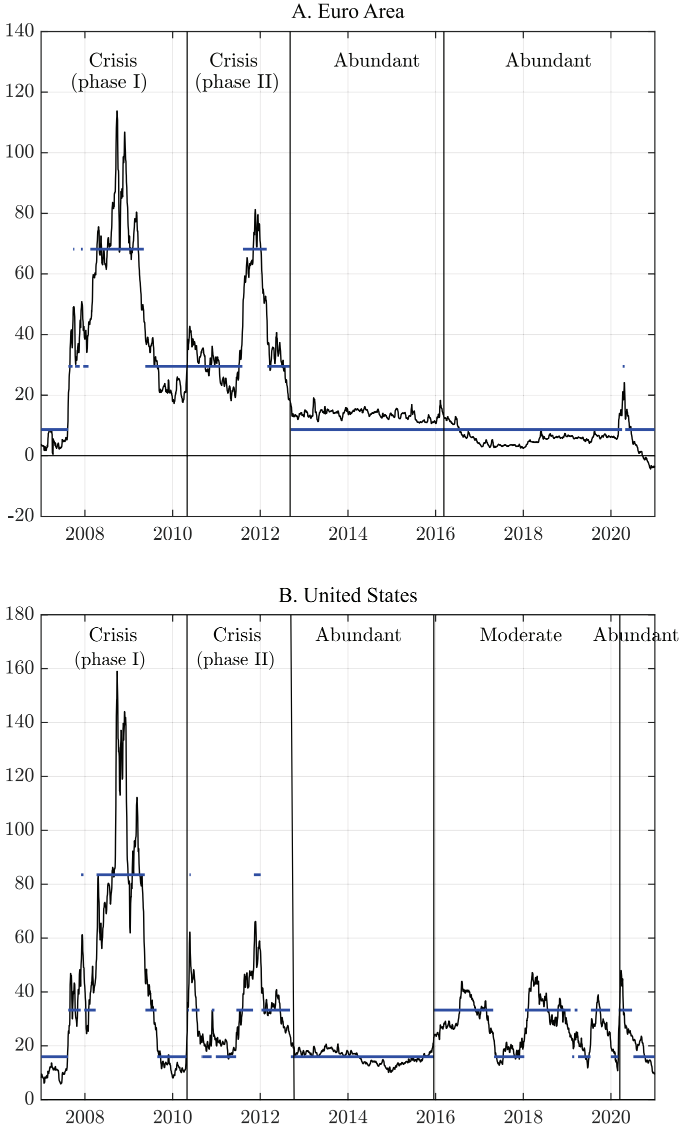
[18] A likelihood-ratio test indicates that the two-state version is rejected under the null hypothesis.

Table 5. Parameter Estimates of a Three-Regime Markov-Switching Model for the RRI

	Euro Area			United States		
	Regime 1	**Regime 2**	**Regime 3**	**Regime 1**	**Regime 2**	**Regime 3**
$\mu_{(k)}$	8.647	29.539	68.185	15.945	33.273	83.492
	(0.104)	(0.318)	(0.857)	(0.100)	(0.217)	(1.532)
$\sigma_{(k)}$	0.246	0.532	2.310	0.153	0.548	7.754
	(0.007)	(0.034)	(0.166)	(0.005)	(0.022)	(0.577)
Transition Matrix						
$P_{1;:}$	0.999	0.003	0.000	0.995	0.007	0.000
$P_{2;:}$	0.001	0.993	0.008	0.005	0.991	0.011
$P_{3;:}$	0.000	0.005	0.992	0.000	0.003	0.989
Log-Likelihood	4,846.3			4,897.6		

Note: Standard errors are in parentheses. The sample period runs from January 2007 to December 2020.

Figure 6. Liquidity Regimes



Note: Panels A and B display the narrative liquidity regimes together with statistical regimes obtained from a Markov-switching model of rollover risk indicator for the euro area and the United States, respectively. The series are smoothed using a five-day moving average. The sample periods run from January 2007 to December 2020.

In summary, these results confirm some correspondence between the narrative liquidity regimes and the statistical regimes based solely on the dynamic behavior of the RRI.

5. Conclusion

In this paper, we build a new indicator of bank rollover risk (RRI) using daily data from euro and dollar interest rates of various maturities. It captures the market expectations of future funding cost and is constructed such that the underlying tenors are consistent with the maturity of the interest rate contracts. This property is crucial because different frequencies of payments imply different underlying rollover risks. Another advantage of RRIs is that they can easily be measured at a daily frequency and therefore are well suited for real-time analyses.

We provide evidence that rollover risk is an important driver of both real activity and bank lending. It suggests that there is room for monetary authorities in a financial crisis mainly driven by liquidity drying. Providing public liquidity to financial institutions can help mitigate the lack of private liquidity and the subsequent increase in funding cost. In this perspective, the quantitative easing implemented in the United States and the euro area have helped reduce the impact of the financial crisis on the real side of the economy.

Our indicator provides central banks with an indication of the market perception of bank funding stress. In crisis times, lower levels of our indicator than the spot BOR-OIS spread point to market participants expecting that funding stress will be temporary. However, increases in the RRI are particularly useful indicators for central banks and market participants because they point to funding stress that may persist. Finally, our indicators help characterize liquidity regimes (crisis, moderate, and abundant) that reflect the levels of liquidity supplied by either the ECB or the Federal Reserve. We show in particular how liquidity regimes help explain why the COVID-19 pandemic had a much larger impact on U.S. funding conditions than on euro-area ones.

Appendix A. Methodology for Constructing Yield Curves

This appendix provides a description of the instruments used for the construction of yield curves and results on the quality of the fit. We define two types of yield curves. The discounting curve corresponds to the OIS curve with overnight rates. The forwarding curves correspond to yield curves with tenors 1 month, 3 months, 6 months, and 12 months. We denote by x the tenor of a given curve.

A.1 Notations

We define $P_x(t, T)$, $t \leq T$, the discount factor, i.e., the price of a zero-coupon bond at time t for maturity T, for underlying rate tenor x, with $P_x(t, t) = 1$ and t is the reference date. The simply compounded zero-coupon rate at date t for maturity T, denoted by $Z_x(t, T)$, is defined from

$$P_x(t, T) = \frac{1}{[1 + Z_x(t, T)]^{\tau_x(t,T)}},$$

where $\tau_x(t, T)$ is the year fraction for interval $[t, T]$ under the convention of curve x. For zero-coupon rates, the time interval is computed as $\tau_x(t, T) = (T - t)/365$.

We define the simply compounded forward rate at date t for the future time interval $[T_{k-1}, T_k]$, with tenor x, as

$$\tilde{F}_{x,k}(t) \equiv \tilde{F}_x(t, T_{k-1}, T_k) = \frac{1}{\tau_{x,k}} \left[\frac{P_x(t, T_k)}{P_x(t, T_{k-1})} - 1 \right],$$

where $\tau_{x,k}$ is the year fraction for interval $[T_{k-1}, T_k]$ under the convention of curve x. For forward rates, the time interval is computed as $\tau_{x,k} = (T_k - T_{k-1})/360$ (actual/360). For example, $\tilde{F}_{3\text{m},6\text{m}}(t)$ denotes the forward rate with tenor three months between $t + 3\text{m}$ and $t + 6\text{m}$.

In the multicurve environment, the following no arbitrage relation holds:

$$P_x(t, T_k) = P_x(t, T_{k-1}) P_x(t, T_{k-1}, T_k), \quad t \leq T_{k-1} \leq T_k,$$

where $P_x(t, T_{k-1}, T_k)$ is the forward discount factor at date t and corresponding to the future time interval $[T_{k-1}, T_k]$, with

$$P_x(t, T_{k-1}, T_k) = \frac{P_x(t, T_k)}{P_x(t, T_{k-1})} = \frac{1}{1 + \tilde{F}_{x,k}(t)\tau_{x,k}}.$$

We typically consider constant time intervals such as $T_k - T_{k-1} = \delta$. The yield curve of the δ-month forward rates is denoted by $\mathcal{C}_x^{(F)} = \left\{T \to \tilde{F}_x(t, T, T+\delta), t \geq T\right\}$.

A.2 Interbank Market Instruments

A.2.1 Overnight Index Swap (OIS)

The reference rate for overnight over-the-counter (OTC) transactions is the federal funds rate in the United States and the EONIA (euro overnight index average) rate in the euro area. An OIS is an interest rate agreement that involves the exchange of the overnight rate and a fixed interest rate. The floating rate is determined by the geometric average of the overnight index rate over the time interval of the contract period. The fixed leg is quoted in the market as a yield that is applied over the duration of the swap. The two counterparties of an OIS contract agree to exchange at maturity the difference between interest accrued at the agreed fixed rate and the floating rate on the notional amount of the contract. No principal is exchanged at the beginning of the contract. For maturities up to one year, there are no intermediate interest payments. Then the broken period is at the beginning.

The floating rate is given by the formula

$$R_d(t, T_k) = \frac{360}{N_k}\left[\prod_{i=1}^{d_k}\left(1 + \frac{r_i n_i}{360}\right) - 1\right] \times 100,$$

where r_i is the overnight rate at date i, $N_k = T_k - t$ is the total number of days, d_k is the number of working days, and n_i is the number of days with rate r_i, with $N_k = \sum_{i=1}^{d_k} n_i$.

A.2.2 Deposit

Interbank deposits are OTC zero-coupon contracts that start at reference date t and cover the period $[t, T]$ with maturities T ranging from one day to one year. The London interbank offered rate (LIBOR) is the reference rate in the United States and the euro-area interbank offered rate (EURIBOR) is the reference rate in the euro area (IBOR, in short). They correspond to the rate at which interbank deposits are offered by a prime bank to another prime bank. Fixing rates are constructed as the trimmed average of the rates submitted by a panel of banks. The IBOR reflects the average cost of funding of banks on the interbank market for a given maturity. The deposit with duration x is selected for the construction of the curve with tenor x.

We denote by $R_x^D(t, T_k)$ the quoted rate (annual, simply compounded) associated with the deposit of maturity T_k, with tenor $x = T_k - t$ months. The implied discount factor at time t for time T_k is given by

$$P_x(t, T_k) = \frac{1}{1 + R_x^D(t, T_k)\tau_{x,x}}, \quad t \leq T_k.$$

A.2.3 Forward Rate Agreement (FRA)

FRA contracts are forward starting deposits. They are defined for forward start dates calculated with the same convention used for the deposits. Therefore, FRAs concatenate exactly with deposits. Market FRAs on x-tenor IBOR contracts can be selected for the construction of the short-term of the yield curve with tenor x.

We denote by $\tilde{F}_{x,k}(t)$ the forward rate reset at time T_{k-1}, with tenor $x = T_k - T_{k-1}$ months. Then the implied discount factor at time T_k is given by

$$P_x(t, T_k) = \frac{P_x(t, T_{k-1})}{1 + \tilde{F}_{x,k}(t)\tau_{x,k}}, \quad t \leq T_{k-1} \leq T_k.$$

A.2.4 Swap

Interest rate swaps are OTC contracts by which two counterparties exchange fixed against floating rate cash flows. On the U.S. market, the floating leg is usually indexed to the three-month LIBOR rate paid with three-month frequency. On the euro market, the floating leg is indexed to the six-month EURIBOR rate paid with six-month frequency. The day count convention (τ_S) is 30/360 (bond basis). Swaps on x-tenor IBOR contracts are selected for the construction of the medium and long term of the yield curve with tenor x.

A swap is defined by two date vectors $T = \{t, T_1, \cdots, T_n\}$ and $S = \{t, S_1, \cdots, S_m\}$ with $t < T_1 < S_1 < \cdots < T_n = S_m$ and $n < m$. The fixed leg pays a fixed rate at times S_j. The floating leg pays the IBOR with tenor $x = T_k - T_{k-1}$ fixed at time T_{k-1}. We denote by $S_x(t, T, S)$ the swap rate with floating leg payment dates T and fixed leg payment dates S, with tenor $x = T_k - T_{k-1}$ months. The price of a swap with payment times T and S is given by the no-arbitrage relation:

$$S_x(t, T, S) \sum_{j=1}^{n} P_d(t, S_j)\tau_j = \sum_{k=1}^{m} P_d(t, T_k)\tilde{F}_{x,k}(t)\tau_{x,k}.$$

Once the curve points at $\{t, T_1, \cdots, T_{k-1}\}$ and $\{t, S_1, \cdots, S_{j-1}\}$ are known, it is possible to bootstrap the yield curve at point $T_i = S_j$. In practice, the fixed leg frequency is annual, whereas the floating leg frequency is given by the IBOR tenor. Some points of the curve are unknown and have to be interpolated.

A.2.5 Basis Swap

Basis swaps are floating versus floating swaps, admitting underlying rates with different tenors. On the U.S. market, the typical basis swaps are 1-month versus 3-month, 3-month versus 6-month, and 3-month versus 12-month. On the euro market, the typical basis swaps are 1-month versus 3-month, 3-month versus 6-month, and 6-month versus 12-month. The quotation convention is to provide the difference (in basis points) between the fixed rate of the higher frequency swap and the fixed rate of the lower frequency swap. Basis swaps are used for the construction of the yield curve with non-quoted swaps (for instance, the six-month curve in the United States and the three-month curve in the euro area).

We define by $BS_{x,y}(t, T_x, T_y)$ the quoted basis spread for a basis swap receiving the long y-month rate and paying the short x-month rate plus the basis spread for maturity T_{m_x}. The price of a basis swap is given by the no-arbitrage relation:

$$\sum_{k=1}^{m_y} P_d(t, T_{y,k}) \tilde{F}_{y,k}(t) \tau_{y,k} = \sum_{j=1}^{m_x} P_d(t, T_{x,j}) (\tilde{F}_{x,j}(t) + BS_{x,y}(t, T_x, T_y)) \tau_{x,j}.$$

A.3 Construction of the Yield Curves

Two main approaches are usually adopted for fitting yield curves and extracting implicit forward rates. Central banks often construct smoothed Treasury yield curves following Nelson and Siegel (1987) or Söderlind and Svensson (1997) methodology. This parametric approach allows us to obtain a smoothed curve when the observed yields are relatively noisy, which is often the case of Treasury curves. In the case of FRA-swap rates, which usually display much smoother patterns, it is more common to use more direct bootstrapping techniques. In the baseline bootstrapping technique, one imposes the interpolated curve to pass through the observed sport rates. The resulting spot curve is rather smooth, but the forward curve often exhibits spikes. This is the reason why the objective function also imposes a smoothing of the forward rates. See Flavell (2010) at textbook level.

We briefly explain below how we construct the yield curve of a given tenor and compute tenor spreads. We consider a curve with a tenor x corresponding to overnight (the discounting curve), 1 month, 3 months, 6 months, and 12 months (the forwarding curves). All the curves are constructed using instruments with the tenor of the curve. The forwarding curves also depend on the OIS curve used for discounting future cash flows. Several techniques can be used for interpolating a yield curve. Usual techniques are the linear or cubic interpolations. These techniques can be applied to the discount factor, the log of the discount factor, or the zero-coupon rate. A feature of the multicurve environment is the scarcity of the data for a given curve (except for the discounting curve). This implies that a large amount of maturities must be interpolated. The selection of the interpolation technique is therefore critical.

Ideally, all the available discount factors should be exactly given by the interpolation, yielding an arbitrage-free curve. However, it would lead to a very erratic yield curve. To cope with this problem, we allow for some arbitrage opportunity to obtain a smooth curve. We minimize a weighted sum of the squared changes in the forward rates under the arbitrage-free restrictions and the squared difference between the market and theoretical prices. The criterion is based on the three-month forward rate. This maturity appears as a reasonable trade-off between the number of parameters to estimate and the ability to generate all the curves with similar data. For a given curve $\mathcal{C}_x^{(F)}$, we solve (imposing $T_k - T_{k-1} = 3\text{m}$ and $T_0 = t$):

$$\min_{\left\{\tilde{F}_x(t,T_{k-1},T_k)\right\}_{k=1}^{N}} w \sum_{k=1}^{N-1} \left(\tilde{F}_x(t,T_k,T_{k+1}) - \tilde{F}_x(t,T_{k-1},T_k)\right)^2 + (1-w)\sum_{j=1}^{n}\left(P_x^{mkt}(t,T_j) - P_x^{theo}(t,T_j)\right)^2,$$

where w is weight of the smoothness relative to the fit of the market prices (we use $w = 0.25$); $N = 120$ is the number of three-month forward rate over the 30 years used for the curve; n is the number of instruments used to construct curve with tenor x; $P_x^{mkt}(t,T_j)$ is the discount factor implied by the market quote, based on the pricing formula presented in Section A.2; $P_x^{theo}(t,T_j)$ is the discount factor implied by the estimated three-month forward rates:

$$P_x^{theo}(t,T_j) = \frac{P_x^{theo}(t,T_{j-1})}{1 + \tilde{F}_x(t,T_{j-1},T_j)\tau_{x,j}}, \qquad j = 1,\cdots,n,$$

with $P_x^{theo}(t,t) = 1$.

A.4 Evolution of the Rollover Risk Indicators

For the United States, the OIS, one-month, three-month, and six-month tenor curves are available on January 2005 up to 5 years, on July 2008 up to 10 years, and on September 2011 up to 30 years. For the euro area, the OIS, three-month, and six-month tenor curves are available on January 2005 up to 3 years, on April 2005 up to 7 years, on July 2005 up to 10 years, and on May 2008 up to

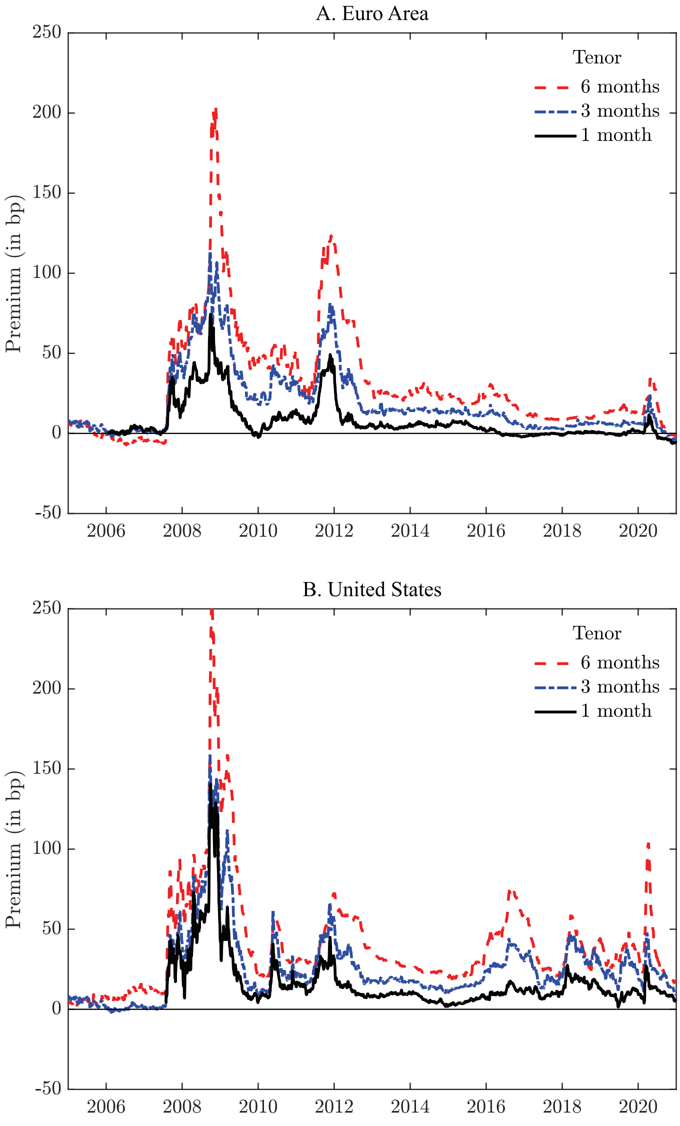
30 years. The one-month tenor curve is available on January 2006 up to 2 years, on May 2007 up to 3 years, and on June 2008 up to 30 years. Figure A.1 displays the time series of the forward funding spreads for the euro area and the United States for tenors of one, three, and six months. Before the start of the financial crisis in 2007, the difference between instruments with the same maturity but a different tenor was considered negligible. RRIs exploded in August 2007 and remain extremely high. They almost always increase with the tenor, although not linearly so. This result is illustrated by two episodes of particular interest in the euro area: during the 2007–09 crisis, RRIs were particularly high for the tenors of three and six months, with a spike above 100 bp for these spreads in January 2009. In contrast, during the sovereign debt crisis, RRIs increased in a more regular way. They increased up to 50, 75, and 120 bp for the one-, three-, and six-month tenors, respectively, in November 2011. In the United States, the financial crisis also generated substantial differences between tenors. The RRIs with a one-month tenor increased to 140 bp in January 2009, while RRIs with three- and six-month tenors jumped to 160 and 250 bp. Since the recent surge in spreads following the change in Federal Reserve interest rate policy (December 2015), we do not observe such large differences between tenors.

A.5 Goodness of Fit

Figure A.2 displays the evolution of the two components of the optimization criterion. In panel A, we report the relative error (in basis points) in the construction of the three-month and six-month curves for the euro area and the United States, which corresponds to the second term in the optimization criterion. Panel B corresponds to the volatility of the three-month forward rate (in basis points), which corresponds to the first term of the criterion. For both zones, the fit of the curve is very good (panel A).

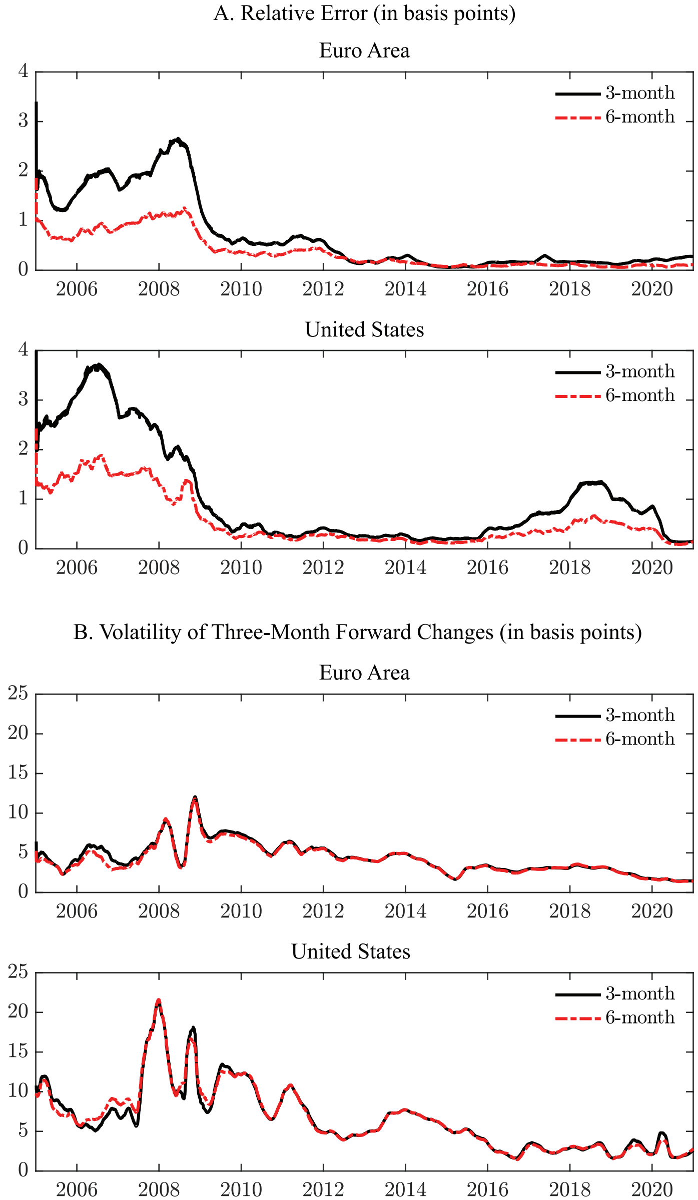
For the euro area, the relative error is below 3 bp for the three-month curve and 1 bp for the six-month curve. After 2009, the relative error is much lower than 1 bp for both curves, with sample averages equal to 0.7 and 0.4 bp, respectively. In the United States, the relative error is always below 4 bp for the three-month curve and 2 bp for the six-month curve. After 2009, the relative error is

Figure A.1. Rollover Risk Indicators for the Euro Area and the United States



Note: Panel A displays the three-month rollover risk indicator for tenors one month, three months, and six months for the euro area. Panel B displays the three-month rollover risk indicator for tenors one month, three months, and six months for the United States. The series are smoothed using a five-day moving average. The sample periods run from January 2005 to December 2020.

Figure A.2. Relative Error in the Fit of Euro-Area and U.S. Curves



Note: Panel A displays the relative error (in basis points) in the construction of the three-month and six-month curves for the euro area and the United States. Panel B displays the volatility of the three-month forward rate (in basis points) for the construction of the three-month and six-month curves for the euro area and the United States. The series are smoothed using a five-day moving average. The sample periods run from January 2005 to December 2020.

usually below 1 bp for both curves, with sample averages equal to 1 and 0.5 bp, respectively.

On average, the relative error is equal to 0.71 bp and 1.05 bp for the three-month curve and 0.39 bp and 0.57 bp for the six-month curve in the euro area and the United States, respectively. In panel B, we also report the volatility of the three-month forward rate, which reflects the extend of the smoothing of the curves. As we note, in the euro area, the volatility rarely exceeds 10 bp. The volatility is higher in the United States (up to 20 bp in 2008 and usually below 10 bp after 2009). These results suggest that the fit of the three-month forward curve is well adjusted over our sample in both zones.

Appendix B. Predictive Content: Full Set of Results

This appendix reports the full set of results relative to the ability of our RRI to predict the evolution of indicators of real activity and bank lending.

Table B.1. Predicting Euro-Area Real Activity Variables

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$			CDS Spread	GM Spread
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**		
A. Real GDP Growth								
Variables in $t-1$								
r	0.139	0.141	0.129	0.136	0.155	0.111	–0.032	–0.083
(t-stat)	(3.510)	(3.953)	(3.067)	(3.248)	(3.984)	(3.184)	(0.805)	(1.231)
term	0.130	0.196	0.268	0.178	0.269	0.358	0.182	0.257
(t-stat)	(2.703)	(3.151)	(2.817)	(3.326)	(3.300)	(3.095)	(1.612)	(1.761)
Lag	0.183	0.188	0.063	0.034	0.177	0.188	0.583	0.372
(t-stat)	(1.007)	(1.184)	(0.353)	(0.153)	(1.072)	(1.223)	(3.411)	(2.281)
Variable	–3.806	–2.222	–1.676	–5.175	–2.860	–2.413	–0.173	–0.499
(t-stat)	(3.008)	(3.759)	(3.405)	(3.371)	(3.641)	(3.276)	(2.253)	(2.327)
Adj. R^2	0.596	0.615	0.683	0.663	0.619	0.632	0.385	0.462
Variables in $t-2$								
r	0.330	0.343	0.280	0.296	0.372	0.272	–0.021	–0.110
(t-stat)	(3.959)	(4.555)	(3.551)	(3.573)	(4.655)	(3.653)	(0.250)	(1.094)
term	0.320	0.471	0.563	0.401	0.636	0.815	0.525	0.613
(t-stat)	(2.576)	(3.793)	(2.812)	(3.093)	(4.053)	(3.543)	(1.517)	(1.714)
Lag	0.033	0.004	–0.003	–0.046	0.020	0.063	0.484	0.249
(t-stat)	(0.183)	(0.024)	(0.022)	(0.273)	(0.126)	(0.467)	(2.390)	(1.351)
Variable	–8.421	–5.109	–3.042	–9.949	–6.353	–5.067	–0.414	–1.007
(t-stat)	(4.027)	(5.061)	(6.188)	(5.745)	(5.261)	(4.614)	(2.029)	(2.865)
Adj. R^2	0.674	0.726	0.623	0.679	0.712	0.676	0.303	0.378

(continued)

Table B.1. (Continued)

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			**12-Month RRI** $\left(RRI^{(xm)}_{12m,12m}\right)$				
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**	**CDS Spread**	**GM Spread**
Variables in $t-4$								
r	0.505	0.502	0.379	0.413	0.560	0.379	–0.233	–0.384
(t-stat)	(3.571)	(3.676)	(2.654)	(2.384)	(3.990)	(2.599)	(0.953)	(2.224)
term	0.504	0.708	0.827	0.597	1.011	1.320	1.006	1.021
(t-stat)	(1.944)	(2.782)	(1.990)	(2.010)	(3.346)	(3.168)	(1.217)	(1.360)
Lag	–0.116	–0.185	–0.224	–0.180	–0.174	–0.162	0.185	–0.073
(t-stat)	(0.966)	(1.514)	(2.158)	(1.505)	(1.430)	(1.529)	(0.886)	(0.494)
Variable	–14.994	–9.084	–5.341	–16.539	–11.330	–9.125	–1.016	–2.088
(t-stat)	(5.721)	(7.863)	(5.526)	(5.471)	(7.664)	(6.676)	(2.069)	(4.259)
Adj. R^2	0.658	0.703	0.555	0.605	0.683	0.619	0.150	0.268
B. Real Consumption Growth								
Variables in $t-1$								
r	0.081	0.087	0.068	0.069	0.094	0.066	–0.038	–0.043
(t-stat)	(3.437)	(3.851)	(2.785)	(2.642)	(4.156)	(2.916)	(1.310)	(1.566)
term	–0.031	0.005	0.031	–0.009	0.045	0.090	0.028	0.048
(t-stat)	(1.009)	(0.195)	(0.774)	(0.274)	(1.668)	(2.325)	(0.458)	(0.740)
Lag	0.013	–0.032	0.035	0.035	–0.028	0.006	0.390	0.222
(t-stat)	(0.053)	(0.147)	(0.169)	(0.146)	(0.127)	(0.030)	(1.602)	(0.880)
Variable	–2.017	–1.270	–0.723	–2.139	–1.599	–1.287	–0.125	–0.265
(t-stat)	(3.632)	(5.269)	(4.988)	(3.975)	(5.265)	(5.246)	(2.030)	(2.720)
Adj. R^2	0.489	0.538	0.491	0.464	0.534	0.520	0.313	0.364

(*continued*)

Table B.1. (Continued)

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$			CDS Spread	GM Spread
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**		
Variables in $t-2$								
r	0.126	0.138	0.101	0.102	0.147	0.107	–0.033	–0.012
(t-stat)	(2.866)	(2.843)	(2.143)	(1.993)	(3.090)	(2.308)	(0.580)	(0.189)
term	0.038	0.082	0.124	0.078	0.142	0.208	0.156	0.145
(t-stat)	(0.567)	(1.545)	(1.426)	(0.993)	(2.606)	(2.900)	(1.295)	(1.176)
Lag	0.358	0.288	0.423	0.434	0.299	0.341	0.695	0.624
(t-stat)	(2.256)	(2.230)	(3.558)	(3.155)	(2.485)	(3.280)	(4.159)	(3.313)
Variable	–2.874	–1.873	–0.883	–2.633	–2.319	–1.808	–0.171	–0.239
(t-stat)	(4.181)	(6.972)	(3.386)	(3.418)	(6.743)	(6.389)	(1.769)	(1.768)
Adj. R^2	0.680	0.714	0.634	0.630	0.705	0.684	0.572	0.556
Variables in $t-4$								
r	0.226	0.241	0.188	0.188	0.266	0.182	–0.112	–0.101
(t-stat)	(1.654)	(1.632)	(1.330)	(1.206)	(1.817)	(1.347)	(0.656)	(0.636)
term	–0.009	0.073	0.186	0.097	0.215	0.365	0.340	0.288
(t-stat)	(0.037)	(0.370)	(0.703)	(0.377)	(1.169)	(1.822)	(0.887)	(0.741)
Lag	0.103	0.028	0.125	0.177	0.043	0.062	0.497	0.322
(t-stat)	(0.530)	(0.146)	(0.662)	(0.887)	(0.229)	(0.331)	(1.798)	(1.074)
Variable	–6.633	–4.165	–2.167	–6.294	–5.186	–4.174	–0.414	–0.708
(t-stat)	(5.082)	(5.794)	(3.564)	(3.406)	(5.357)	(5.427)	(1.556)	(2.147)
Adj. R^2	0.545	0.586	0.464	0.458	0.576	0.542	0.313	0.311

(*continued*)

Table B.1. (Continued)

Tenor *x*	**3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$**			**12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$**			**CDS Spread**	**GM Spread**
	1m	**3m**	**6m**	**1m**	**3m**	**6m**		
C. Real Investment Growth								
Variables in $t-1$								
r	0.040	0.052	–0.018	–0.002	0.099	–0.065	–0.707	–0.878
(t-stat)	(0.176)	(0.253)	(0.095)	(0.008)	(0.494)	(0.330)	(1.970)	(2.315)
term	–0.346	–0.111	0.109	–0.179	0.150	0.460	–0.199	0.204
(t-stat)	(1.871)	(0.636)	(0.677)	(1.053)	(0.858)	(2.513)	(0.560)	(0.565)
Lag	–0.556	–0.571	–0.606	–0.601	–0.585	–0.583	–0.385	–0.506
(t-stat)	(3.802)	(3.917)	(4.272)	(4.313)	(4.016)	(3.861)	(1.631)	(2.847)
Variable	–13.452	–8.017	–5.422	–16.211	–10.297	–8.662	–0.850	–2.241
(t-stat)	(4.480)	(6.147)	(6.961)	(6.737)	(6.377)	(5.972)	(2.667)	(3.113)
Adj. R^2	0.419	0.442	0.486	0.467	0.447	0.448	0.128	0.301
Variables in $t-2$								
r	0.249	0.261	0.133	0.159	0.328	0.104	–0.601	–0.825
(t-stat)	(0.969)	(1.130)	(0.630)	(0.585)	(1.436)	(0.572)	(2.300)	(3.301)
term	0.059	0.364	0.622	0.240	0.745	1.201	0.665	0.885
(t-stat)	(0.189)	(1.467)	(1.670)	(0.799)	(2.653)	(3.208)	(0.846)	(1.173)
Lag	–0.010	–0.068	–0.082	–0.060	–0.062	–0.051	0.325	0.138
(t-stat)	(0.067)	(0.537)	(0.673)	(0.451)	(0.515)	(0.495)	(1.466)	(0.857)
Variable	–19.083	–11.877	–7.430	–22.151	–14.830	–12.354	–1.203	–2.721
(t-stat)	(4.777)	(7.231)	(8.585)	(7.214)	(7.833)	(7.378)	(2.728)	(4.194)
Adj. R^2	0.533	0.592	0.561	0.547	0.575	0.569	0.190	0.315

(*continued*)

Table B.1. (Continued)

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$			CDS Spread	GM Spread
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**		
Variables in $t-4$								
r	0.222	0.172	–0.085	–0.009	0.295	–0.128	–1.585	–1.779
(t-stat)	(0.455)	(0.398)	(0.204)	(0.016)	(0.705)	(0.418)	(2.854)	(4.226)
term	0.144	0.489	0.855	0.316	1.167	1.967	1.784	1.673
(t-stat)	(0.186)	(0.784)	(0.836)	(0.379)	(1.730)	(2.251)	(0.858)	(0.888)
Lag	–0.069	–0.180	–0.194	–0.140	–0.191	–0.177	0.279	0.040
(t-stat)	(0.503)	(1.398)	(1.517)	(1.068)	(1.532)	(1.720)	(1.055)	(0.201)
Variable	–34.784	–21.674	–12.763	–38.535	–27.418	–22.346	–2.797	–5.046
(t-stat)	(6.135)	(8.900)	(6.549)	(6.376)	(9.086)	(8.293)	(2.658)	(5.113)
Adj. R^2	0.631	0.701	0.577	0.589	0.691	0.647	0.214	0.321
D. Unemployment Rate Change								
Variables in $t-1$								
r	–0.015	–0.014	–0.007	–0.010	–0.018	–0.006	0.007	0.027
(t-stat)	(1.465)	(1.531)	(0.769)	(0.761)	(1.971)	(0.757)	(0.762)	(1.420)
term	0.003	–0.010	–0.020	–0.003	–0.029	–0.052	–0.039	–0.041
(t-stat)	(0.194)	(0.786)	(1.523)	(0.178)	(2.252)	(3.143)	(1.220)	(1.143)
Lag	0.534	0.501	0.413	0.466	0.497	0.508	0.869	0.718
(t-stat)	(4.850)	(4.896)	(3.928)	(3.356)	(4.643)	(5.066)	(8.093)	(8.204)
Variable	0.962	0.583	0.435	1.225	0.748	0.621	0.029	0.101
(t-stat)	(3.673)	(4.382)	(4.738)	(4.389)	(4.277)	(3.641)	(1.824)	(1.850)
Adj. R^2	0.799	0.805	0.837	0.824	0.808	0.808	0.698	0.720

(continued)

Table B.1. (Continued)

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$			CDS Spread	GM Spread
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**		
Variables in $t-2$								
r	–0.055	–0.051	–0.033	–0.043	–0.061	–0.031	0.014	0.055
(t-stat)	(2.326)	(2.198)	(1.426)	(1.457)	(2.776)	(1.612)	(0.356)	(1.661)
term	–0.033	–0.058	–0.093	–0.058	–0.113	–0.174	–0.169	–0.157
(t-stat)	(0.710)	(1.257)	(1.329)	(1.124)	(2.481)	(2.947)	(1.348)	(1.225)
Lag	0.426	0.349	0.355	0.405	0.361	0.393	0.856	0.656
(t-stat)	(3.644)	(2.730)	(2.876)	(3.179)	(2.872)	(3.097)	(4.028)	(3.489)
Variable	2.627	1.612	0.979	2.977	2.021	1.610	0.111	0.278
(t-stat)	(6.548)	(7.145)	(10.465)	(8.947)	(7.246)	(5.687)	(1.822)	(2.716)
Adj. R^2	0.831	0.841	0.805	0.832	0.838	0.810	0.589	0.628
Variables in $t-4$								
r	–0.095	–0.071	–0.033	–0.061	–0.092	–0.017	0.166	0.222
(t-stat)	(1.435)	(1.028)	(0.413)	(0.726)	(1.400)	(0.260)	(1.208)	(2.359)
term	–0.095	–0.115	–0.195	–0.145	–0.232	–0.359	–0.396	–0.337
(t-stat)	(0.548)	(0.680)	(0.729)	(0.698)	(1.390)	(1.705)	(0.900)	(0.781)
Lag	0.268	0.136	0.165	0.244	0.129	0.145	0.629	0.394
(t-stat)	(1.708)	(0.788)	(0.711)	(1.295)	(0.737)	(0.711)	(1.648)	(1.169)
Variable	6.168	3.724	2.109	6.622	4.694	3.726	0.390	0.753
(t-stat)	(10.153)	(13.662)	(8.564)	(7.612)	(11.652)	(9.580)	(2.138)	(4.422)
Adj. R^2	0.785	0.800	0.665	0.730	0.789	0.716	0.317	0.400

Note: This table reports predictive regressions for euro-area real activity variables. Predictive horizons are one, two, and four quarters. Presented are the parameter estimates, Newey-West adjusted t-statistics in parentheses, and adjusted R^2 values. The sample period runs from January 2005 to December 2019.

Table B.2. Predicting Euro-Area Bank Lending Variables

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$			CDS Spread	GM Spread
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**		
A. Bank Lending Growth								
Variables in $t-1$								
r	0.159	0.158	0.153	0.156	0.164	0.148	0.026	0.041
(t-stat)	(3.406)	(3.527)	(3.314)	(3.520)	(3.605)	(3.209)	(0.346)	(0.681)
term	0.048	0.078	0.086	0.060	0.110	0.137	0.067	0.106
(t-stat)	(1.069)	(1.548)	(1.640)	(1.266)	(2.109)	(2.478)	(1.208)	(2.087)
Lag	0.842	0.844	0.821	0.826	0.843	0.825	0.745	0.748
(t-stat)	(17.177)	(17.170)	(15.928)	(16.189)	(17.286)	(16.410)	(14.465)	(14.309)
Variable	–1.781	–1.012	–0.626	–2.006	–1.287	–1.068	–0.239	–0.389
(t-stat)	(6.058)	(5.812)	(4.826)	(7.394)	(5.833)	(4.629)	(3.594)	(3.271)
Adj. R^2	0.836	0.835	0.834	0.837	0.835	0.835	0.827	0.839
Variables in $t-2$								
r	0.455	0.456	0.437	0.445	0.478	0.424	0.035	0.096
(t-stat)	(3.984)	(4.366)	(3.865)	(4.190)	(4.559)	(4.003)	(0.174)	(0.616)
term	0.244	0.342	0.335	0.280	0.457	0.522	0.223	0.356
(t-stat)	(1.874)	(2.200)	(1.843)	(1.927)	(2.792)	(2.880)	(1.410)	(1.997)
Lag	0.834	0.831	0.773	0.802	0.829	0.785	0.627	0.653
(t-stat)	(12.438)	(12.001)	(10.349)	(11.515)	(12.348)	(11.341)	(9.008)	(9.136)
Variable	–6.348	–3.566	–2.045	–6.929	–4.515	–3.604	–0.755	–1.170
(t-stat)	(5.864)	(6.459)	(4.936)	(7.469)	(6.951)	(5.193)	(3.741)	(3.113)
Adj. R^2	0.845	0.839	0.822	0.843	0.839	0.831	0.802	0.825

(*continued*)

Table B.2. (Continued)

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$			CDS Spread	GM Spread
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**		
Variables in $t-4$								
r	1.198	1.227	1.220	1.184	1.306	1.169	0.039	0.254
(t-stat)	(4.296)	(5.119)	(4.652)	(4.273)	(5.623)	(5.495)	(0.095)	(0.770)
term	0.703	1.051	0.998	0.811	1.429	1.611	0.553	0.977
(t-stat)	(2.193)	(2.818)	(2.169)	(2.334)	(3.653)	(3.727)	(1.600)	(2.044)
Lag	0.780	0.778	0.662	0.723	0.777	0.688	0.396	0.476
(t-stat)	(7.902)	(8.394)	(6.455)	(7.843)	(9.223)	(8.552)	(3.015)	(4.300)
Variable	–19.168	–11.199	–6.268	–20.592	–14.279	–11.320	–2.244	–3.282
(t-stat)	(5.662)	(7.938)	(6.030)	(8.018)	(9.247)	(7.318)	(4.319)	(3.412)
Adj. R^2	0.833	0.844	0.803	0.828	0.848	0.836	0.761	0.791
B. Consumer Loan Growth								
Variables in $t-1$								
r	0.043	0.049	0.027	0.031	0.052	0.031	–0.137	–0.102
(t-stat)	(0.832)	(0.942)	(0.500)	(0.581)	(1.001)	(0.630)	(2.387)	(2.351)
term	–0.224	–0.194	–0.197	–0.212	–0.168	–0.145	–0.185	–0.170
(t-stat)	(2.326)	(1.896)	(1.788)	(2.069)	(1.575)	(1.287)	(1.784)	(1.666)
Lag	0.588	0.584	0.589	0.595	0.583	0.569	0.503	0.504
(t-stat)	(6.305)	(6.369)	(6.586)	(6.431)	(6.419)	(6.315)	(5.173)	(6.063)
Variable	–1.497	–0.971	–0.433	–1.400	–1.187	–0.978	–0.288	–0.397
(t-stat)	(3.023)	(3.825)	(2.086)	(2.649)	(3.693)	(3.187)	(2.456)	(3.053)
Adj. R^2	0.657	0.664	0.647	0.649	0.662	0.660	0.669	0.669

(*continued*)

Table B.2. (Continued)

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			**12-Month RRI** $\left(RRI^{(xm)}_{12m,12m}\right)$			**CDS Spread**	**GM Spread**
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**		
Variables in $t-2$								
r	0.144	0.157	0.109	0.112	0.170	0.107	–0.359	–0.287
(t-stat)	(1.040)	(1.113)	(0.768)	(0.771)	(1.210)	(0.801)	(2.846)	(2.653)
term	–0.539	–0.436	–0.413	–0.490	–0.348	–0.275	–0.475	–0.414
(t-stat)	(2.288)	(1.749)	(1.573)	(1.920)	(1.362)	(1.050)	(1.712)	(1.518)
Lag	0.477	0.480	0.471	0.484	0.479	0.451	0.365	0.341
(t-stat)	(3.333)	(3.426)	(3.327)	(3.335)	(3.410)	(3.146)	(2.941)	(2.535)
Variable	–5.009	–3.055	–1.692	–5.015	–3.759	–3.154	–0.746	–1.143
(t-stat)	(4.387)	(5.610)	(4.158)	(4.666)	(5.847)	(5.095)	(2.953)	(3.539)
Adj. R^2	0.682	0.693	0.670	0.666	0.688	0.685	0.673	0.687
Variables in $t-4$								
r	0.546	0.572	0.458	0.468	0.623	0.443	–0.617	–0.491
(t-stat)	(1.671)	(1.688)	(1.318)	(1.299)	(1.861)	(1.380)	(1.916)	(1.746)
term	–0.877	–0.589	–0.514	–0.718	–0.311	–0.149	–0.867	–0.640
(t-stat)	(1.493)	(1.006)	(0.772)	(1.108)	(0.530)	(0.241)	(1.193)	(0.850)
Lag	0.423	0.431	0.416	0.433	0.433	0.391	0.298	0.257
(t-stat)	(2.264)	(2.378)	(2.220)	(2.211)	(2.398)	(2.093)	(1.637)	(1.544)
Variable	–14.219	–8.388	–4.669	–14.517	–10.541	–8.533	–1.547	–2.634
(t-stat)	(7.496)	(9.119)	(6.394)	(7.516)	(9.884)	(8.187)	(2.884)	(4.667)
Adj. R^2	0.778	0.789	0.738	0.745	0.786	0.767	0.667	0.719

(*continued*)

Table B.2. (Continued)

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$			CDS Spread	GM Spread
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**		
C. Real Estate Loan Growth								
Variables in $t-1$								
r	0.069	0.069	0.060	0.066	0.072	0.061	–0.015	–0.002
(t-stat)	(1.767)	(1.670)	(1.480)	(1.686)	(1.670)	(1.490)	(0.451)	(0.052)
term	0.027	0.044	0.052	0.038	0.063	0.084	0.057	0.062
(t-stat)	(0.526)	(0.752)	(0.742)	(0.682)	(0.960)	(1.046)	(0.771)	(0.715)
Lag	0.796	0.796	0.795	0.791	0.797	0.788	0.803	0.788
(t-stat)	(9.753)	(10.273)	(9.737)	(8.965)	(10.717)	(10.714)	(11.033)	(10.521)
Variable	–1.071	–0.608	–0.348	–1.215	–0.764	–0.646	–0.114	–0.168
(t-stat)	(2.368)	(2.532)	(2.115)	(2.804)	(2.448)	(2.045)	(1.762)	(1.312)
Adj. R^2	0.778	0.777	0.773	0.778	0.777	0.776	0.769	0.769
Variables in $t-2$								
r	0.236	0.233	0.199	0.218	0.248	0.208	–0.038	0.008
(t-stat)	(2.106)	(1.937)	(1.657)	(1.877)	(1.985)	(1.740)	(0.469)	(0.091)
term	0.158	0.211	0.225	0.189	0.279	0.334	0.237	0.261
(t-stat)	(0.968)	(1.144)	(1.007)	(1.058)	(1.397)	(1.400)	(1.019)	(0.997)
Lag	0.710	0.705	0.706	0.703	0.703	0.689	0.706	0.688
(t-stat)	(6.005)	(6.023)	(5.612)	(5.427)	(6.184)	(6.017)	(5.909)	(6.021)
Variable	–3.644	–2.009	–1.053	–3.847	–2.586	–2.079	–0.366	–0.535
(t-stat)	(4.057)	(3.668)	(2.608)	(4.200)	(3.498)	(2.630)	(2.121)	(1.990)
Adj. R^2	0.732	0.726	0.706	0.724	0.727	0.719	0.696	0.696

(*continued*)

Table B.2. (Continued)

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$			CDS Spread	GM Spread
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**		
Variables in $t-4$								
r	0.562	0.566	0.486	0.508	0.604	0.504	–0.277	–0.062
(t-stat)	(1.961)	(1.846)	(1.596)	(1.636)	(1.951)	(1.710)	(1.203)	(0.248)
term	0.606	0.734	0.758	0.659	0.910	1.047	0.798	0.883
(t-stat)	(1.534)	(1.671)	(1.413)	(1.485)	(1.969)	(1.964)	(1.356)	(1.416)
Lag	0.629	0.611	0.598	0.612	0.607	0.578	0.541	0.548
(t-stat)	(4.843)	(4.668)	(4.106)	(4.223)	(4.727)	(4.415)	(4.217)	(4.190)
Variable	–9.978	–5.476	–2.854	–9.857	–6.946	–5.613	–1.255	–1.638
(t-stat)	(5.519)	(5.070)	(3.622)	(4.493)	(4.564)	(3.816)	(2.856)	(3.400)
Adj. R^2	0.713	0.697	0.648	0.677	0.696	0.679	0.651	0.641
D. C&I Loan Growth								
Variables in $t-1$								
r	0.105	0.108	0.111	0.106	0.117	0.102	–0.041	–0.048
(t-stat)	(1.960)	(2.129)	(2.421)	(2.116)	(2.310)	(1.932)	(0.409)	(0.627)
term	0.019	0.033	0.067	0.035	0.073	0.108	–0.009	0.086
(t-stat)	(0.209)	(0.335)	(0.831)	(0.396)	(0.715)	(1.122)	(0.087)	(1.404)
Lag	0.923	0.901	0.884	0.903	0.899	0.875	0.778	0.806
(t-stat)	(17.473)	(18.770)	(23.450)	(18.517)	(19.061)	(21.638)	(12.246)	(15.966)
Variable	–2.438	–1.282	–0.925	–2.815	–1.629	–1.407	–0.302	–0.562
(t-stat)	(5.170)	(4.276)	(6.391)	(6.520)	(4.385)	(5.256)	(4.437)	(4.833)
Adj. R^2	0.882	0.878	0.888	0.887	0.878	0.881	0.876	0.898

Table B.2. (Continued)

	3-Month RRI $\left(RRI_{3m,3m}^{(xm)}\right)$			12-Month RRI $\left(RRI_{12m,12m}^{(xm)}\right)$			CDS Spread	GM Spread
Tenor *x*	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**		
Variables in $t-2$								
r	0.260	0.282	0.287	0.266	0.318	0.267	–0.147	–0.195
(t-stat)	(1.695)	(2.091)	(2.534)	(1.908)	(2.371)	(1.922)	(0.520)	(0.877)
term	0.146	0.244	0.307	0.189	0.404	0.483	–0.115	0.256
(t-stat)	(0.633)	(0.964)	(1.465)	(0.820)	(1.615)	(2.029)	(0.364)	(1.726)
Lag	0.956	0.926	0.875	0.911	0.921	0.859	0.643	0.724
(t-stat)	(12.902)	(14.723)	(15.770)	(12.762)	(15.736)	(15.246)	(5.467)	(9.429)
Variable	–9.010	–5.019	–3.271	–10.042	–6.374	–5.187	–0.909	–1.712
(t-stat)	(6.533)	(7.506)	(9.637)	(9.162)	(8.339)	(8.836)	(4.155)	(4.306)
Adj. R^2	0.889	0.886	0.903	0.898	0.888	0.890	0.846	0.901
Variables in $t-4$								
r	0.683	0.723	0.762	0.706	0.849	0.707	–0.351	–0.528
(t-stat)	(1.452)	(1.929)	(2.794)	(1.697)	(2.345)	(2.102)	(0.537)	(1.026)
term	0.244	0.824	0.982	0.434	1.376	1.677	–0.480	0.640
(t-stat)	(0.350)	(1.311)	(1.626)	(0.648)	(2.076)	(2.578)	(0.620)	(1.234)
Lag	0.883	0.896	0.802	0.823	0.890	0.787	0.354	0.539
(t-stat)	(7.294)	(9.844)	(8.895)	(7.972)	(9.720)	(8.853)	(1.791)	(4.610)
Variable	–27.828	–16.771	–10.284	–30.724	–21.346	–17.192	–2.757	–4.833
(t-stat)	(5.920)	(10.505)	(10.413)	(10.118)	(11.908)	(12.015)	(4.369)	(4.466)
Adj. R^2	0.830	0.860	0.875	0.850	0.866	0.876	0.755	0.840

Note: This table reports predictive regressions for euro-area bank lending variables. Predictive horizons are one, two, and four quarters. Presented are the parameter estimates, Newey-West adjusted *t*-statistics in parentheses, and adjusted R^2 values. The sample period runs from January 2005 to December 2019.

Table B.3. Predicting U.S. Real Activity Variables

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$					
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**	**CDS Spread**	**GZ Spread**	**Goldberg Var.**
A. Real GDP Growth									
Variables in $t-1$									
r	–0.004	–0.103	–0.125	–0.014	–0.115	–0.168	–0.076	–0.005	–0.062
(t-stat)	(0.075)	(1.933)	(2.225)	(0.273)	(2.075)	(2.326)	(1.534)	(0.107)	(1.560)
term	0.022	–0.050	–0.042	0.010	–0.055	–0.062	0.053	0.093	–0.075
(t-stat)	(0.396)	(0.856)	(0.626)	(0.156)	(0.835)	(0.831)	(0.740)	(1.430)	(1.724)
Lag	–0.148	–0.120	–0.147	–0.121	–0.079	–0.039	0.181	0.046	0.302
(t-stat)	(1.200)	(0.952)	(1.431)	(0.883)	(0.646)	(0.341)	(1.166)	(0.294)	(2.296)
Variable	–2.665	–1.964	–1.258	–3.000	–2.186	–1.610	–0.473	–0.207	–0.033
(t-stat)	(4.377)	(3.568)	(4.627)	(3.564)	(3.390)	(3.285)	(2.196)	(2.361)	(4.747)
Variable									0.035
(t-stat)									(2.258)
Adj. R^2	0.428	0.398	0.343	0.402	0.358	0.308	0.210	0.206	0.179
Variables in $t-2$									
r	–0.054	–0.245	–0.294	–0.066	–0.274	–0.390	–0.196	–0.050	–0.141
(t-stat)	(0.628)	(2.159)	(2.629)	(0.722)	(2.218)	(2.301)	(1.878)	(0.550)	(1.472)
term	0.011	–0.128	–0.119	–0.004	–0.137	–0.162	0.100	0.168	–0.124
(t-stat)	(0.122)	(1.170)	(0.995)	(0.037)	(1.076)	(1.068)	(0.919)	(1.451)	(1.230)
Lag	–0.205	–0.289	–0.334	–0.237	–0.241	–0.207	–0.107	–0.117	0.306
(t-stat)	(1.660)	(1.330)	(1.971)	(1.361)	(1.130)	(1.072)	(1.000)	(0.723)	(3.645)
Variable	–4.907	–4.023	–2.597	–5.942	–4.531	–3.355	–0.969	–0.427	–0.071
(t-stat)	(4.770)	(3.451)	(4.388)	(3.785)	(3.117)	(2.914)	(2.257)	(2.167)	(3.562)
Variable									0.024
(t-stat)									(0.912)
Adj. R^2	0.519	0.502	0.412	0.523	0.461	0.377	0.276	0.208	0.214

(*continued*)

Table B.3. (Continued)

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$			CDS Spread	GZ Spread	Goldberg Var.
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**			
Variables in $t-4$									
r	–0.343	–0.622	–0.737	–0.357	–0.677	–0.905	–0.602	–0.265	–0.431
(t-stat)	(1.457)	(2.262)	(2.819)	(1.558)	(2.375)	(2.497)	(2.234)	(1.146)	(1.738)
term	–0.121	–0.352	–0.395	–0.154	–0.366	–0.454	0.161	0.252	–0.218
(t-stat)	(0.643)	(1.500)	(1.733)	(0.766)	(1.432)	(1.472)	(0.859)	(1.917)	(1.054)
Lag	–0.241	–0.356	–0.515	–0.327	–0.375	–0.426	–0.240	–0.630	0.162
(t-stat)	(2.800)	(2.400)	(3.436)	(2.920)	(2.309)	(2.196)	(1.387)	(3.142)	(1.208)
Variable	–6.706	–5.760	–4.269	–8.819	–7.083	–5.694	–2.329	–1.099	–0.113
(t-stat)	(4.329)	(4.209)	(4.043)	(4.587)	(3.976)	(3.605)	(2.580)	(4.239)	(3.442)
Variable									0.013
(t-stat)									(0.309)
Adj. R^2	0.426	0.443	0.440	0.481	0.453	0.387	0.428	0.319	0.162
B. Real Consumption Growth									
Variables in $t-1$									
r	–0.032	–0.095	–0.104	–0.038	–0.107	–0.143	–0.088	–0.025	–0.055
(t-stat)	(0.839)	(2.149)	(3.254)	(1.008)	(2.403)	(3.051)	(2.930)	(0.628)	(1.633)
term	–0.019	–0.065	–0.054	–0.027	–0.069	–0.071	0.033	0.039	–0.046
(t-stat)	(0.500)	(1.582)	(1.608)	(0.694)	(1.614)	(1.645)	(0.643)	(0.875)	(1.421)
Lag	0.079	0.040	0.074	–0.012	0.038	0.079	0.138	0.237	0.476
(t-stat)	(0.687)	(0.291)	(0.545)	(0.094)	(0.276)	(0.594)	(1.154)	(1.631)	(3.394)
Variable	–1.533	–1.272	–0.767	–2.108	–1.533	–1.152	–0.475	–0.129	–0.009
(t-stat)	(4.237)	(4.502)	(4.309)	(4.965)	(4.534)	(4.672)	(3.119)	(3.257)	(1.102)
Variable									0.023
(t-stat)									(1.534)
Adj. R^2	0.410	0.429	0.393	0.457	0.429	0.404	0.384	0.311	0.250

(*continued*)

Table B.3. (Continued)

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$			CDS Spread	GZ Spread	Goldberg Var.
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**			
Variables in $t-2$									
r	–0.101	–0.182	–0.205	–0.110	–0.206	–0.252	–0.186	–0.099	–0.118
(t-stat)	(1.267)	(2.031)	(2.793)	(1.386)	(2.267)	(2.780)	(2.698)	(1.222)	(1.544)
term	–0.016	–0.076	–0.074	–0.035	–0.091	–0.092	0.068	0.029	–0.024
(t-stat)	(0.202)	(0.898)	(0.940)	(0.439)	(1.048)	(1.087)	(0.768)	(0.279)	(0.286)
Lag	0.347	0.305	0.280	0.228	0.268	0.318	0.324	0.607	0.665
(t-stat)	(3.524)	(2.621)	(2.142)	(2.214)	(2.363)	(2.807)	(3.177)	(3.064)	(5.466)
Variable	–2.010	–1.665	–1.102	–2.995	–2.153	–1.531	–0.750	–0.068	–0.021
(t-stat)	(3.791)	(4.010)	(3.062)	(4.573)	(4.071)	(3.941)	(3.576)	(0.605)	(1.901)
Variable									0.026
(t-stat)									(1.730)
Adj. R^2	0.557	0.557	0.542	0.591	0.566	0.540	0.575	0.473	0.487
Variables in $t-4$									
r	–0.332	–0.519	–0.603	–0.355	–0.579	–0.733	–0.594	–0.311	–0.329
(t-stat)	(1.588)	(2.259)	(2.774)	(1.759)	(2.547)	(2.966)	(3.089)	(1.437)	(1.640)
term	0.006	–0.163	–0.205	–0.060	–0.209	–0.261	0.144	0.180	0.057
(t-stat)	(0.029)	(0.786)	(1.071)	(0.334)	(1.061)	(1.363)	(0.912)	(0.831)	(0.246)
Lag	0.207	0.105	–0.006	0.070	0.035	0.015	–0.062	0.297	0.564
(t-stat)	(1.597)	(0.693)	(0.046)	(0.581)	(0.240)	(0.093)	(0.510)	(1.417)	(3.710)
Variable	–4.109	–3.661	–2.732	–6.077	–4.928	–3.917	–2.138	–0.337	–0.072
(t-stat)	(3.715)	(4.325)	(3.414)	(4.281)	(4.300)	(4.340)	(4.265)	(1.913)	(2.790)
Variable									0.002
(t-stat)									(0.058)
Adj. R^2	0.503	0.517	0.523	0.557	0.547	0.511	0.613	0.394	0.402

(*continued*)

Table B.3. (Continued)

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$			CDS Spread	GZ Spread	Goldberg Var.
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**			
C. Real Investment Growth									
Variables in $t-1$									
r	–0.033	–0.326	–0.423	–0.066	–0.352	–0.500	–0.150	–0.021	–0.106
(t-stat)	(0.346)	(2.247)	(2.364)	(0.627)	(2.246)	(2.262)	(1.679)	(0.280)	(1.374)
term	0.346	0.127	0.149	0.301	0.110	0.082	0.277	0.643	0.013
(t-stat)	(3.061)	(0.989)	(1.204)	(2.310)	(0.761)	(0.511)	(1.900)	(3.233)	(0.107)
Lag	0.317	0.294	0.223	0.327	0.332	0.350	0.618	0.279	0.643
(t-stat)	(2.495)	(1.834)	(1.368)	(2.103)	(2.121)	(2.514)	(4.918)	(1.437)	(7.225)
Variable	–7.459	–5.575	–3.832	–8.274	–6.099	–4.532	–0.774	–0.794	–0.141
(t-stat)	(4.360)	(3.009)	(3.189)	(3.025)	(2.646)	(2.474)	(1.645)	(2.440)	(3.674)
Variable									0.023
(t-stat)									(0.840)
Adj. R^2	0.715	0.670	0.639	0.680	0.639	0.604	0.510	0.566	0.585
Variables in $t-2$									
r	–0.187	–0.833	–1.069	–0.253	–0.896	–1.267	–0.476	–0.207	–0.280
(t-stat)	(0.727)	(1.852)	(2.118)	(0.888)	(1.781)	(1.740)	(1.505)	(0.959)	(1.194)
term	0.788	0.322	0.315	0.713	0.286	0.182	0.864	1.503	0.235
(t-stat)	(2.448)	(0.760)	(0.786)	(1.985)	(0.607)	(0.338)	(2.458)	(2.937)	(0.654)
Lag	0.191	0.121	0.032	0.180	0.157	0.152	0.439	0.000	0.526
(t-stat)	(1.231)	(0.525)	(0.139)	(0.909)	(0.675)	(0.630)	(2.778)	(0.000)	(5.339)
Variable	–15.654	–12.178	–8.245	–17.831	–13.406	–10.142	–2.343	–1.929	–0.300
(t-stat)	(4.275)	(2.783)	(3.032)	(2.997)	(2.400)	(2.072)	(1.591)	(1.770)	(3.298)
Variable									0.066
(t-stat)									(1.018)
Adj. R^2	0.691	0.634	0.578	0.649	0.585	0.526	0.413	0.470	0.476

(*continued*)

Table B.3. (Continued)

	3-Month RRI ($RRI^{(xm)}_{3m,3m}$)			12-Month RRI ($RRI^{(xm)}_{12m,12m}$)					
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**	**CDS Spread**	**GZ Spread**	**Goldberg Var.**
Variables in $t-4$									
r	–0.823	–1.823	–2.195	–0.948	–1.938	–2.487	–1.353	–1.027	–0.823
(t-stat)	(1.018)	(1.677)	(1.964)	(1.106)	(1.639)	(1.624)	(1.464)	(1.159)	(1.236)
term	1.778	1.006	0.926	1.645	0.988	0.778	2.392	2.597	1.163
(t-stat)	(1.902)	(0.869)	(0.813)	(1.596)	(0.793)	(0.553)	(2.900)	(3.146)	(1.428)
Lag	0.163	0.104	0.031	0.132	0.112	0.105	0.290	–0.053	0.431
(t-stat)	(1.443)	(0.667)	(0.202)	(0.914)	(0.658)	(0.548)	(1.603)	(0.245)	(3.377)
Variable	–23.489	–18.088	–12.078	–27.543	–20.566	–14.891	–5.238	–2.967	–0.563
(t-stat)	(4.939)	(3.551)	(3.757)	(3.650)	(2.917)	(2.332)	(1.700)	(3.135)	(5.220)
Variable									0.081
(t-stat)									(0.516)
Adj. R^2	0.597	0.558	0.522	0.577	0.526	0.457	0.433	0.435	0.456
D. Unemployment Rate Change									
Variables in $t-1$									
r	0.018	0.067	0.090	0.024	0.072	0.104	0.032	0.016	0.024
(t-stat)	(1.210)	(3.712)	(4.676)	(1.407)	(3.406)	(3.354)	(2.426)	(0.871)	(1.725)
term	–0.014	0.023	0.023	–0.008	0.024	0.031	–0.014	–0.091	0.014
(t-stat)	(0.925)	(1.208)	(1.382)	(0.412)	(1.071)	(1.181)	(0.612)	(2.049)	(0.630)
Lag	0.409	0.327	0.218	0.380	0.357	0.336	0.675	0.093	0.735
(t-stat)	(6.508)	(3.826)	(2.601)	(4.823)	(3.732)	(3.363)	(5.394)	(0.359)	(6.882)
Variable	1.104	0.908	0.696	1.314	1.020	0.829	0.109	0.192	1.120
(t-stat)	(7.594)	(4.172)	(5.962)	(4.486)	(3.311)	(3.109)	(1.947)	(2.637)	(0.982)
Variable									–0.288
(t-stat)									(0.460)
Adj. R^2	0.760	0.735	0.756	0.745	0.715	0.698	0.592	0.701	0.593

(continued)

Table B.3. (Continued)

Tenor x	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$ 1m	3m	6m	12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$ 1m	3m	6m	CDS Spread	GZ Spread	Goldberg Var.
Variables in $t-2$									
r	0.050	0.164	0.210	0.064	0.178	0.253	0.093	0.062	0.046
(t-stat)	(1.456)	(3.041)	(3.947)	(1.644)	(2.823)	(2.551)	(2.119)	(1.421)	(1.428)
term	–0.055	0.032	0.040	–0.038	0.038	0.061	–0.086	–0.193	–0.012
(t-stat)	(1.892)	(0.671)	(0.935)	(0.978)	(0.640)	(0.805)	(1.554)	(3.010)	(0.298)
Lag	0.323	0.217	0.116	0.277	0.237	0.208	0.560	–0.075	0.715
(t-stat)	(6.319)	(1.810)	(0.997)	(3.066)	(1.681)	(1.156)	(3.525)	(0.246)	(5.431)
Variable	2.531	2.083	1.474	3.033	2.369	1.879	0.382	0.417	4.244
(t-stat)	(7.307)	(4.187)	(5.548)	(4.539)	(3.300)	(2.727)	(1.683)	(2.790)	(2.360)
Variable									–0.624
(t-stat)									(0.616)
Adj. R^2	0.821	0.787	0.764	0.800	0.751	0.703	0.574	0.670	0.612
Variables in $t-4$									
r	0.197	0.424	0.516	0.235	0.464	0.628	0.320	0.259	0.168
(t-stat)	(1.599)	(2.575)	(3.386)	(1.778)	(2.532)	(2.535)	(1.975)	(1.764)	(1.581)
term	–0.142	0.047	0.079	–0.094	0.063	0.137	–0.267	–0.285	–0.106
(t-stat)	(1.318)	(0.291)	(0.534)	(0.691)	(0.339)	(0.591)	(2.133)	(2.779)	(1.184)
Lag	0.185	0.078	–0.021	0.113	0.062	0.007	0.290	–0.141	0.547
(t-stat)	(3.071)	(0.716)	(0.223)	(1.209)	(0.486)	(0.048)	(1.602)	(0.800)	(3.555)
Variable	4.825	3.922	2.713	5.907	4.646	3.693	1.105	0.681	9.667
(t-stat)	(6.801)	(5.188)	(6.051)	(5.313)	(4.244)	(3.661)	(1.816)	(4.356)	(3.472)
Variable									–2.339
(t-stat)									(0.818)
Adj. R^2	0.702	0.683	0.664	0.697	0.655	0.591	0.471	0.545	0.448

Note: This table reports predictive regressions for U.S. real activity variables. Predictive horizons are one, two, and four quarters. "Goldberg (2020) var." denotes the liquidity supply and demand variables, respectively. Presented are the parameter estimates, Newey-West adjusted t-statistics in parentheses, and adjusted R^2 values. The sample period runs from January 2005 to December 2019.

Table B.4. Predicting U.S. Bank Lending Variables

	3-Month RRI $\left(RRI_{3m,3m}^{(xm)}\right)$			12-Month RRI $\left(RRI_{12m,12m}^{(xm)}\right)$					
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**	**CDS Spread**	**GZ Spread**	**Goldberg Var.**
A. Bank Lending Growth									
Variables in $t-1$									
r	0.042	0.006	–0.015	0.046	–0.006	–0.061	0.010	0.072	0.004
(t-stat)	(0.446)	(0.068)	(0.147)	(0.489)	(0.067)	(0.580)	(0.102)	(0.653)	(0.039)
term	–0.296	–0.317	–0.282	–0.292	–0.317	–0.319	–0.309	–0.195	–0.348
(t-stat)	(1.710)	(2.113)	(2.029)	(1.851)	(2.320)	(2.528)	(1.616)	(1.121)	(2.053)
Lag	0.186	0.177	0.197	0.176	0.170	0.162	0.147	0.167	0.217
(t-stat)	(1.248)	(1.329)	(1.684)	(1.353)	(1.444)	(1.532)	(1.066)	(1.304)	(1.359)
Variable	–0.867	–0.885	–0.916	–1.316	–1.334	–1.348	–0.195	–0.176	–0.027
(t-stat)	(0.958)	(1.245)	(2.524)	(1.280)	(1.768)	(2.329)	(0.623)	(1.871)	(1.279)
Variable									0.039
(t-stat)									(1.250)
Adj. R^2	0.260	0.273	0.315	0.272	0.290	0.315	0.252	0.286	0.252
Variables in $t-2$									
r	0.110	0.007	–0.043	0.117	–0.028	–0.180	–0.003	0.209	0.020
(t-stat)	(0.576)	(0.035)	(0.227)	(0.626)	(0.151)	(0.926)	(0.015)	(0.883)	(0.094)
term	–0.524	–0.555	–0.453	–0.521	–0.578	–0.592	–0.403	–0.149	–0.736
(t-stat)	(1.398)	(1.753)	(1.442)	(1.536)	(1.997)	(2.257)	(1.017)	(0.353)	(1.711)
Lag	0.141	0.147	0.191	0.123	0.125	0.118	0.104	0.171	0.059
(t-stat)	(0.813)	(0.977)	(1.386)	(0.808)	(0.932)	(0.973)	(0.646)	(1.017)	(0.260)
Variable	–2.623	–2.832	–2.474	–3.735	–3.775	–3.704	–1.129	–0.532	0.025
(t-stat)	(1.781)	(2.323)	(3.646)	(2.117)	(2.867)	(3.734)	(1.866)	(3.262)	(0.641)
Variable									0.007
(t-stat)									(0.093)
Adj. R^2	0.353	0.405	0.483	0.380	0.431	0.493	0.385	0.434	0.290

(*continued*)

Table B.4. (Continued)

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$			CDS Spread	GZ Spread	Goldberg Var.
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**			
Variables in $t-4$									
r	0.330	–0.016	–0.133	0.333	–0.086	–0.446	–0.008	0.504	0.059
(t-stat)	(1.013)	(0.052)	(0.496)	(1.043)	(0.294)	(1.838)	(0.021)	(1.329)	(0.160)
term	–0.530	–0.731	–0.468	–0.590	–0.812	–0.845	–0.416	0.380	–1.157
(t-stat)	(1.033)	(1.648)	(1.145)	(1.228)	(1.901)	(2.440)	(0.589)	(0.609)	(1.606)
Lag	0.243	0.239	0.320	0.197	0.191	0.198	0.156	0.323	0.183
(t-stat)	(1.977)	(2.136)	(3.620)	(1.687)	(1.773)	(2.228)	(0.947)	(2.272)	(0.944)
Variable	–9.237	–8.063	–6.054	–11.675	–10.089	–9.055	–2.789	–1.343	–0.071
(t-stat)	(6.022)	(6.749)	(9.907)	(6.028)	(7.279)	(11.004)	(2.627)	(5.803)	(0.964)
Variable									0.039
(t-stat)									(0.446)
Adj. R^2	0.614	0.682	0.766	0.658	0.714	0.792	0.561	0.671	0.366
B. Consumer Loan Growth									
Variables in $t-1$									
r	–0.277	–0.194	–0.182	–0.224	–0.185	–0.196	–0.187	–0.115	–0.221
(t-stat)	(1.769)	(1.309)	(1.129)	(1.553)	(1.196)	(1.149)	(1.151)	(0.661)	(1.181)
term	–0.662	–0.522	–0.469	–0.567	–0.488	–0.455	–0.473	–0.323	–0.556
(t-stat)	(2.686)	(2.643)	(2.137)	(2.656)	(2.469)	(2.234)	(2.495)	(1.350)	(2.111)
Lag	0.285	0.370	0.411	0.346	0.397	0.424	0.395	0.450	0.289
(t-stat)	(2.190)	(3.384)	(3.080)	(3.051)	(3.516)	(3.480)	(3.426)	(3.293)	(1.558)
Variable	1.303	0.222	–0.148	0.738	–0.103	–0.455	–0.073	–0.135	0.048
(t-stat)	(1.096)	(0.247)	(0.303)	(0.535)	(0.107)	(0.657)	(0.214)	(1.190)	(1.122)
Variable									–0.052
(t-stat)									(1.512)
Adj. R^2	0.380	0.366	0.366	0.369	0.365	0.369	0.366	0.378	0.385

(*continued*)

Table B.4. (Continued)

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$			CDS Spread	GZ Spread	Goldberg Var.
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**			
Variables in $t-2$									
r	–0.349	–0.287	–0.211	–0.294	–0.304	–0.399	–0.387	0.120	–0.524
(t-stat)	(1.003)	(1.027)	(0.688)	(1.003)	(1.035)	(1.243)	(1.129)	(0.432)	(1.248)
term	–1.079	–0.862	–0.530	–0.978	–0.840	–0.744	–0.971	–0.007	–1.354
(t-stat)	(1.579)	(1.813)	(1.335)	(1.769)	(1.982)	(1.936)	(1.897)	(0.021)	(2.002)
Lag	0.334	0.434	0.567	0.369	0.444	0.492	0.335	0.576	0.185
(t-stat)	(1.419)	(2.538)	(4.080)	(1.912)	(3.039)	(3.882)	(1.941)	(4.809)	(0.800)
Variable	–0.740	–2.055	–2.534	–1.791	–2.898	–3.342	–0.556	–0.734	0.085
(t-stat)	(0.284)	(1.125)	(3.592)	(0.629)	(1.590)	(2.799)	(0.839)	(4.138)	(1.270)
Variable									–0.051
(t-stat)									(0.929)
Adj. R^2	0.404	0.419	0.458	0.408	0.429	0.459	0.412	0.489	0.411
Variables in $t-4$									
r	–0.781	–0.824	–0.747	–0.708	–0.888	–1.115	–1.058	0.173	–1.266
(t-stat)	(0.816)	(0.960)	(0.894)	(0.793)	(1.053)	(1.408)	(1.248)	(0.219)	(1.552)
term	–2.629	–2.385	–1.925	–2.484	–2.395	–2.168	–2.535	–0.343	–3.323
(t-stat)	(1.613)	(1.690)	(1.501)	(1.705)	(1.827)	(1.886)	(2.217)	(0.321)	(2.581)
Lag	0.210	0.299	0.403	0.237	0.294	0.366	0.161	0.489	0.047
(t-stat)	(0.802)	(1.257)	(1.806)	(0.992)	(1.318)	(1.770)	(0.821)	(2.222)	(0.210)
Variable	–4.821	–6.112	–5.323	–7.255	–7.683	–8.293	–1.847	–1.802	0.164
(t-stat)	(1.446)	(2.441)	(3.128)	(1.994)	(2.625)	(3.586)	(1.559)	(4.062)	(1.774)
Variable									0.083
(t-stat)									(0.618)
Adj. R^2	0.513	0.546	0.574	0.528	0.555	0.602	0.526	0.650	0.513

(*continued*)

Table B.4. (Continued)

Tenor x	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$ 1m	3m	6m	12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$ 1m	3m	6m	CDS Spread	GZ Spread	Goldberg Var.
C. Real Estate Loan Growth									
Variables in $t-1$									
r	0.029	0.010	–0.017	0.020	0.013	0.007			
(t-stat)	(0.138)	(0.148)	(0.040)	(0.215)	(0.074)	(0.123)	(0.148)	(0.095)	(0.051)
term	–0.489	–0.480	–0.443	–0.462	–0.463	–0.458	–0.476	–0.511	–0.475
(t-stat)	(1.704)	(1.944)	(1.923)	(1.779)	(2.106)	(2.207)	(1.764)	(1.579)	(2.247)
Lag	0.288	0.293	0.319	0.300	0.303	0.307	0.290	0.282	0.326
(t-stat)	(1.164)	(1.271)	(1.477)	(1.367)	(1.492)	(1.567)	(1.494)	(1.190)	(1.574)
Variable	0.053	–0.076	–0.387	–0.411	–0.582	–0.641	–0.033	0.025	–0.015
(t-stat)	(0.039)	(0.071)	(0.635)	(0.256)	(0.475)	(0.673)	(0.082)	(0.181)	(0.584)
Variable									0.032
(t-stat)									(1.264)
Adj. R^2	0.419	0.419	0.426	0.421	0.424	0.428	0.419	0.419	0.414
Variables in $t-2$									
r	–0.007	–0.028	–0.070	0.016	–0.050	–0.146	–0.038	0.060	–0.014
(t-stat)	(0.026)	(0.120)	(0.302)	(0.066)	(0.213)	(0.595)	(0.162)	(0.237)	(0.058)
term	–0.747	–0.702	–0.602	–0.692	–0.687	–0.668	–0.553	–0.442	–0.792
(t-stat)	(1.553)	(1.713)	(1.620)	(1.587)	(1.891)	(2.042)	(1.341)	(0.895)	(1.919)
Lag	0.409	0.426	0.464	0.417	0.426	0.438	0.404	0.470	0.368
(t-stat)	(1.860)	(2.087)	(2.415)	(2.106)	(2.334)	(2.505)	(2.249)	(2.194)	(1.647)
Variable	–0.282	–1.066	–1.397	–1.410	–1.998	–2.208	–0.822	–0.265	0.060
(t-stat)	(0.147)	(0.662)	()1.511)	(0.585)	(1.090)	(1.567)	(1.604)	(1.235)	(1.812)
Variable									–0.016
(t-stat)									(0.211)
Adj. R^2	0.529	0.536	0.558	0.534	0.547	0.563	0.552	0.544	0.531

(*continued*)

Table B.4. (Continued)

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$			CDS Spread	GZ Spread	Goldberg Var.
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**			
Variables in $t-4$									
r	–0.327	–0.520	–0.667	–0.289	–0.565	–0.891	–0.477	–0.200	–0.452
(t-stat)	(0.725)	(1.217)	(1.670)	(0.666)	(1.360)	(2.285)	(1.076)	(0.470)	(0.975)
term	–1.216	–1.240	–0.970	–1.161	–1.248	–1.179	–0.966	0.015	–1.514
(t-stat)	(1.167)	(1.337)	(1.139)	(1.226)	(1.457)	(1.578)	(1.070)	(0.019)	(1.509)
Lag	0.512	0.528	0.589	0.506	0.514	0.546	0.464	0.669	0.475
(t-stat)	(2.721)	(3.248)	(4.475)	(3.041)	(3.550)	(4.623)	(2.687)	(4.496)	(2.202)
Variable	–4.558	–4.978	–4.539	–7.143	–7.010	–7.144	–2.226	–1.186	0.065
(t-stat)	(1.973)	(2.605)	(3.552)	(2.411)	(3.124)	(4.246)	(2.414)	(4.567)	(0.834)
Variable									0.035
(t-stat)									(0.406)
Adj. R^2	0.674	0.701	0.747	0.696	0.722	0.764	0.702	0.742	0.644
D. C&I Loan Growth									
Variables in $t-1$									
r	0.331	0.172	0.118	0.308	0.139	0.009	0.181	0.395	0.215
(t-stat)	(3.107)	(1.604)	(0.952)	(2.607)	(1.166)	(0.067)	(1.312)	(3.391)	(1.997)
term	0.297	0.148	0.190	0.241	0.118	0.069	0.238	0.530	0.096
(t-stat)	(1.842)	(0.932)	(1.540)	(1.475)	(0.712)	(0.402)	(1.001)	(4.438)	(0.523)
Lag	0.861	0.824	0.814	0.831	0.806	0.774	0.816	0.744	0.929
(t-stat)	(11.03)	(12.24)	(15.06)	(11.72)	(12.28)	(12.37)	(11.51)	(15.54)	(10.05)
Variable	–3.955	–3.107	–2.570	–4.486	–3.749	–3.260	–0.769	–0.653	–0.125
(t-stat)	(3.476)	(3.569)	(5.672)	(3.088)	(3.306)	(3.629)	(1.492)	(5.957)	(2.266)
Variable									0.074
(t-stat)									(0.955)
Adj. R^2	0.768	0.772	0.814	0.765	0.773	0.782	0.722	0.814	0.749

(*continued*)

Table B.4. (Continued)

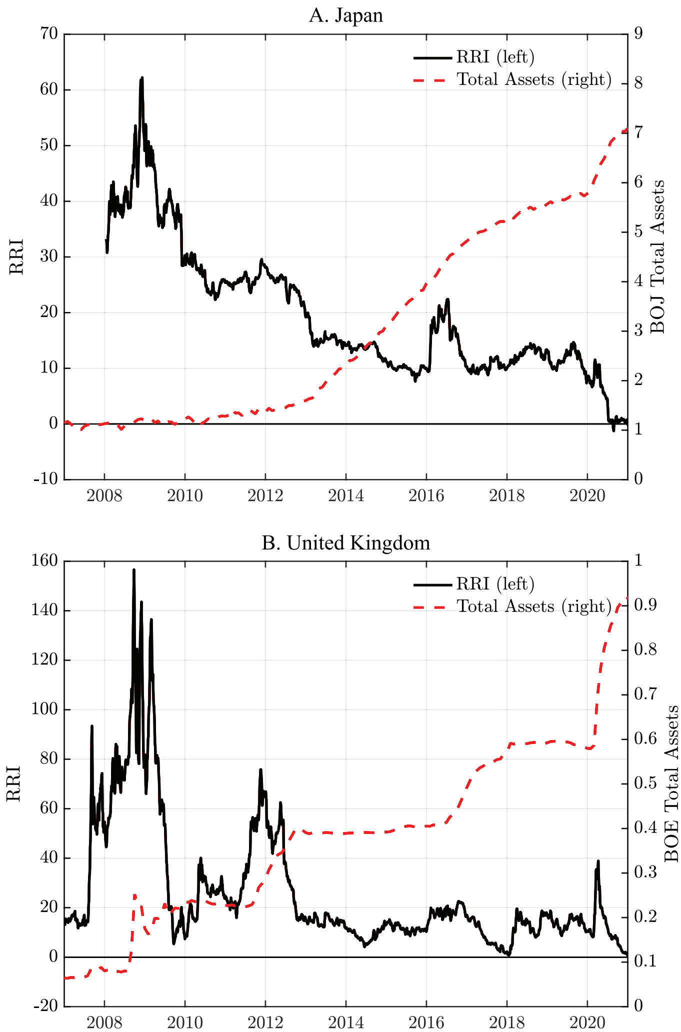
	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$					
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**	**CDS Spread**	**GZ Spread**	**Goldberg Var.**
Variables in $t-2$									
r	1.059	0.567	0.409	0.991	0.440	–0.013	0.552	1.282	0.624
(t-stat)	(3.147)	(1.779)	(1.240)	(2.697)	(1.253)	(0.036)	(1.195)	(4.343)	(1.429)
term	0.996	0.622	0.737	0.847	0.468	0.257	1.118	1.900	0.136
(t-stat)	(1.877)	(1.309)	(2.072)	(1.610)	(0.946)	(0.560)	(1.705)	(5.591)	(0.152)
Lag	0.782	0.746	0.740	0.740	0.707	0.652	0.734	0.654	0.732
(t-stat)	(6.491)	(6.798)	(8.562)	(6.617)	(6.844)	(7.260)	(8.701)	(11.049)	(5.659)
Variable	–12.384	–10.483	–7.926	–14.488	–12.263	–10.590	–3.432	–2.101	–0.143
(t-stat)	(5.344)	(4.645)	(6.827)	(4.165)	(4.014)	(4.488)	(1.863)	(8.747)	(1.457)
Variable									0.150
(t-stat)									(0.705)
Adj. R^2	0.694	0.735	0.809	0.697	0.727	0.757	0.633	0.847	0.533
Variables in $t-4$									
r	2.145	0.798	0.502	1.968	0.431	–0.812	0.690	2.830	0.560
(t-stat)	(2.337)	(0.956)	(0.643)	(2.006)	(0.465)	(0.920)	(0.473)	(4.138)	(0.366)
term	0.800	–0.141	0.374	0.471	–0.572	–1.120	0.741	3.690	–2.326
(t-stat)	(0.502)	(0.111)	(0.402)	(0.322)	(0.431)	(1.021)	(0.336)	(4.111)	(0.741)
Lag	0.387	0.357	0.386	0.335	0.293	0.234	0.290	0.337	0.191
(t-stat)	(3.853)	(3.383)	(4.133)	(3.616)	(3.007)	(2.573)	(2.319)	(4.093)	(0.972)
Variable	–34.528	–28.842	–20.605	–40.960	–33.598	–28.601	–8.539	–5.379	–0.215
(t-stat)	(10.63)	(7.673)	(10.07)	(7.078)	(6.256)	(7.221)	(1.809)	(15.43)	(0.931)
Variable									0.438
(t-stat)									(0.984)
Adj. R^2	0.589	0.668	0.750	0.613	0.657	0.718	0.408	0.812	0.230

Note: This table reports predictive regressions for U.S. bank lending variables. Predictive horizons are one, two, and four quarters. "Goldberg (2020) var." denotes the liquidity supply and demand variables, respectively. Presented are the parameter estimates, Newey-West adjusted t-statistics in parentheses, and adjusted R^2 values. The sample period runs from January 2005 to December 2019.

Appendix C. Data for Japan and the United Kingdom

This appendix displays the RRI and the total assets of the central bank for Japan and the United Kingdom.

Figure C.1. Rollover Risk Indicator and Central Banks Total Assets in Japan and the United Kingdom



Note: Panel A displays the three-month rollover risk indicator (in bp) and the Bank of Japan total assets (in JPY trillion). Panel B displays the three-month rollover risk indicator (in bp) and the Bank of England total assets (in GBP trillion). The spread series are smoothed using a five-day moving average. The sample periods are January 2007 to December 2020.

References

Acharya, V. V., D. Gale, and T. Yorulmazer. 2011. "Rollover Risk and Market Freezes." *Journal of Finance* 66 (4): 1177–1209.

Ametrano, F. M., and M. Bianchetti. 2009. "Bootstrapping the Illiquidity: Multiple Yield Curves Construction for Market Coherent Forward Rates Estimation." In *Modelling Interest Rates*, ed. F. Mercurio. Risk Books.

Bagehot, W. 1873. *Lombard Street: A Description of the Money Market*. London: H.S. King.

Bank for International Settlements. 2019. "International Banking and Financial Market Developments." *BIS Quarterly Review* (December).

Bechtel, A., A. Ranaldo, and J. Wrampelmeyer. 2023. "Liquidity Risk and Funding Cost." *Review of Finance* 27 (2): 399–422.

Benzoni, L., O. Chyruk, and D. Kelley. 2018. "Why Does the Yield-Curve Slope Predict Recessions?" Working Paper No. 2018-15, Federal Reserve Bank of Chicago.

Berger, A. N., L. K. Black, C. H. S. Bouwman, and J. Dlugosz. 2014. "The Federal Reserve's Discount Window and TAF Programs: 'Pushing on a String?'." Working Paper No. 14-06, University of Pennsylvania.

Bernanke, B. 2018. "The Real Effects of the Financial Crisis." *Brookings Papers on Economic Activity* 2018 (2, Fall): 251–342.

Bianchetti, M. 2009. "Two Curves, One Price: Pricing and Hedging Interest Rate Derivatives Decoupling Forwarding and Discounting Yield Curves." Working Paper. Available at https://arxiv.org/abs/0905.2770.

Brunnermeier, M. K. 2009. "Deciphering the Liquidity and Credit Crunch 2007-2008." *Journal of Economic Perspectives* 23 (1): 77–100.

Brunnermeier, M. K., and Y. Sannikov. 2014. "A Macroeconomic Model of the Financial Sector." *American Economic Review* 104 (2): 379–421.

Calomiris, C. W., M. Flandreau, and L. Laeven. 2016. "Political Foundations of the Lender of Last Resort: A Global Historical Narrative." *Journal of Financial Intermediation* 28 (October): 48–65.

Carpinelli, L., and M. Crosignani. 2017. “The Effect of Central Bank Liquidity Injections on Bank Credit Supply.” Working Paper No. 2017-038, Board of Governors of the Federal Reserve System.

Chodorow-Reich, G., O. Darmouni, S. Luck, and M. C. Plosser. 2022. “Bank Liquidity Provision across the Firm Size Distribution.” *Journal of Financial Economics* 144 (3): 908–32.

Cochrane, J., and M. Piazzesi. 2005. “Bond Risk Premia.” *American Economic Review* 95 (1): 138–60.

Copeland, A., D. Duffie, and Y. Yang. 2021. “Reserves Were Not So Ample after All.” Working Paper No. 29090, National Bureau of Economic Research.

Copeland, A., A. Martin, and M. Walker. 2014. “Repo Runs: Evidence from the Tri-party Repo Market.” *Journal of Finance* 69 (6): 2343–80.

Covitz, D., N. Liang, and G. A. Suarez. 2013. “The Evolution of a Financial Crisis: Collapse of the Asset-backed Commercial Paper Market.” *Journal of Finance* 68 (3): 815–48.

Diamond, D. W., and Z. He. 2014. “A Theory of Debt Maturity: The Long and Short of Debt Overhang.” *Journal of Finance* 69 (2): 719–62.

Diamond, D. W., and R. G. Rajan. 2001. “Liquidity Risk, Liquidity Creation, and Financial Fragility: A Theory of Banking.” *Journal of Political Economy* 109 (2): 287–327.

Engstrom, E., and S. Sharpe. 2019. “The Near-Term Forward Yield Spread as a Leading Indicator: A Less Distorted Mirror.” *Financial Analysts Journal* 75 (4): 37–49.

Falato, A., I. Goldstein, and A. Hortaçsu. 2021. “Financial Fragility in the COVID-19 Crisis: The Case of Investment Funds in Corporate Bond Markets.” *Journal of Monetary Economics* 123 (October): 35–52.

Fama, E. F., and R. Bliss. 1987. “The Information in Long-Maturity Forward Rates.” *American Economic Review* 77 (4): 680–92.

Filipović, D., and A. B. Trolle. 2013. “The Term Structure of Interbank Risk.” *Journal of Financial Economics* 109 (3): 707–33.

Flavell, R. 2010. *Swaps and Other Derivatives.* Wiley Finance.

Freixas, X., A. Martin, and D. Skeie. 2011. “Bank Liquidity, Interbank Markets, and Monetary Policy.” *Review of Financial Studies* 24 (8): 2656–92.

Gallitschke, J., S. Seifried, and F. T. Seifried. 2017. "Interbank Interest Rates: Funding Liquidity Risk and XIBOR Basis Spreads." *Journal of Banking and Finance* 78 (May): 142–52.

Gilchrist, S., and B. Mojon. 2018. "Credit Risk in the Euro Area." *Economic Journal* 128 (608): 118–58.

Gilchrist, S., B. Wei, V. Z. Yue, and E. Zakrajšek. 2020. "The Fed Takes on Corporate Credit Risk: An Analysis of the Efficacy of the SMCCF." Working Paper No. 27809, National Bureau of Economic Research.

Gilchrist, S., and E. Zakrajšek. 2012a. "Credit Spreads and Business Cycle Fluctuations." *American Economic Review* 102 (4): 1692–1720.

———. 2012b. "Credit Supply Shocks and Economic Activity in a Financial Accelerator Model." In *Rethinking the Financial Crisis,* ed. A. S. Blinder, A. W. Lo, and R. M. Solow, 37–72 (chapter 3). Russel Sage Foundation.

Goldberg, J. 2020. "Liquidity Supply by Broker-Dealers and Real Activity." *Journal of Financial Economics* 136 (3): 806–27.

Gorton, G., and A. Metrick. 2012. "Securitized Banking and the Run on Repo." *Journal of Financial Economics* 104 (3): 425–51.

Haddad, V., A. Moreira, and T. Muir. 2021. "When Selling Becomes Viral: Disruptions in Debt Markets in the COVID-19 Crisis and the Fed's Response." *Review of Financial Studies* 34 (11): 5309–51.

Hansen, S., M. McMahon, and M. Tong. 2019. "The Long-Run Information Effect of Central Bank Communication." *Journal of Monetary Economics* 108 (December): 185–202.

Hartmann, P., and F. Smets. 2018. "The European Central Bank's Monetary Policy during Its First 20 Years." *Brookings Papers on Economic Activity* 49 (Fall): 1–146.

He, Z., and W. Xiong. 2012. "Rollover Risk and Credit Risk." *Journal of Finance* 67 (2): 391–430.

Henrard, M. 2007. "The Irony in the Derivatives Discounting." *Wilmott Magazine* 30 (July): 92–98.

———. 2010. "The Irony in the Derivatives Discounting — Part II: The Crisis." *Wilmott Journal* 2: 301–16.

Holmström, B., and J. Tirole. 1998. "Private and Public Supply of Liquidity." *Journal of Political Economy* 106 (1): 1–40.

Hull, J., and A. White. 2013. "LIBOR vs. OIS: The Derivatives Discounting Dilemma." *Journal of Investment Management* 11 (3): 14–27.

Istrefi, K., and S. Mouabbi. 2018. "Subjective Interest Rate Uncertainty and the Macroeconomy: A Cross-country Analysis." *Journal of International Money and Finance* 88 (November): 296–313.

Jasova, M., C. Mendicino, and D. Supera. 2021. "Policy Uncertainty, Lender of Last Resort and the Real Economy." *Journal of Monetary Economics* 118 (March): 381–98.

Kacperczyk, M., and P. Schnabl. 2010. "When Safe Proved Risky: Commercial Paper during the Financial Crisis of 2007-2009." *Journal of Economic Perspectives* 24 (1): 29–50.

Mayordomo, S., J. Ignacio Peña, and E. S. Schwartz. 2014. "Are All Credit Default Swap Databases Equal?" *European Financial Management* 20 (4): 677–713.

Mercurio, F. 2009. "Interest Rates and the Credit Crunch: New Formulas and Market Models." Working Paper. Available at http://ssrn.com/abstract=1332205.

———. 2010. "A LIBOR Market Model with Stochastic Basis." Working Paper. Available at http://ssrn.com/abstract=1583081.

Morris, S., and H. S. Shin. 2016. "Illiquidity Component of Credit Risk." *International Economic Review* 57 (4): 1135–48.

Nakamura, E., and J. Steinsson. 2018. "High Frequency Identification of Monetary Non-neutrality: The Information Effect." *Quarterly Journal of Economics* 133 (3): 1283–1330.

Nelson, C. R., and A. F. Siegel. 1987. "Parsimonious Modeling of Yield Curves." *Journal of Business* 60 (4): 473–89.

Nyborg, K. 2017. *Collateral Frameworks: The Open Secret of Central Banks*. Cambridge: Cambridge University Press.

Pelizzon, L., M. G. Subrahmanyam, D. Tomio, and J. Uno. 2016. "Sovereign Credit Risk, Liquidity, and European Central Bank Intervention: Deus Ex Machina?" *Journal of Financial Economics* 122 (1): 86–115.

Rochet, J. C., and X. Vives. 2004. "Coordination Failures and the Lender of Last Resort: Was Bagehot Right after All?" *Journal of the European Economic Association* 2 (6): 1116–1147.

Segura, A., and J. Suarez. 2017. "How Excessive is Banks Maturity Transformation?" *Review of Financial Studies* 30 (10): 3538–80.

Söderlind, P., and L. E. Svensson. 1997. "New Techniques to Extract Market Expectations from Financial Instruments." *Journal of Monetary Economics* 40 (2): 383–429.

Stambaugh, R. F. 1988. "The Information in Forward Rates: Implications for Models of the Term Structure." *Journal of Financial Economics* 21 (1): 41–70.

Stein, J. C. 2012. "Monetary Policy as Financial Stability Regulation." *Quarterly Journal of Economics* 127 (1): 57–95.

Thornton, H. 1802. *An Enquiry into the Nature and Effects of the Paper Credit of Great Britain.* London: J. Hatchard.