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Bank Funding Cost and Liquidity Supply Regimes*

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Abstract

Designing operations for liquidity support requires central banks to properly measure and monitor bank funding risk in real time. We construct a new indicator of rollover risk for banks, called the *forward funding spread*. By accounting for market participants' expectations of how funding costs will evolve over time, it serves as a better signal of the change in the stance of monetary policy than the usual spot InterBank Offered Rate–Overnight Interest Swap spread. Our indicator helps to contrast three liquidity regimes, which coincide with the levels of excess liquidity supplied by central banks.

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1 Introduction

Once again, as Covid-19 hits the global economy, liquidity threatens to dry up in money markets, credit markets, and stock markets. The illusory belief that money markets can always provide reliable funding for financial institutions lay at the heart of the banking system's fragility during the 2007–09 financial crisis. As funding liquidity evaporated, many solvent and well-capitalized financial institutions had to sell illiquid assets to meet their financial obligations, resulting in fire-sale externalities. These losses severely affected the ability of financial institutions and nonfinancial corporations to operate and created fears about their solvency.

In such circumstances, the public sector, typically central banks, should intervene to curb market failures, avoid the collapse of asset prices or the disruption of credit flows that result from liquidity crises (Brunnermeier, 2009; Aikman, Bridges, Kashyap, and Siegart, 2018; Bernanke, 2018).[1] Following the Thornton (1802)-Bagehot (1873) principle, central banks should lend early and freely to illiquid but solvent financial institutions. By lending freely, central banks may be able to reduce the huge panic-driven demands for liquidity. By lending only to solvent firms and against good collateral, and by charging a penalty rate, central banks can limit the moral hazard associated with public intervention in private financial markets. By providing a huge amount of liquidity to institutions, they can avoid disruptions to payments and credit intermediation that result from liquidity risk, allowing continuity in the supply of bank credit (Calomiris, Flandreau, and Laeven, 2016). Consequently, central banks are expected to supply public liquidity when private liquidity vanishes (Holmström and Tirole, 1998; Rochet and Vives, 2004; Brunnermeier and Sannikov, 2014; Freixas, Martin, and Skeie, 2011).[2]

[1] Bernanke (2018) shows that the depth of the 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] Rochet and Vives (2004) provide a rationale for Thorton-Bagehot's doctrine by showing that the coor-

Designing operations for liquidity support requires central banks to properly measure and monitor bank funding risk in real time. A commonly used indicator for the funding conditions of large banks is the IBOR-OIS spread, defined as the difference between an InterBank Offered Rate (IBOR), which reflects the cost for a bank of issuing an unsecured interbank loan, and the Overnight Interest Swap (OIS) rate with the same maturity. While the IBOR-OIS spread encompasses both a funding liquidity risk and a credit (or default) risk, several authors provided evidence that funding liquidity risk is the predominant component of the spread during systemic crises, for short and medium horizons (Bianchetti and Carlicchi, 2012; Filipović and Trolle, 2013; Gallitschke, Seifried, and Seifried, 2017; Bernanke, 2018). As a difference in spot rates, the IBOR-OIS spread measures the perception of *current* funding costs. In other words, it is a *spot funding spread* (SFS) that reflects the immediate risk for the lender of a market freeze or of a borrower default. However, the significant maturity mismatch between banks assets and the use of short-term debt as a major source of funding reveal a crucial *rollover risk* (Kacperczyk and Schnabl, 2010; Covitz, Liang, and Suarez, 2013, Gorton and Metrick, 2012; Copeland, Martin, and Walker, 2014).[3] Future liquidity planning for financial institutions must take into account the possibility of a sudden loss of substantial amounts of secured financing and market participants have to form expectation on how such costs will evolve over time.

In this paper, we construct a daily indicator of the *expected* cost of funding of large banks based on forward interest rates.[4] The rates at which forward contracts are negotiated (i.e.,

dination failure, faced by investors in the interbank market during a crisis, can be avoided by appropriate solvency and liquidity requirements and eliminated or alleviated by using discount-window loans.

[3]Acharya, Gale, and Yorulmazer (2011) and Morris and Shin (2016) proposed theoretical mechanisms underlying rollover risk in market-based funding by (i) highlighting the fragility of the collateral assets' debt capacity or (ii) separating the contributions of liquidity and solvency concerns.

[4]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 (2018) use the difference between the 6-quarter-ahead forward rate on U.S. Treasuries and the current 3-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 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

based on an 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. Using forward rates captures the way banks manage the impact of interest rate fluctuations on their financing structure and cover their exposures to short-term interest rate fluctuations. By reflecting changes in the expected cost of funding, our so-called *forward funding spread* (FFS) represents a natural indicator for rollover risks, which may be especially useful during periods when central banks saturate markets with liquidity and expected spreads serve as better signals of the change in the stance of monetary policy than SFS. FFS can be computed for different starting forward dates, different maturities, and different frequencies of payments (tenors). It has several desirable properties as an indicator of bank funding conditions: (i) it is available at a daily frequency for the dollar, the euro, and most of the major currencies;[5] (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 measure the market price of funding.

We illustrate the usefulness of FFS to contrast three liquidity regimes in the United States and the euro area and why the Covid-19 crisis had a much larger impact on funding costs in dollars than in euros. Since the 2007–09 financial crisis, the three liquidity regimes are the following: (i) a *crisis* regime, associated with a lack of liquidity in the financial system and a strong connection between liquidity and credit risks, (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 and credit risks, and (iii) a regime of *moderate liquidity*, characterized by uncertainty over the expected cost of liquidity but little correlation between liquidity and credit risks. In the United States, the

recession within the next year. Hansen, McMahon, and Tong (2019) and Nakamura and Steinsson (2018) also use forward rates on long-term government bonds.

[5] 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/.

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. Since December 2015, the U.S. economy has been in a moderate liquidity regime, in which liquidity risk is independent of credit risk. In the euro area, the crisis period lasted until the end of 2012 with the announcement of the Outright Monetary Transactions programme. 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 expected bank funding cost. When the Covid-19 hit, the United States and the euro area were characterized by a different liquidity regime. The United States was in a moderate liquidity regime while the euro area still stood in an abundant liquidity regime. Not surprisingly, the pandemic triggered much larger spikes in spot and forward funding spreads in dollars than in euros as would be expected given the very different prevailing liquidity conditions.

We also provide evidence that FFS helps forecast macroeconomic developments in the United States and the euro area. Based on the sample from 2005 to 2019, they have higher predictive content for economic activity than SFS and bank credit risk measures (credit default swap and bank bond spreads). This result indicates that (i) the expectations of market participants regarding the future cost of funding matters more for the business cycle than the current cost and (ii) the information content of these indicators reflects the attitude of banks towards credit supply and that this attitude depends on their expected cost of funding. This might be particularly relevant when central banks supply large amounts of liquidity, crushing SFS, and the market shifts its attention to the persistence of such policies. FFS also 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 the euro area (where banks dominate the financial system). In turn, credit supply is correlated with future economic fluctuations.

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

2 Forward Funding Spread

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

2.1 Definition of Forward Funding Spread

A common indicator of stress on interbank markets is the spot IBOR-OIS spread. It is computed as the difference between the interbank offered rate of a given tenor and the OIS rate with the same maturity, which is usually viewed as the risk-free rate for this maturity. The tenor of a financial contract refers to the frequency with which coupon payments are exchanged.[6] Typical spreads are the 1-month and 3-month IBOR-OIS spreads (see, e.g., Bernanke, 2018). In the following, we define the *spot funding spread* (SFS) as the 3-month

[6]For instance, for a 2-year swap with a 3-month tenor, bank A will pay the fixed rate every 3 months for 2 years, 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 rate 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 premia, reflecting the different views and interests of the market counterparts.

IBOR-OIS spread

$$SFS_{3m}^{(3m)} = R_{3m}^{(3m)} - R_{3m}^{(ois)}, \tag{1}$$

where $R_{3m}^{(3m)}$ denotes the 3-month spot rate with a 3-month tenor and $R_{3m}^{(ois)}$ denotes the 3-month OIS contract, which reflects market expectations of the average overnight rate over the next 3 months. Before the financial crisis, SFS 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 SFS is now considered an indicator of market stress or panic. This spread is usually interpreted as reflecting rollover risk, which combines funding liquidity risk and credit (or default) risk.

To understand why SFS reflects rollover risk, we consider the two following strategies. On the one hand, bank A borrows at the 3-month IBOR. At maturity, the bank repays the notional plus interest ($R_{3m}^{(3m)}$). On the other hand, bank B borrows cash on a daily basis at the overnight federal funds rate for 3 months and simultaneously enters into an OIS swap, receiving the floating rate (the overnight effective federal funds rate) and paying the fixed rate (the OIS rate, $R_{3m}^{(ois)}$). In both cases, the interest rate for the 3-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 3 months. Bank B, in contrast, may be unable to roll its funding if it cannot find a counterpart and therefore may become insolvent. 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 3-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, SFS essentially measures the rollover risk coming from the 3-month floating leg.

A limitation of SFS is that it measures the current funding cost but does not inform on the expected funding cost. In contrast, forward rates allow us to extract such market participants' expectations from the yield curve. We now explain how we compute FFS. Consider the 3-month FFS starting in 3 months for the 3-month tenor, defined as

$$FFS^{(3m)}_{3m,3m} = F^{(3m)}_{3m,3m} - F^{(ois)}_{3m,3m}, \tag{2}$$

where the forward rate $F^{(3m)}_{3m,3m} = 2R^{(3m)}_{6m} - R^{(3m)}_{3m}$ is computed from the 3-month tenor curve and the forward rate $F^{(ois)}_{3m,3m} = 2R^{(ois)}_{6m} - R^{(ois)}_{3m}$ is computed from the OIS curve. The 6-month rate is obtained from the 3-month tenor curve in the former case and from the OIS curve in the latter case. As rollover risk is negligible for the OIS curve, FFS measures the funding cost originating from the 3-month tenor segment.

For some starting dates, maturities, and tenors, the forward rates can be obtained directly from market data when the relevant forward rate agreements (FRA) or interest rate swaps (IRS) are quoted. However, in general, as not all starting dates, maturities, and tenors are available on interbank markets, the best approach is to construct a complete yield curve for each tenor. We briefly describe this approach in the next section.

2.2 Data and Construction of the Forward Funding Spreads

The FFS indicator measures the cost of funding of large banks. Therefore, we use interbank data through deposits, forward rate agreements, overnight index swaps, and interest rate swaps. For major currencies, these instruments correspond to very wide markets and exhibit extremely large turnover. As the BIS triennial report reveals (Bank of International Settlements, 2019), as of the first half of 2019 the notional amount outstanding represents USD 89 trillion on the FRA market and 389.3 trillion on the swap market (including OIS and IRS). Gross market values are equal to USD 232 billion and 7′793 billion, respectively.[7] Focusing on gross market values, USD and EUR instruments are by far the largest segments of the market: overall, interest rate contracts in USD and EUR represent 1′745 billion and 4′352 billion (22% and 54%, respectively, of all interest rate contracts). Daily turnover also posts impressive numbers. On a net-net basis, as of April 2019, the daily turnover on the FRA and swap segments amounts to USD 1′902 billion and 4′146 billion, respectively. USD and EUR markets correspond to 52% and 22% of total turnover.

We collected from Bloomberg quotes for all USD and EUR interest rate instruments on the interbank markets starting in January 2005 and ending September 2020. Data before 2005 is irrelevant as the spread between IBOR and OIS rate was essentially nil. These instruments include bank deposits (unsecured EONIA and federal funds) and FRA, OIS, and 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 after the 2007–09 financial crisis (see, among others, Henrard, 2007, 2010; Bianchetti, 2009; Ametrano and 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.[8] The forwarding curves, also called funding curves, correspond to different

[7] 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.

[8] 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 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 rates may be more relevant because it reflects the risk of the interbank sector as a whole (Bianchetti, 2009; Ametrano and Bianchetti, 2009). Hull and White (2013) provide theoretical arguments that, in all cases, OIS discounting should be preferred.

tenors (from 1 to 12 months). For instance, the 3-month funding curve in the United Sates is based on the 3-month IBOR, a sequence of 3-month FRA, and a sequence of IRS with a 3-month tenor.

The discounting and forwarding curves are constructed using a standard optimization procedure. The estimation of the yield curve of a given tenor produces a sequence of 3-month forward rates that minimize the difference between theoretical and market prices of the available instruments, while maintaining sufficient smoothing of the yield curve.[9]

Tenor yield curves are available at a daily frequency from January 2005 onward for the United States and the euro area. Specifically, for the United States, the OIS, 1-month, 3-month, and 6-month tenor curves are available on January 2005 up to five years, on July 2008 up to 10 years, and on September 2011 up to 30 years. For the euro area, the OIS, 3-month, and 6-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 1-month tenor curve is available on January 2006 up to two years, on May 2007 up to 3 years, and on June 2008 up to 30 years. Data are available upon request and are updated regularly.

The estimated yield curves fit the observed prices very well. Indeed, the relative error is always below 4 basis points (bp) and 3 bp for the 3-month curve and 2 bp and 1 bp for the 6-month curve in the United States and the euro area, respectively. After 2009, the relative error is usually below 1 bp for both curves and both zones.[10]

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.

[9] Additional details on the interpolation methodology of the tenor yield curves are provided in Section A of the Online Appendix.

[10] On average, the relative error is equal to 1.05 bp and 0.71 bp for the 3-month curve and 0.57 bp and 0.39 bp for the 6-month curve in the United states and the euro area, respectively. 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 2008–2009 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

In summary, FFS 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 1-, 3- and 6-month tenors. In addition, the resulting curves closely match observed prices, so that FFS is very accurate and timely.

3 Forward Funding Spread and Liquidity Regimes

The evolution of the forward funding spread 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 appears, but unrelated to credit risk. A statistical approach based on a simple Markov-Switching model of FFS confirms this narrative liquidity regimes.[11]

Figures 1 and 2 display the SFS and FFS indicators, the statistical regimes, and the size of the central bank balance sheet. The latter provides an indication of changes in the supply of central bank liquidity. To cross-check what FFS 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.

arbitrage opportunities. Details on the quality of the optimization are provided in Section A of the Online Appendix.

[11]See Section B of the Online Appendix for details on the Markov-Switching model with regime-dependent means and volatilities.

3.1 The United States

3.1.1 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 FFS and SFS to approximately 50 and 100 bp, respectively (see Panel A of Figure 4). 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, Black, Bouwman, and Dlugosz (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, FFS and SFS jumped to levels close to 150 bp and 300 bp, respectively. 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 Fed 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 Fed 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 funding: in early 2010, both funding spread indicators returned to their pre-crisis levels (approximately 10 bp). Note that over most of this period, FFS was below SFS, suggesting that market participants were anticipating an acute lack of funding liquidity but that the liquidity shortage would recede somewhat within three months.

3.1.2 Crisis regime – Phase II: between QE2 and QE3 (2010–12)

The period 2010–2012 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. SFS and FFS increased by 50 bp and 20 bp, respectively (see Panel B of Figure 4). In reaction, 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, FFS increased to 35 bp, while SFS remained essentially flat. It was only in August 2011 that SFS started to react to events. The relatively high level of FFS suggests that market participants expected the stress on money markets to resume.

3.1.3 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 Figure 1, 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. Both FFS and SFS stabilized at approximately 25 bp. A highly likely consequence of this larger scale of excess liquidity was that the funding costs of large U.S. banks (Panel C of Figure 4) 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%). Interestingly, the taper tantrum that hit global financial markets in Q2 and Q3 of 2013 had no effect on the expected cost of bank funding.

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.

3.1.4 Normalization of Federal Reserve monetary policy (2016–February 2020)

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 D of Figure 4). It also began to gradually reduce its securities holdings from January 2018. As shown in Panel B of Figure 1, the Federal Reserve's balance sheet was reduced to a level of USD 3.8 trillion in the summer of 2019. Between December 2015 and September 2017, SFS and FFS evolved closely to one another, first increasing until autumn of 2016 and then decreasing until the end of 2017. However, from January 2018, the two indicators diverged, and we observe a greater variance of SFS.

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. (Panel C of Figure 1). The Federal Reserve had to inject a massive amount of liquidity (over USD 50 billion) into the repo market the next day. FFS 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. In contrast, SFS fell below FFS before the crisis but increased on September 17 and remained at a relatively higher level afterwards. 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 (Panel B of Figure 1).

3.2 The Euro Area

3.2.1 Crisis regime – Phase I: the interbank crisis (Summer 2007–May 2010)

Similar to the United States, the funding spreads were negligible, below 5 bp, until mid-2007 (Panel A of Figure 5). In the Fall of 2007, FFS and SFS increased to approximately 50 bp and 80 bp, respectively. In September 2008, both indicators jumped again, although to a different extent. FFS did not exceed 120 bp, whereas SFS reached 180 bp.

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. FFS almost instantaneously reacted to this measure, returning to 60 bp, while SFS hardly responded.

In a second round, the ECB sought to satisfy the increased demand for liquidity by adjusting both the timing and the maturity of open market operations: 3- and 6-month full allotment 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 the funding spreads albeit to different extents: by the beginning of 2009, FFS and SFS decreased to 60 bp and 90 bp, respectively.

3.2.2 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 Programme (SMP). The SMP was effective at mitigating upward pressures on the interbank market: SFS and FFS remained relatively low, close to 20 bp, suggesting that there was no lack of liquidity in the euro market at that time (Panel B of Figure 5). 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, FFS and SFS increased in parallel, from 25 to 60 bp at the end of the month. FFS then stabilized while the spot indicator continued to rise.

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 Programme (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 increased from approximately EUR 2 trillion in mid-2011 to almost EUR 3 trillion in mid-2012. These measures likely explain the decline in banks' funding costs. SFS and FFS started to fall at the beginning of 2012 and they reached a first plateau at 30 bp in April despite still-elevated bank CDS rates.[12]

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 Programme (OMT) (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 funding costs of banks stabilized: by end-2012, SFS went below 10 bp, and FFS was close to 15 bp.

3.2.3 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 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 FFS flat at a low level (Panel C of Figure 5).

Given the lack of 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 Programme (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 Programme (CSPP) was launched, and Targeted Longer-Term Refinancing Operations (TLTRO-II) were announced with a maturity of four years.

[12] A substantial literature has evaluated these measures, in most cases finding that the programs worked as intended. For instance, Pelizzon, Subrahmanyam, Tomio, and Uno (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.

This new package of measures allowed funding spreads to decrease considerably (Panel D of Figure 5). FFS declined from an already low 15 bp to 5 bp. SFS even went negative in March 2017. We note that a persistent positive gap was created between SFS and FFS. One reason is that FFS never went negative during the sample period, as it represented a pure funding risk premium.

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

3.3 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 funding cost spreads in very different proportions on the two sides of the Atlantic. And this is what happened (see Panels D in Figures 4 and 5).

In the euro area, the spike in FFS has been moderate, reaching approximately 24 bp as of end of April, before falling back to 10 bp at the end of May 2020. In the United States, SFS and FFS jumped to 140 and 50 bp, respectively. In addition, the rise in FFS 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 Federal Reserve responded swiftly. 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).[13] Beyond the size of these operations, the Federal Reserve has made liquidity available through differentiated instruments to target various forms of funding stress.[14]

These multiple measures provided the U.S. money market with abundant liquidity conditions, and SFS and FFS fell sharply to both reach 25 bp at the end of May 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 Predictive Content of Forward Funding Spreads

We investigate whether macroeconomic and banking variables are mainly driven by liquidity or credit risks by comparing the predictive ability of FFS with that of widely used indicators of bank liquidity and credit risks.

[13]Interestingly, the ECB also 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 Programme (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 the continuation of this regime. From June 4, the envelope for the pandemic emergency purchase programme (PEPP) is increased by EUR 600 billion to a total of EUR $1,350$ billion.

[14]See, among others, Chodorow-Reich, Darmouni, Luck, and Plosser (2020), Falato, Goldstein, and Hortaçsu (2020), Gilchrist, Wei, Yue, and Zakrajšek (2020), and Haddad, Moreira, and Muir (2020) for analysis about the effects of Fed actions on markets and the economy in 2020.

4.1 Bank Credit Risk Indicators

We consider two indicators of bank credit and default risks: the credit default swap (CDS) 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 OTC market. These indexes are based on 5-year maturity senior unsecured debt, as these contracts are usually considered the most liquid. The data start in January 2004.[15]

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. Indeed, total debt securities represent a relatively small fraction of total bank financing.[16] 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:

[15] Gefang, Koop, and Potter (2014) compare several databases collecting CDS prices. They report that CMA quotes lead the price discovery process. We also estimated predictive regressions with Thomson Reuters indexes, starting in December 2007, and reached very similar conclusions.

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

$S_t^{GZ} = \frac{1}{N_t} \sum_i \sum_k S_{i,t}[k]$, 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.[17]

Figure 6 displays the monthly evolution of the 3-month FFS (3-month tenor) (denoted by $FFS^{(3)}_{3m-3m}$) and 12-month FFS (6-month tenor) ($FFS^{(6)}_{12m-12m}$), the CDS spread, and the GZ and GM spreads for the United States and the euro area between 2005 and 2019. We observe some substantial differences between the indicators across the two zones. In the United States (Panel A), the four indicators exhibit a peak during the financial crisis but with different timings. The 3- and 12-month FFS 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 FFS display similar correlation patterns. They have high correlation with the GZ spread (77% and 79%, respectively) and relatively lower correlation with the CDS spread (65% and 70%, respectively). All this evidence suggests that the indicators may capture different phenomenons.

In the euro area (Panel B), 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

[17] The GZ spread for banks covers the period from January 1985 to December 2012 and has not been updated since, while the spread for nonfinancial 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.

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 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 FFS). 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 FFS and the credit spreads is relatively low. The correlation is below 50% with the CDS spread and below 70% with the GM spread. As expected, the correlation between the CDS and GM spreads is much higher, approximately 90%.

In summary, in the United States, the similarity between the series suggests that predictive ability should be more similar across indicators. In contrast, in the euro area, they are likely to exhibit different predictive properties because of their different temporal evolution.[18]

4.2 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:

$$\Delta^h y_{t+h} = \alpha_h + \beta_h S_t + \gamma_h \Delta^h y_t + \delta_{1,h} r_t + \delta_{2,h} term_t + \epsilon_{t+h}, \tag{3}$$

[18] 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 Section C of the Online Appendix.

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 ($term_t$).[19]

As for the spread indicators, we consider the (spot and forward) funding spreads, 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 FFS with 1-, 3- and 6-month tenors, for different starting dates and maturities. Specifically, we test 3-, 6-, and 12-month FFS with x-month tenor, denoted by $F^{(x)}_{(3m,3m)}$, $F^{(x)}_{(6m,6m)}$, and $F^{(x)}_{(12m,12m)}$. We also consider alternative combinations of starting dates and maturities such as a 12-month forward spread starting in 6 months ($F^{(x)}_{(6m,12m)}$) or a 12-month forward spread starting in 24 months ($F^{(x)}_{(24m,12m)}$), 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 $F^{(x)}_{(3m,3m)}$ and 12-month forward rates $F^{(x)}_{(12m,12m)}$. All results are available upon request. For SFS, we report results for the 1-, 3-, and 6-month spreads, which are the most widely used indicators.

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 loans, and commercial and industrial loans). The results related to real activity are reported in Tables 1 and 2 for the United States and the euro area, respectively. The results related to bank lending are reported in Tables 3 and 4. In all tables, we focus on 2- and 4-quarter predictability. We do not report estimates of γ_h, $\delta_{1,h}$, and $\delta_{2,h}$ to save space.[20]

Given data limitations, we perform our analysis from January 2005 to December 2019.

[19] 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).

[20] Section C of the Online Appendix reports all results, with 1-, 2-, and 4-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.

This period covers a single business cycle, the origin of which was clearly in the financial sector. We do not include data for 2020 to avoid the regressions to be polluted by the extreme shock associated with the Covid-19 pandemic, which caused a sharp drop in real activity.

4.3 Predicting Real Activity

GDP growth. We begin with the ability of the spread indicators to predict real GDP growth. As Table 1 (Panel A) reveals, FFS is the best predictors of U.S. GDP growth. 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% and 48%, for the 2- and 4-quarter horizons, respectively. On average, an increase of 1% in FFS predicts a decrease of 5.9% and 8.8% in the subsequent quarters. The parameters are all highly significant. They increase with the forecast horizon and decrease with the tenor. SFS also has relatively high adjusted R^2 values but they remain below 42% for the 2-quarter horizon and below 40% for the 4-quarter horizons. The CDS and GZ spreads have a similar predictive ability.

In the euro area (Table 2, Panel A), the best predictor is again FFS. For instance, the adjusted R^2 values are equal to 73%, and 70%, for the 2- and 4-quarter horizons, respectively, for the 3-month FFS (3-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%). On average, an increase of 1% in the 3-month FFS predicts a decrease in GDP of 5.1% and 9.1% in the subsequent quarters. Credit spreads have much lower predictive performance. For the GM spread, the adjusted R^2 is approximately equal to 38% and 27%, for the 2- and 4-quarter horizons, respectively, also with highly significant parameters. For CDS spreads, the adjusted R^2 values are all below these values. The better prediction generated by FFS 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.

[Please Insert Tables 1 and 2 here]

Consumption growth. We now consider the ability of spread indicators to predict real consumption growth. The results reported in Panel B indicate that FFS has a predictive ability in the same range as the CDS spread in the United States: the 12-month FFS (1-month tenor) produces the best forecast for the 2-quarter horizon, with an adjusted R^2 equal to 59%, whereas the adjusted R^2 of the CDS spread is equal to 57.5%. For the 4-quarter horizon, the adjusted R^2 values are equal to 56% and 61%, respectively.

In the euro area, the 3-month FFS (3-month tenor) again strongly outperform the other indicators for all horizons. For instance, for the 4-quarter horizon, the adjusted R^2 is as high as 59%, whereas it is below 50% for SFS and below 32% for credit spreads.

Investment growth. Panel C reports that in terms of predicting U.S. investment growth, the spot 1-month SFS and the 3-month FFS (1-month tenor) dominate the other indicators for all horizons: for both variables, the adjusted R^2 values are close to 70% and 60% for the 2- and 4-quarter horizons, respectively. Credit spreads produce R^2 values that are close to 40%-45%. It is worth emphasizing that SFS performs well for investment growth, whereas FFS clearly 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.

For the euro area, the gain of using FFS is as large for investment as for consumption. The adjusted R^2 values of the 3-month FFS (3-month tenor) are equal to 59% and 70% for the 2- and 4-quarter horizons but at best 55% and 57% for SFS and only 31% and 32% for the GM spread. The results with the CDS spread are even worse (adjusted R^2 close to

20%). A 1% increase in the 3-month FFS (3-month tenor) predicts, on average, a decline in investment of 11.9% and 21.7% in the subsequent quarters.

Unemployment rate. For the unemployment rate (Panel D), the predictive ability of FFS is again very strong. For the 2- and 4-quarter horizons, the 3-month FFS (1-month tenor) produces adjusted R^2 values equal to 82% and 70% for the United States. The performance is similar but lower for SFS. The GZ spread also performs well for a short horizon, while the CDS spread generates R^2 values that are 20 percentage points below the R^2 values of FFS.

In the euro area, the predictive ability of the 3-month FFS (3-month tenor) is considerable with adjusted R^2 values equal to 84% and 80% for the 2- and 4-quarter horizons. The adjusted R^2 values are below 63% for the credit spreads.

In summary, these results indicate that expected bank funding cost (measured by FFS) brings additional information which helps to have a better prediction of real activity in the United States and the euro area. In general, the tenor of FFS is longer for the euro area than for the United States (3 months versus 1 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 impacted the expectations process.

4.4 Predicting Bank Lending

Tables 3 and 4 present the results of the predictive regressions for bank lending in the United States and the euro area, respectively. We investigated several specifications of the forward funding spreads and we found that predicting lending relies on relatively long expectations. In the United States, predictions are often improved when we consider a more distant starting date (such as the 12-month FFS) 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.

In the United States, the 12-month FFS for one year (with a 6-month tenor) has by the highest predictive ability for bank lending. The adjusted R^2 is as high as 49% and 79% for the 2- and 4-quarter horizons. In comparison, CDS and GZ spreads generate R^2 values close to 40% and 60% for these horizons.

In the euro area, we obtain the same conclusion as for real activity: In all cases, the best predictions are obtained with 3-month FFS (with 1-month or 3-month tenor). The adjusted R^2 is as high as 84% for the 2- and 4-quarter horizons. Credit spreads also perform well, with adjusted R^2 values close to 80%. SFS produces similar performances.

We now decompose bank lending into its main components: consumer loans, real-estate loans, and commercial and industrial loans. In the United States, we find that spread indicators usually exhibit good predictive performance. For consumer loans, the adjusted R^2 of the GZ spread is the highest. For real-estate loans, the 3-month and 12-month FFS have the highest performance. For commercial and industrial loans, the GZ spread again slightly dominates, with R^2 values in the same ballpark. For FFS, the adjusted R^2 values are close to 85% for the 2-quarter horizon and 81% for the 4-quarter horizon. It is remarkable that FFS and GZ indicators have similar predictive ability, despite being built on different types of information.

For the euro area, the 3-month FFS 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 FFS are remarkably high, between 65% and 80%. For commercial and industrial loans, SFS and the GM spread are similar to one another but are still slightly dominated by FFS.

We have then explored two categories of variables: (1) real activity variables rely on relatively short expectations, so SFS and short-horizon FFS perform quite well, while CDS and GZ/GM spreads usually fail at predicting real activity; (2) bank lending variables rely on relatively long expectations, so SFS fails but long-horizon FFS performs better in the United States. The main advantage of the FFS indicators is that they allow us to adapt the predictor to the length of the expectations needed. Short horizons (typically the 3-month FFS) are sufficient for real activity variables; long horizons (typically the 12-month FFS) are useful for bank lending variables.

[Please Insert Tables 3 and 4 here]

5 Conclusion

In this paper, we build a new indicator of bank funding costs, called the *forward funding spread* or FFS, using transaction data from dollar and euro 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. The estimation can easily be performed at a daily frequency for most of the major currencies to perform real-time analyses. Another advantage of tenor spreads is that they can easily be measured at a daily frequency and therefore are well suited for real-time analyses.

FFS provides central banks with an indication of the market perception of bank funding stress. In crisis times, it is typically smaller than SFS, which is consistent with market participants expecting that funding stress will be temporary. Henceforth, increases in FFS are particularly useful indicators of funding stress for central banks and market participants. We actually characterize liquidity regimes (crisis, moderate, and abundant) that coincide with the levels of liquidity supplied by either the Federal Reserve or the ECB. 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.

Our results confirm that bank funding cost is an important driver of both real activity and bank lending. This evidence 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 QE implemented in the United States and the euro area may have helped reduce the impact of the financial crisis on the real side of the economy.

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Table 1. Predicting U.S. Real Activity Variables using Funding and Credit Spreads

	IBOR-OIS spread (SFS)			3-month FFS ($F^{(x)}_{3m,3m}$)			12-month FFS ($F^{(x)}_{12m,12m}$)			CDS spread	GZ spread
Tenor x	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$		
Panel A: Real GDP growth											
Variables in $t-2$											
Variable	-2.928	-2.380	-2.374	-4.907	-4.023	-2.597	-5.942	-4.531	-3.355	-0.969	-0.427
(t-stat)	(4.828)	(5.700)	(4.508)	(4.770)	(3.451)	(4.388)	(3.785)	(3.117)	(2.914)	(2.257)	(2.167)
Adj. R^2	0.420	0.411	0.407	0.519	0.502	0.412	0.523	0.461	0.377	0.276	0.208
Variables in $t-4$											
Variable	-4.398	-3.465	-3.695	-6.706	-5.760	-4.269	-8.819	-7.083	-5.694	-2.329	-1.099
(t-stat)	(2.999)	(3.472)	(3.965)	(4.329)	(4.209)	(4.043)	(4.587)	(3.976)	(3.605)	(2.580)	(4.239)
Adj. R^2	0.371	0.377	0.395	0.426	0.443	0.440	0.481	0.453	0.387	0.428	0.319
Panel B: Real consumption growth											
Variables in $t-2$											
Variable	-1.175	-0.843	-0.921	-2.010	-1.665	-1.102	-2.995	-2.153	-1.531	-0.750	-0.068
(t-stat)	(2.369)	(2.349)	(2.730)	(3.791)	(4.010)	(3.062)	(4.573)	(4.071)	(3.941)	(3.576)	(0.605)
Adj. R^2	0.537	0.521	0.530	0.557	0.557	0.542	0.591	0.566	0.540	0.575	0.473
Variables in $t-4$											
Variable	-2.579	-2.042	-2.211	-4.109	-3.661	-2.732	-6.077	-4.928	-3.917	-2.138	-0.337
(t-stat)	(2.453)	(2.744)	(3.131)	(3.715)	(4.325)	(3.414)	(4.281)	(4.300)	(4.340)	(4.265)	(1.913)
Adj. R^2	0.478	0.478	0.487	0.503	0.517	0.523	0.557	0.547	0.511	0.613	0.394
Panel C: Real investment growth											
Variables in $t-2$											
Variable	-10.980	-8.317	-7.993	-15.654	-12.178	-8.245	-17.831	-13.406	-10.142	-2.343	-1.929
(t-stat)	(8.196)	(5.721)	(3.425)	(4.275)	(2.783)	(3.032)	(2.997)	(2.400)	(2.072)	(1.591)	(1.770)
Adj. R^2	0.669	0.627	0.596	0.691	0.634	0.578	0.649	0.585	0.526	0.413	0.470
Variables in $t-4$											
Variable	-17.471	-12.492	-11.250	-23.489	-18.088	-12.078	-27.543	-20.566	-14.891	-5.238	-2.967
(t-stat)	(4.631)	(5.071)	(4.048)	(4.939)	(3.551)	(3.757)	(3.650)	(2.917)	(2.332)	(1.700)	(3.135)
Adj. R^2	0.601	0.569	0.520	0.597	0.558	0.522	0.577	0.526	0.457	0.433	0.435
Panel D: Unemployment rate change											
Variables in $t-2$											
Variable	1.735	1.396	1.440	2.531	2.083	1.474	3.033	2.369	1.879	0.382	0.417
(t-stat)	(10.718)	(11.647)	(7.185)	(7.307)	(4.187)	(5.548)	(4.539)	(3.300)	(2.727)	(1.683)	(2.790)
Adj. R^2	0.806	0.798	0.781	0.821	0.787	0.764	0.800	0.751	0.703	0.574	0.670
Variables in $t-4$											
Variable	3.467	2.626	2.562	4.825	3.922	2.713	5.907	4.646	3.693	1.105	0.681
(t-stat)	(5.210)	(6.303)	(6.310)	(6.801)	(5.188)	(6.051)	(5.313)	(4.244)	(3.661)	(1.816)	(4.356)
Adj. R^2	0.688	0.686	0.664	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 2 and 4 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 Euro Area Real Activity Variables using Funding and Credit Spreads

	IBOR-OIS spread (SFS)			3-month FFS ($F^{(x)}_{3m,3m}$)			12-month FFS ($F^{(x)}_{12m,12m}$)			CDS spread	GM spread
Tenor x	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$		
Panel A: Real GDP growth											
Variables in $t-2$											
Variable	-4.262	-3.222	-2.861	-8.421	-5.109	-3.042	-9.949	-6.353	-5.067	-0.414	-1.007
(t-stat)	(8.549)	(6.004)	(5.137)	(4.027)	(5.061)	(6.188)	(5.745)	(5.261)	(4.614)	(2.029)	(2.865)
Adj. R^2	0.475	0.573	0.598	0.674	0.726	0.623	0.679	0.712	0.676	0.303	0.378
Variables in $t-4$											
Variable	-8.087	-5.910	-5.114	-14.994	-9.084	-5.341	-16.539	-11.330	-9.125	-1.016	-2.088
(t-stat)	(4.497)	(5.605)	(5.425)	(5.721)	(7.863)	(5.526)	(5.471)	(7.664)	(6.676)	(2.069)	(4.259)
Adj. R^2	0.393	0.532	0.520	0.658	0.703	0.555	0.605	0.683	0.619	0.150	0.268
Panel B: Real consumption growth											
Variables in $t-2$											
Variable	-1.227	-0.997	-0.901	-2.874	-1.873	-0.883	-2.633	-2.319	-1.808	-0.171	-0.239
(t-stat)	(1.934)	(3.095)	(3.604)	(4.181)	(6.972)	(3.386)	(3.418)	(6.743)	(6.389)	(1.769)	(1.768)
Adj. R^2	0.599	0.638	0.644	0.680	0.714	0.634	0.630	0.705	0.684	0.572	0.556
Variables in $t-4$											
Variable	-3.310	-2.460	-2.184	-6.633	-4.165	-2.167	-6.294	-5.186	-4.174	-0.414	-0.708
(t-stat)	(2.328)	(3.228)	(3.584)	(5.082)	(5.794)	(3.564)	(3.406)	(5.357)	(5.427)	(1.556)	(2.147)
Adj. R^2	0.418	0.479	0.483	0.545	0.586	0.464	0.458	0.576	0.542	0.313	0.311
Panel C: Real investment growth											
Variables in $t-2$											
Variable	-11.170	-8.052	-7.275	-19.083	-11.877	-7.430	-22.151	-14.830	-12.354	-1.203	-2.721
(t-stat)	(6.685)	(7.813)	(7.393)	(4.777)	(7.231)	(8.585)	(7.214)	(7.833)	(7.378)	(2.728)	(4.194)
Adj. R^2	0.419	0.521	0.548	0.533	0.592	0.561	0.547	0.575	0.569	0.190	0.315
Variables in $t-4$											
Variable	-19.711	-14.268	-12.593	-34.784	-21.674	-12.763	-38.535	-27.418	-22.346	-2.797	-5.046
(t-stat)	(5.046)	(6.442)	(6.340)	(6.135)	(8.900)	(6.549)	(6.376)	(9.086)	(8.293)	(2.658)	(5.113)
Adj. R^2	0.423	0.563	0.568	0.631	0.701	0.577	0.589	0.691	0.647	0.214	0.321
Panel D: Unemployment rate change											
Variables in $t-2$											
Variable	1.609	1.125	1.004	2.627	1.612	0.979	2.977	2.021	1.610	0.111	0.278
(t-stat)	(10.472)	(10.283)	(10.224)	(6.548)	(7.145)	(10.465)	(8.947)	(7.246)	(5.687)	(1.822)	(2.716)
Adj. R^2	0.790	0.817	0.820	0.831	0.841	0.805	0.832	0.838	0.810	0.589	0.628
Variables in $t-4$											
Variable	3.636	2.475	2.169	6.168	3.724	2.109	6.622	4.694	3.726	0.390	0.753
(t-stat)	(5.281)	(7.297)	(8.186)	(10.153)	(13.622)	(8.564)	(7.612)	(11.652)	(9.580)	(2.138)	(4.422)
Adj. R^2	0.625	0.700	0.688	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 2 and 4 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 U.S. Bank Lending Variables using Funding and Credit Spreads

	IBOR-OIS spread (SFS)			3-month FFS ($F^{(x)}_{3m,3m}$)			12-month FFS ($F^{(x)}_{12m,12m}$)			CDS spread	GZ spread
Tenor x	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$		
Panel A: Bank credit growth											
Variables in $t-2$											
Variable	-1.650	-2.004	-2.246	-2.623	-2.832	-2.474	-3.735	-3.775	-3.704	-1.129	-0.532
(t-stat)	(1.861)	(2.855)	(3.342)	(1.781)	(2.323)	(3.646)	(2.117)	(2.867)	(3.734)	(1.866)	(3.262)
Adj. R^2	0.335	0.407	0.472	0.353	0.405	0.483	0.380	0.431	0.493	0.385	0.434
Variables in $t-4$											
Variable	-6.190	-5.481	-5.649	-9.237	-8.063	-6.054	-11.675	-10.089	-9.055	-2.789	-1.343
(t-stat)	(6.004)	(7.239)	(9.255)	(6.022)	(6.749)	(9.907)	(6.028)	(7.279)	(11.004)	(2.627)	(5.803)
Adj. R^2	0.551	0.665	0.760	0.614	0.682	0.766	0.658	0.714	0.792	0.561	0.671
Panel B: Consumer loan growth											
Variables in $t-2$											
Variable	0.169	-2.121	-2.472	-0.740	-2.055	-2.534	-1.791	-2.898	-3.342	-0.556	-0.734
(t-stat)	(0.091)	(2.679)	(4.085)	(0.284)	(1.125)	(3.592)	(0.629)	(1.590)	(2.799)	(0.839)	(4.138)
Adj. R^2	0.402	0.432	0.462	0.404	0.419	0.458	0.408	0.429	0.459	0.412	0.489
Variables in $t-4$											
Variable	-0.905	-3.795	-5.594	-4.821	-6.112	-5.323	-7.255	-7.683	-8.293	-1.847	-1.802
(t-stat)	(0.327)	(1.952)	(4.007)	(1.446)	(2.441)	(3.128)	(1.994)	(2.625)	(3.586)	(1.559)	(4.062)
Adj. R^2	0.492	0.529	0.589	0.513	0.546	0.572	0.528	0.555	0.602	0.526	0.650
Panel C: Real estate loan growth											
Variables in $t-2$											
Variable	-0.068	-0.796	-1.119	-0.282	-1.066	-1.397	-1.410	-1.998	-2.208	-0.822	-0.265
(t-stat)	(0.062)	(0.886)	(1.272)	(0.147)	(0.662)	(1.511)	(0.585)	(1.090)	(1.567)	(1.604)	(1.235)
Adj. R^2	0.529	0.537	0.549	0.529	0.536	0.558	0.534	0.547	0.563	0.552	0.544
Variables in $t-4$											
Variable	-2.865	-3.336	-4.178	-4.558	-4.978	-4.539	-7.143	-7.010	-7.144	-2.226	-1.186
(t-stat)	(1.770)	(2.674)	(3.437)	(1.973)	(2.605)	(3.552)	(2.411)	(3.124)	(4.246)	(2.414)	(4.567)
Adj. R^2	0.665	0.697	0.741	0.674	0.701	0.747	0.696	0.722	0.764	0.702	0.742
Panel D: C&I loan growth											
Variables in $t-2$											
Variable	-9.077	-7.876	-7.477	-12.384	-10.483	-7.926	-14.488	-12.263	-10.590	-3.432	-2.101
(t-stat)	(11.466)	(7.809)	(7.942)	(5.344)	(4.645)	(6.827)	(4.165)	(4.014)	(4.488)	(1.863)	(8.747)
Adj. R^2	0.675	0.775	0.816	0.694	0.735	0.809	0.697	0.727	0.757	0.633	0.847
Variables in $t-4$											
Variable	-23.618	-20.181	-19.610	-34.528	-28.842	-20.605	-40.960	-33.598	-28.601	-8.539	-5.379
(t-stat)	(7.471)	(9.828)	(11.954)	(10.627)	(7.673)	(10.069)	(7.078)	(6.256)	(7.221)	(1.809)	(15.428)
Adj. R^2	0.507	0.671	0.773	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 2 and 4 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 Euro Area Bank Lending Variables using Funding and Credit Spreads

	IBOR-OIS spread (SFS)			3-month FFS ($F^{(x)}_{3m,3m}$)			12-month FFS ($F^{(x)}_{12m,12m}$)			CDS spread	GM spread
Tenor x	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$		
Panel A: Bank credit growth											
Variables in $t-2$											
Variable	-3.715	-2.332	-2.002	-6.348	-3.566	-2.045	-6.929	-4.515	-3.604	-0.755	-1.170
(t-stat)	(5.717)	(5.163)	(4.381)	(5.864)	(6.459)	(4.936)	(7.469)	(6.951)	(5.193)	(3.741)	(3.113)
Adj. R^2	0.806	0.816	0.814	0.845	0.839	0.822	0.843	0.839	0.831	0.802	0.825
Variables in $t-4$											
Variable	-11.000	-7.362	-6.299	-19.168	-11.199	-6.268	-20.592	-14.279	-11.320	-2.244	-3.282
(t-stat)	(5.469)	(6.281)	(5.542)	(5.662)	(7.938)	(6.030)	(8.018)	(9.247)	(7.318)	(4.319)	(3.412)
Adj. R^2	0.740	0.787	0.785	0.833	0.844	0.803	0.828	0.848	0.836	0.761	0.791
Panel B: Consumer loan growth											
Variables in $t-2$											
Variable	-2.603	-1.848	-1.627	-5.009	-3.055	-1.692	-5.015	-3.759	-3.154	-0.746	-1.143
(t-stat)	(3.642)	(4.268)	(4.058)	(4.387)	(5.610)	(4.158)	(4.666)	(5.847)	(5.095)	(2.953)	(3.539)
Adj. R^2	0.644	0.664	0.664	0.682	0.693	0.670	0.666	0.688	0.685	0.673	0.687
Variables in $t-4$											
Variable	-8.406	-5.479	-4.734	-14.219	-8.388	-4.669	-14.517	-10.541	-8.533	-1.547	-2.634
(t-stat)	(6.099)	(6.900)	(6.652)	(7.496)	(9.119)	(6.394)	(7.516)	(9.884)	(8.187)	(2.884)	(4.667)
Adj. R^2	0.716	0.745	0.741	0.778	0.789	0.738	0.745	0.786	0.767	0.667	0.719
Panel C: Real estate loan growth											
Variables in $t-2$											
Variable	-1.924	-1.139	-0.961	-3.644	-2.009	-1.053	-3.847	-2.586	-2.079	-0.366	-0.535
(t-stat)	(3.629)	(2.809)	(2.259)	(4.057)	(3.668)	(2.608)	(4.200)	(3.498)	(2.630)	(2.121)	(1.990)
Adj. R^2	0.708	0.706	0.703	0.732	0.726	0.706	0.724	0.727	0.719	0.696	0.696
Variables in $t-4$											
Variable	-5.397	-3.231	-2.689	-9.978	-5.476	-2.854	-9.857	-6.946	-5.613	-1.255	-1.638
(t-stat)	(3.620)	(3.687)	(3.207)	(5.519)	(5.070)	(3.622)	(4.493)	(4.564)	(3.816)	(2.856)	(3.400)
Adj. R^2	0.652	0.650	0.640	0.713	0.697	0.648	0.677	0.696	0.679	0.651	0.641
Panel D: C&I loan growth											
Variables in $t-2$											
Variable	-5.979	-3.825	-3.317	-9.010	-5.019	-3.271	-10.042	-6.374	-5.187	-0.909	-1.712
(t-stat)	(8.668)	(8.557)	(9.348)	(6.533)	(7.506)	(9.637)	(9.162)	(8.339)	(8.836)	(4.155)	(4.306)
Adj. R^2	0.873	0.891	0.895	0.889	0.886	0.903	0.898	0.888	0.890	0.846	0.901
Variables in $t-4$											
Variable	-16.256	-12.212	-10.679	-27.828	-16.771	-10.284	-30.724	-21.346	-17.192	-2.757	-4.833
(t-stat)	(5.720)	(8.996)	(9.594)	(5.920)	(10.505)	(10.413)	(10.118)	(11.908)	(12.015)	(4.369)	(4.466)
Adj. R^2	0.756	0.842	0.858	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 2 and 4 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.

Figure 1. Funding Spreads in the United States, Federal Reserve Total Assets, and Liquidity Regimes

Note: Panel A displays the forward funding spread (FFS), the spot funding spread (SFS), and the difference between the two spreads. Panel B displays the Federal Reserve total assets (in USD trillion). Panel C displays the narrative liquidity regimes together with statistical regimes obtained from a Markov-Switching model of FFS. The spread series are smoothed using a 5-day moving average. The sample periods run from January 2007 to September 2020.

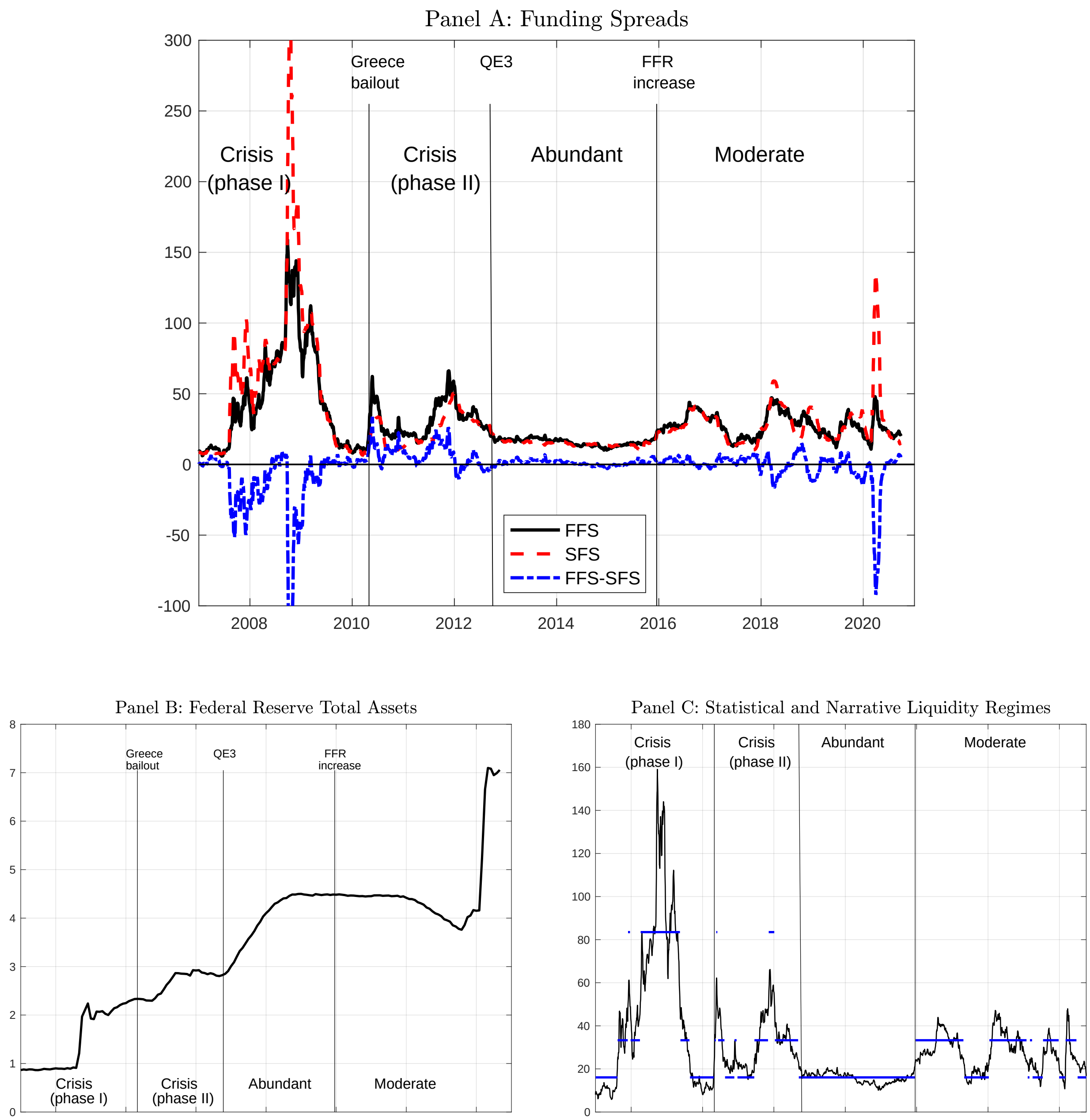


Figure 2. Funding Spreads in the Euro Area, ECB Total Assets, and Liquidity Regimes

Note: Panel A displays the forward funding spread (FFS), the spot funding spread (SFS), and the difference between the two spreads. Panel B displays the ECB total assets (in EUR trillion). Panel C displays the narrative liquidity regimes together with statistical regimes obtained from a Markov-Switching model of FFS. The spread series are smoothed using a 5-day moving average. The sample periods run from January 2007 to September 2020.

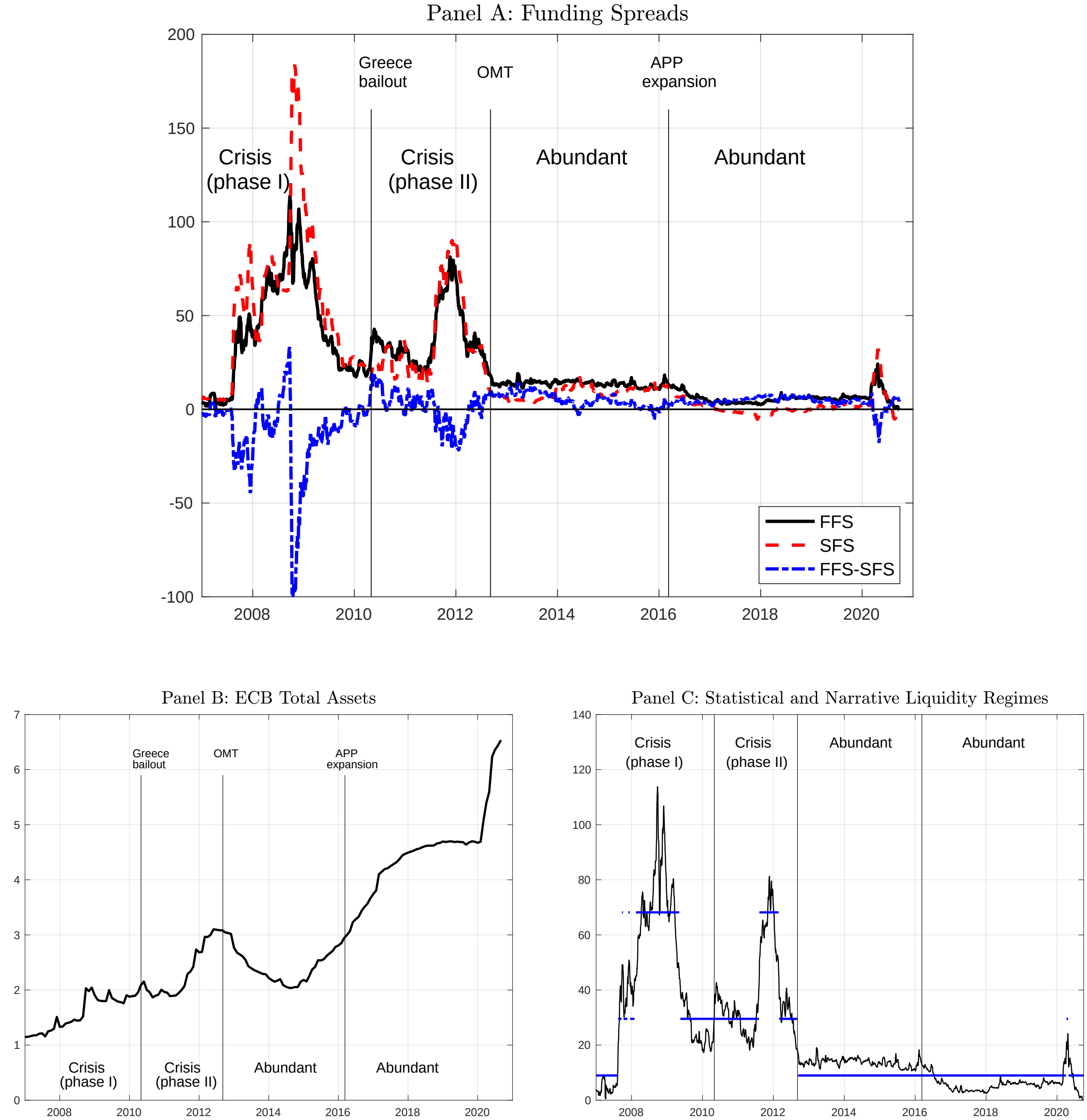


Figure 3. Bank CDS Spreads and Uncertainty in Short-Term Interest Rates

Note: Panels A and B display the bank CDS spread and the forward funding spread (FFS) for the United States and the euro area, respectively. Panels C and D display the uncertainty in 3-month interest rates in 3 months, as measured as the sum of disagreement among forecasters and the perceived variability of future aggregate shocks for the United States and the euro area, respectively. See Istrefi and Mouabbi (2018). The spread series are smoothed using a 5-day moving average. The sample periods run from January 2007 to September 2020.

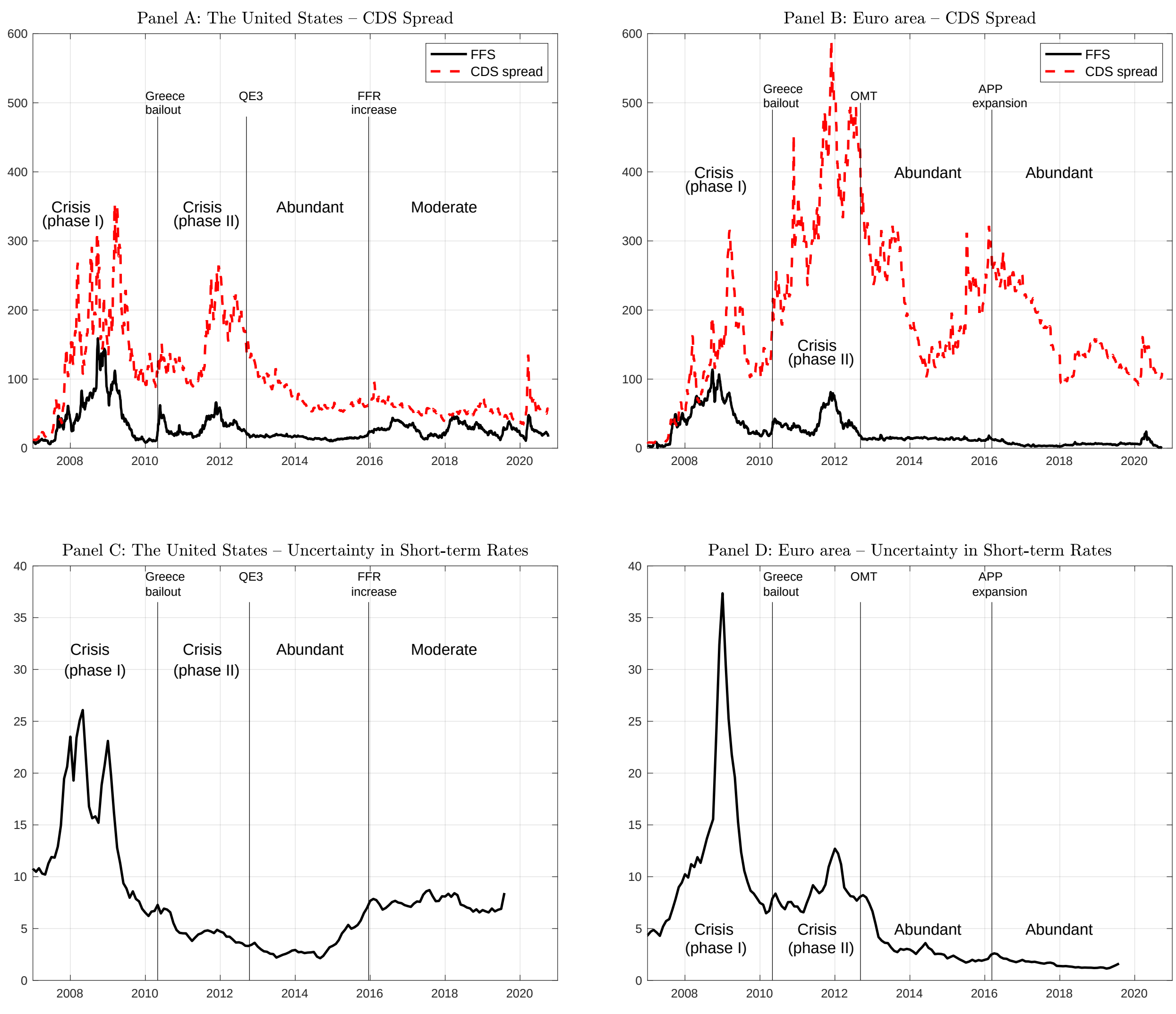


Figure 4. Funding Spreads for the United States – Subsamples

Note: The figure displays the forward funding spread (FFS), the spot funding spread (SFS), and the difference between the two spreads for the United States for four subsamples. The series are smoothed using a 5-day moving average.

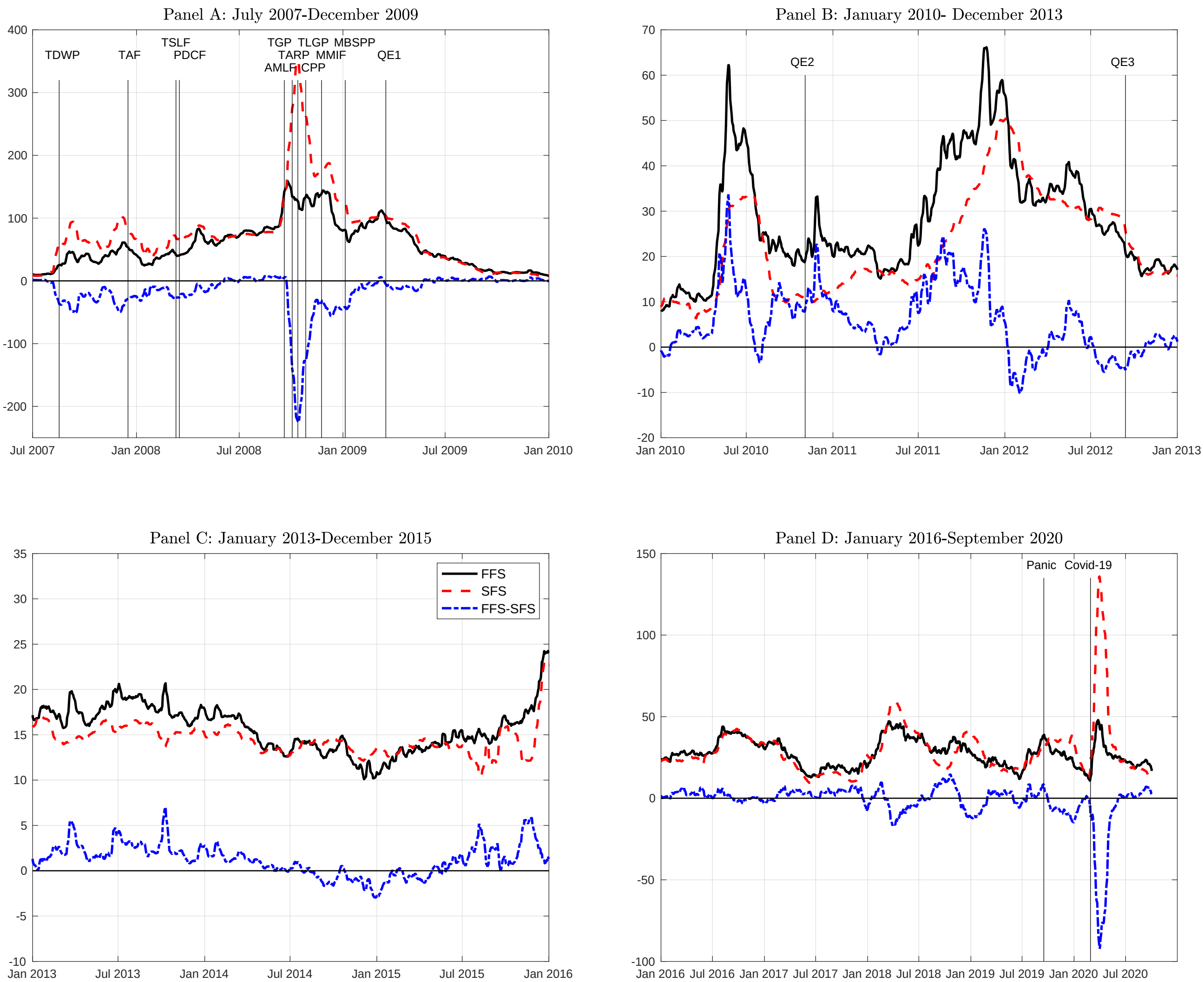


Figure 5. Funding Spreads for the Euro Area – Subsamples

Note: The figure displays the forward funding spread (FFS), the spot funding spread (SFS), and the difference between the two spreads for the euro area for four subsamples. The series are smoothed using a 5-day moving average.

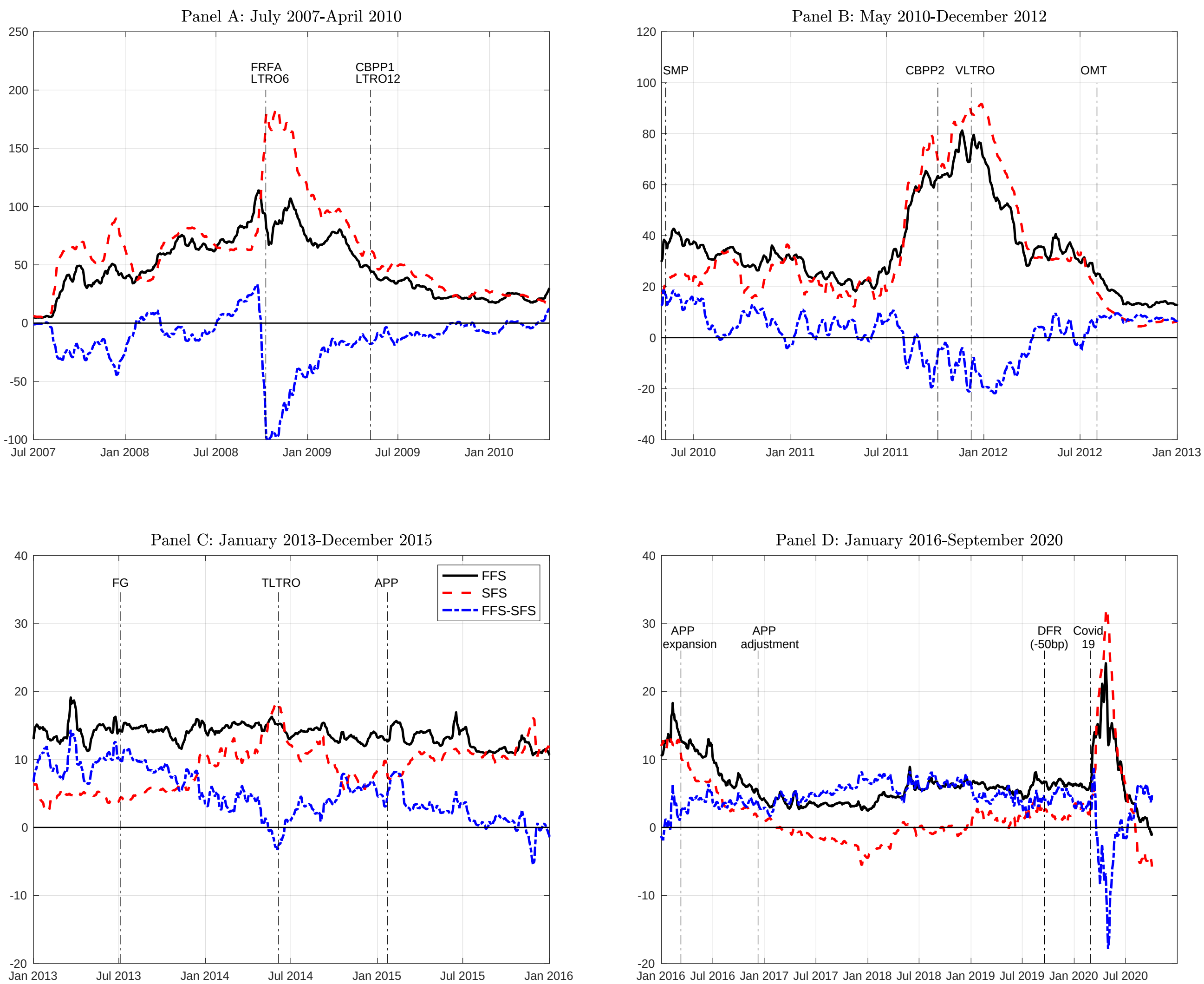
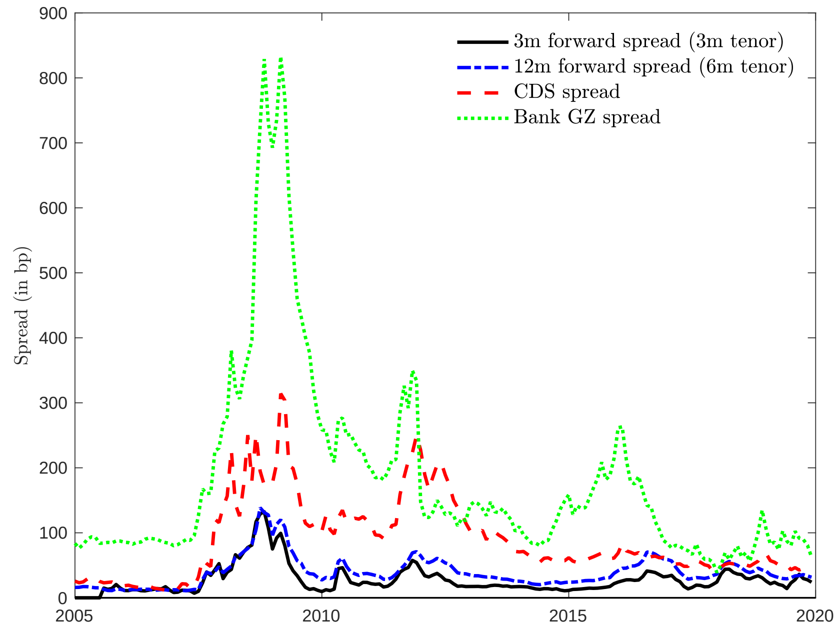


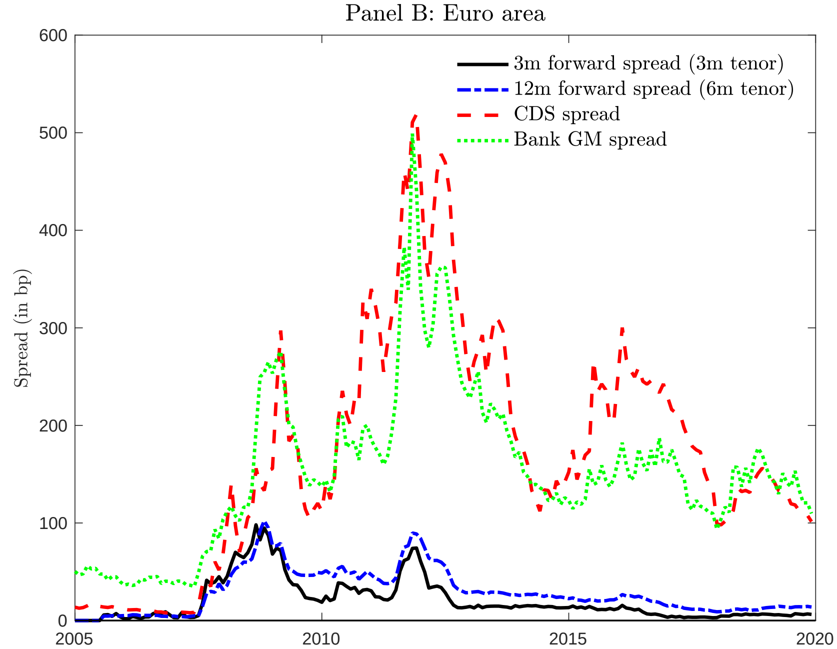
Figure 6. Funding and Credit Risk Indicators

Note: Panel A displays the bank credit risk indicators for the United States: the 3-month and 12-month FFS, the CDS spread, and the bank GZ spread (Gilchrist and Zakrajšek, 2012b). Panel B displays the bank credit risk indicators for the euro area: the 3-month and 12-month FFS, the CDS spread, and the GM spread (Gilchrist and Mojon, 2018). The sample periods run from January 2005 to December 2019.

Panel A: The United States



Panel B: Euro area



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Online Appendix for "Bank Funding Cost and Liquidity Supply Regimes"[1]

This online appendix provides details on the data, the methodology, and the empirical results related to our paper "Bank Funding Cost and Liquidity Supply Regimes." Section A describes the methodology. Section B describes the results associated with the estimation of a Markov-Switching model of FFS. Section C reports the full set of results relative to the ability of FFS to predict the evolution of indicators of real activity and bank lending. Finally, Section D displays the spot and forward funding spreads and the total assets of the central bank for Japan and the United Kingdom.

Contents

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A Methodology for Constructing Yield Curves

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 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 3 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: $\mathcal{C}_x^{(F)} = \left\{ T \rightarrow \tilde{F}_x(t,T,T+\delta), t \geq T \right\}$.

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 (European 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 1 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 Libor rate is the reference rate in the United States and the Euribor rate 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 to 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 3-month Libor rate payed with 3-month frequency. On the euro market, the floating leg is indexed to the 6-month Euribor rate payed with 6-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 vs 3-month, 3-month vs 6-month, and 3-month vs 12-month. On the euro market, the typical basis swaps are 1-month vs 3-month, 3-month vs 6-month, and 6-month vs 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 6-month curve in the United States and the 3-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 extract 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 3-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 $T_0 = t$):

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

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 3-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 3-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 Forward Funding Spreads

Figure OA1 displays the time series of the forward funding spreads for the United States and the euro area for tenors of 1, 3 and 6 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. FFS 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, FFS was particularly high for the tenors of 3 and 6 months, with a spike above 100 bp for these spreads in January 2009. In contrast, during the sovereign debt crisis, FFS increased in a more regular way. They increased up to 50, 75, and 120 bp for the 1-, 3- and 6-month tenors, respectively, in November 2011. In the United States, the financial crisis also generated substantial differences between tenors. The FFS with a 1-month tenor increased to 140 bp in January 2009, while FFS with 3- and 6-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 OA2 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 3-month and

6-month curves for the United States and the euro area, which corresponds to the second term in the optimization criterion. Panel B corresponds to the volatility of the 3-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). In the United States, the relative error is always below 4 bp for the 3-month curve and 2 bp for the 6-month curve. After 2009, the relative error is usually below 1 bp for both curves, with sample averages equal to 1 and 0.5 bp, respectively. For the euro area, the relative error is below 3 bp for the 3-month curve and 1 bp for the 6-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.

On average, the relative error is equal to 1.05 bp and 0.71 bp for the 3-month curve and 0.57 bp and 0.39 bp for the 6-month curve in the United states and the euro area, respectively.

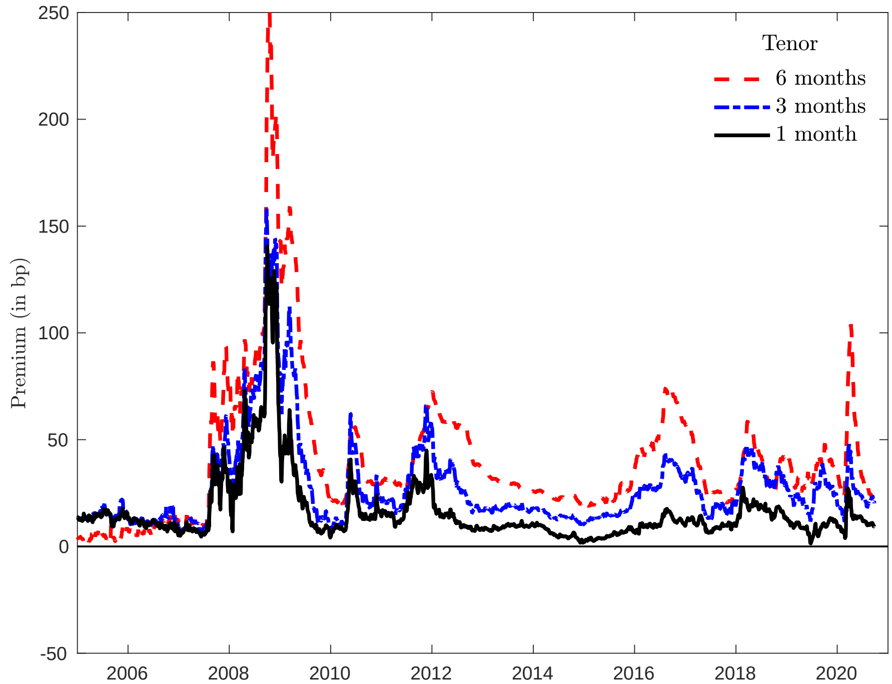
In Panel B, we also report the volatility of the 3-month forward rate, which reflects the extend of the smoothing of the curves. As we note, the volatility is higher in the United States (up to 20 bp in 2008 and usually below 10 bp after 2009). In the euro area, the volatility rarely exceeds 10 bp.

These results suggest that the fit of the 3-month forward curve is well adjusted over our sample in both zones.

Figure OA1. Forward Funding Spreads for the United States and the Euro Area

Note: Panel A displays the 3-month forward funding spread for tenors 1 month, 3 months, and 6 months for the United States. Panel B displays the 3-month forward funding spread for tenors 1 month, 3 months, and 6 months for the euro area. The series are smoothed using a 5-day moving average. The sample periods run from January 2005 to September 2020.

Panel A: The United States



Panel B: Euro area

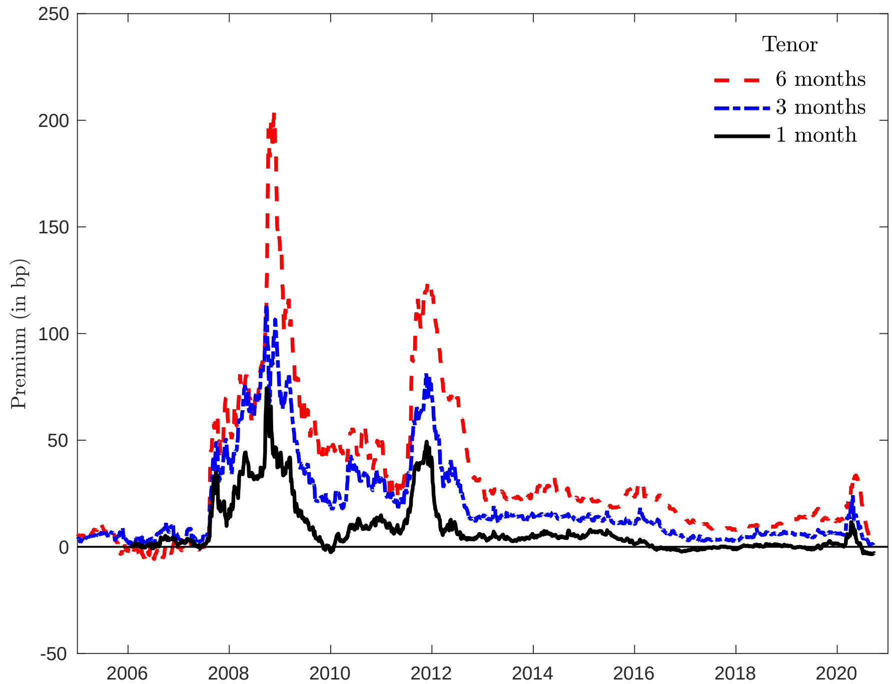
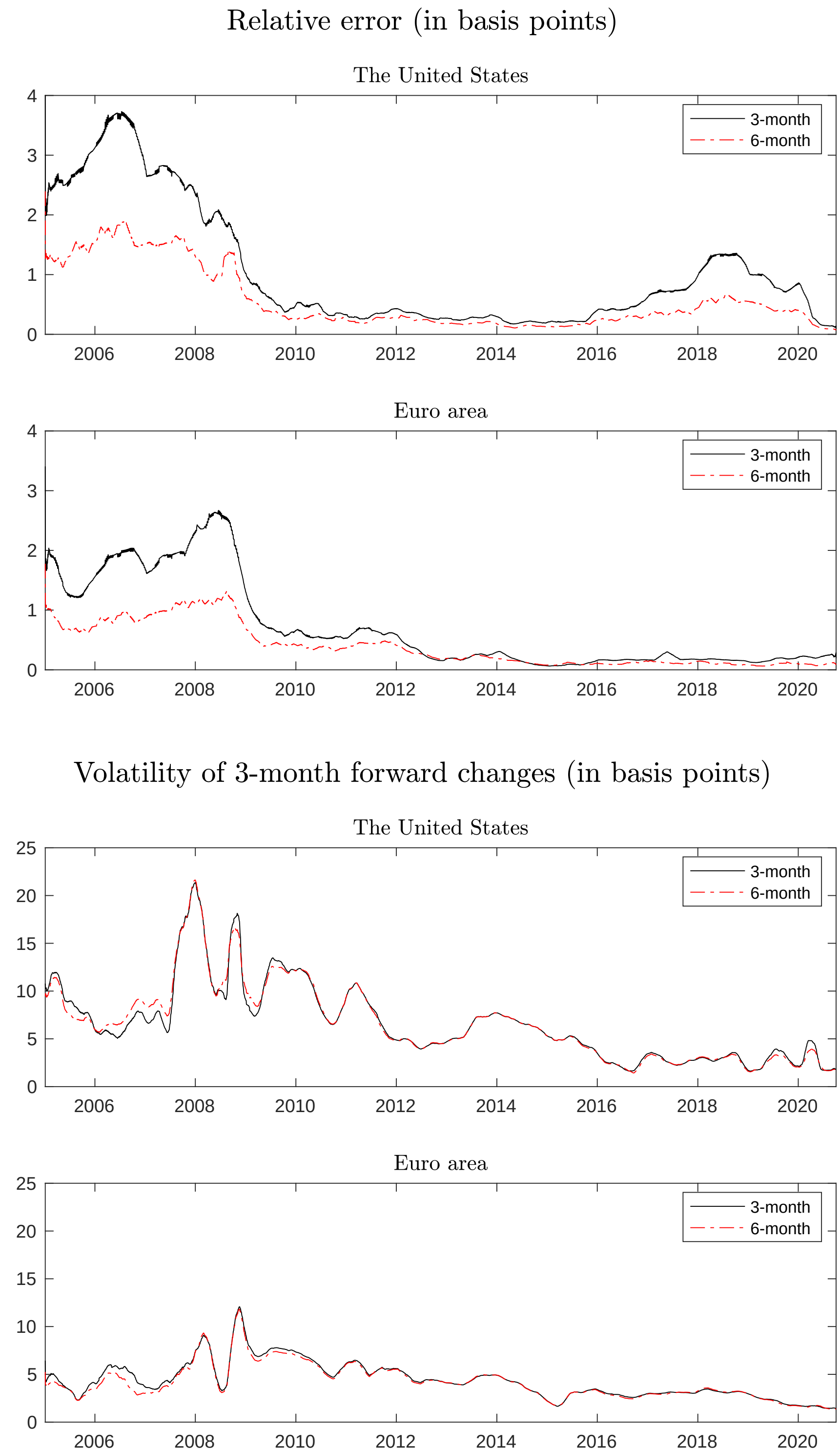


Figure OA2. Relative Error in the Fit of U.S. and Euro Area Curves

Note: Panel A displays the relative error (in basis points) in the construction of the 3-month and 6-month curves for the United States and the euro area. Panel B displays the volatility of the 3-month forward rate (in basis points) for the construction of the 3-month and 6-month curves for the United States and the euro area. The series are smoothed using a 5-day moving average. The sample periods run from January 2005 to September 2020.



B A Statistical Approach of Regimes

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. FFS is assumed to be driven by the following process:

$$FFS_{t+1} = \mu(\mathcal{S}_{t+1}) + \varepsilon_{t+1}, \tag{A.1}$$

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 $\varepsilon_{t+1} = \sigma(\mathcal{S}_{t+1})z_{t+1}$, 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 $p_{ij} = \Pr(\mathcal{S}_t = j|\mathcal{S}_{t-1} = i)$, $i, j \in \{1, ..., k\}$. 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 3-state model using standard likelihood maximization over the period from January 2007 to September 2020.[2] Table OA1 reports the parameter estimates. For the United States, we observe a sequence of regime switches, from the high FFS regime ($\mu_{(3)} = 84$ bp, $\sigma_{(3)} = 7.8$) to the low FFS regime ($\mu_{(1)} = 16$ bp, $\sigma_{(1)} = 0.16$), 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 FFS regime corresponding to period from September 2012 to December 2015, with an average FFS equal to 16 bp. From December 2015 onward, we observe that FFS is mainly in the intermediate regime ($\mu_{(2)} = 33$ bp, $\sigma_{(2)} = 0.55$), which corresponds to our moderate liquidity regime.

In the euro area, FFS 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, FFS remains in the low regime ($\mu_{(1)} = 9$ bp, $\sigma_{(1)} = 0.22$) until the end of the sample, with an exception in April 2020 during the Covid-19 pandemic.

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

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

Table OA1. Parameter Estimates of a 3-Regime Markov-Switching Model of FFS

	The United States			**Euro Area**		
	Regime 1	Regime 2	Regime 3	Regime 1	Regime 2	Regime 3
$\mu_{(k)}$	16.06	33.31	83.50	8.97	29.53	68.18
	(0.100)	(0.213)	(1.532)	(0.099)	(0.318)	(0.857)
$\sigma_{(k)}$	0.155	0.546	7.753	0.215	0.532	2.310
	(0.006)	(0.022)	(0.577)	(0.007)	(0.034)	(0.166)
Transition matrix						
$P_{1;:}$	0.995	0.007	0.000	0.999	0.003	0.000
$P_{2;:}$	0.005	0.991	0.011	0.001	0.993	0.008
$P_{3;:}$	0.000	0.003	0.989	0.000	0.005	0.992
Log-likelihood	4775.0			4897.3		

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

C Predictive Content: Full Set of Results

Table OA2. Predicting U.S. Real Activity Variables using Funding and Credit Spreads

	IBOR-OIS spread (SFS)			3-month FFS ($F^{(x)}_{3m,3m}$)			12-month FFS ($F^{(x)}_{12m,12m}$)			CDS spread	GZ spread	Goldberg var.
Tenor x	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$			
Panel A: Real GDP growth												
variables in $t-1$												
r	-0.002	-0.075	-0.123	-0.004	-0.103	-0.125	-0.014	-0.115	-0.168	-0.076	-0.005	-0.062
(t-stat)	(0.051)	(1.543)	(2.201)	(0.075)	(1.933)	(2.225)	(0.273)	(2.075)	(2.326)	(1.534)	(0.107)	(1.560)
$term$	-0.005	-0.053	-0.042	0.022	-0.050	-0.042	0.010	-0.055	-0.062	0.053	0.093	-0.075
(t-stat)	(0.097)	(0.897)	(0.605)	(0.396)	(0.856)	(0.626)	(0.156)	(0.835)	(0.831)	(0.740)	(1.430)	(1.724)
lag	-0.059	-0.158	-0.156	-0.148	-0.120	-0.147	-0.121	-0.079	-0.039	0.181	0.046	0.302
(t-stat)	(0.638)	(1.680)	(1.566)	(1.200)	(0.952)	(1.431)	(0.883)	(0.646)	(0.341)	(1.166)	(0.294)	(2.296)
variable	-1.751	-1.348	-1.191	-2.665	-1.964	-1.258	-3.000	-2.186	-1.610	-0.473	-0.207	-0.033
(t-stat)	(6.150)	(6.330)	(4.733)	(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	0.360	0.369	0.350	0.428	0.398	0.343	0.402	0.358	0.308	0.210	0.206	0.179
variables in $t-2$												
r	-0.052	-0.180	-0.288	-0.054	-0.245	-0.294	-0.066	-0.274	-0.390	-0.196	-0.050	-0.141
(t-stat)	(0.675)	(2.025)	(2.556)	(0.628)	(2.159)	(2.629)	(0.722)	(2.218)	(2.301)	(1.878)	(0.550)	(1.472)
$term$	-0.018	-0.121	-0.121	0.011	-0.128	-0.119	-0.004	-0.137	-0.162	0.100	0.168	-0.124
(t-stat)	(0.197)	(1.163)	(0.994)	(0.122)	(1.170)	(0.995)	(0.037)	(1.076)	(1.068)	(0.919)	(1.451)	(1.230)
lag	-0.011	-0.198	-0.314	-0.205	-0.289	-0.334	-0.237	-0.241	-0.207	0.107	-0.117	0.306
(t-stat)	(0.264)	(1.820)	(1.970)	(1.660)	(1.330)	(1.971)	(1.361)	(1.130)	(1.072)	(1.000)	(0.723)	(3.645)
variable	-2.928	-2.380	-2.374	-4.907	-4.023	-2.597	-5.942	-4.531	-3.355	-0.969	-0.427	-0.071
(t-stat)	(4.828)	(5.700)	(4.508)	(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	0.420	0.411	0.407	0.519	0.502	0.412	0.523	0.461	0.377	0.276	0.208	0.214
variables in $t-4$												
r	-0.323	-0.521	-0.714	-0.343	-0.622	-0.737	-0.357	-0.677	-0.905	-0.602	-0.265	-0.431
(t-stat)	(1.508)	(2.208)	(2.612)	(1.457)	(2.262)	(2.819)	(1.558)	(2.375)	(2.497)	(2.234)	(1.146)	(1.738)
$term$	-0.125	-0.312	-0.389	-0.121	-0.352	-0.395	-0.154	-0.366	-0.454	0.161	0.252	-0.218
(t-stat)	(0.700)	(1.533)	(1.729)	(0.643)	(1.500)	(1.733)	(0.766)	(1.432)	(1.472)	(0.859)	(1.917)	(1.054)
lag	-0.123	-0.276	-0.460	-0.241	-0.356	-0.515	-0.327	-0.375	-0.426	-0.240	-0.630	0.162
(t-stat)	(1.751)	(2.753)	(3.199)	(2.800)	(2.400)	(3.436)	(2.920)	(2.309)	(2.196)	(1.387)	(3.142)	(1.208)
variable	-4.398	-3.465	-3.695	-6.706	-5.760	-4.269	-8.819	-7.083	-5.694	-2.329	-1.099	-0.113
(t-stat)	(2.999)	(3.472)	(3.965)	(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	0.371	0.377	0.395	0.426	0.443	0.440	0.481	0.453	0.387	0.428	0.319	0.162
Panel B: Real consumption growth												
variables in $t-1$												
r	-0.031	-0.066	-0.098	-0.032	-0.095	-0.104	-0.038	-0.107	-0.143	-0.088	-0.025	-0.055
(t-stat)	(0.956)	(2.065)	(2.969)	(0.839)	(2.149)	(3.254)	(1.008)	(2.403)	(3.051)	(2.930)	(0.628)	(1.633)
$term$	-0.029	-0.053	-0.052	-0.019	-0.065	-0.054	-0.027	-0.069	-0.071	0.033	0.039	-0.046
(t-stat)	(0.820)	(1.539)	(1.558)	(0.500)	(1.582)	(1.608)	(0.694)	(1.614)	(1.645)	(0.643)	(0.875)	(1.421)
lag	0.255	0.179	0.102	0.079	0.040	0.074	-0.012	0.038	0.079	0.138	0.237	0.476
(t-stat)	(1.799)	(1.254)	(0.765)	(0.687)	(0.291)	(0.545)	(0.094)	(0.276)	(0.594)	(1.154)	(1.631)	(3.394)

	IBOR-OIS spread (SFS)			3-month FFS ($F^{(x)}_{3m,3m}$)			12-month FFS ($F^{(x)}_{12m,12m}$)			CDS spread	GZ spread	Goldberg var.
Tenor x	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$			
variable	-0.762	-0.629	-0.675	-1.533	-1.272	-0.767	-2.108	-1.533	-1.152	-0.475	-0.129	-0.009
(t-stat)	(2.284)	(3.181)	(4.026)	(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	0.320	0.341	0.378	0.410	0.429	0.393	0.457	0.429	0.404	0.384	0.311	0.250
variables in $t-2$												
r	-0.092	-0.144	-0.193	-0.101	-0.182	-0.205	-0.110	-0.206	-0.252	-0.186	-0.099	-0.118
(t-stat)	(1.259)	(1.931)	(2.521)	(1.267)	(2.031)	(2.793)	(1.386)	(2.267)	(2.780)	(2.698)	(1.222)	(1.544)
term	-0.013	-0.054	-0.066	-0.016	-0.076	-0.074	-0.035	-0.091	-0.092	0.068	0.029	-0.024
(t-stat)	(0.157)	(0.650)	(0.835)	(0.202)	(0.898)	(0.940)	(0.439)	(1.048)	(1.087)	(0.768)	(0.279)	(0.286)
lag	0.462	0.414	0.328	0.347	0.305	0.280	0.228	0.268	0.318	0.324	0.607	0.665
(t-stat)	(4.482)	(3.223)	(2.469)	(3.524)	(2.621)	(2.142)	(2.214)	(2.363)	(2.807)	(3.177)	(3.064)	(5.466)
variable	-1.175	-0.843	-0.921	-2.010	-1.665	-1.102	-2.995	-2.153	-1.531	-0.750	-0.068	-0.021
(t-stat)	(2.369)	(2.349)	(2.730)	(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	0.537	0.521	0.530	0.557	0.557	0.542	0.591	0.566	0.540	0.575	0.473	0.487
variables in $t-4$												
r	-0.305	-0.434	-0.565	-0.332	-0.519	-0.603	-0.355	-0.579	-0.733	-0.594	-0.311	-0.329
(t-stat)	(1.559)	(2.068)	(2.482)	(1.588)	(2.259)	(2.774)	(1.759)	(2.547)	(2.966)	(3.089)	(1.437)	(1.640)
term	0.038	-0.093	-0.167	0.006	-0.163	-0.205	-0.060	-0.209	-0.261	0.144	0.180	0.057
(t-stat)	(0.173)	(0.430)	(0.827)	(0.029)	(0.786)	(1.071)	(0.334)	(1.061)	(1.363)	(0.912)	(0.831)	(0.246)
lag	0.323	0.214	0.079	0.207	0.105	-0.006	0.070	0.035	0.015	-0.062	0.297	0.564
(t-stat)	(2.617)	(1.502)	(0.512)	(1.597)	(0.693)	(0.046)	(0.581)	(0.240)	(0.093)	(0.510)	(1.417)	(3.710)
variable	-2.579	-2.042	-2.211	-4.109	-3.661	-2.732	-6.077	-4.928	-3.917	-2.138	-0.337	-0.072
(t-stat)	(2.453)	(2.744)	(3.131)	(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	0.478	0.478	0.487	0.503	0.517	0.523	0.557	0.547	0.511	0.613	0.394	0.402
Panel C: Real investment growth												
variables in $t-1$												
r	-0.010	-0.267	-0.432	-0.033	-0.326	-0.423	-0.066	-0.352	-0.500	-0.150	-0.021	-0.106
(t-stat)	(0.104)	(2.174)	(2.489)	(0.346)	(2.247)	(2.364)	(0.627)	(2.246)	(2.262)	(1.679)	(0.280)	(1.374)
term	0.275	0.124	0.151	0.346	0.127	0.149	0.301	0.110	0.082	0.277	0.643	0.013
(t-stat)	(2.636)	(1.098)	(1.246)	(3.061)	(0.989)	(1.204)	(2.310)	(0.761)	(0.511)	(1.900)	(3.233)	(0.107)
lag	0.367	0.227	0.196	0.317	0.294	0.223	0.327	0.332	0.350	0.618	0.279	0.643
(t-stat)	(4.735)	(1.873)	(1.228)	(2.495)	(1.834)	(1.368)	(2.103)	(2.121)	(2.514)	(4.918)	(1.437)	(7.225)
variable	-5.252	-4.151	-3.760	-7.459	-5.575	-3.832	-8.274	-6.099	-4.532	-0.774	-0.794	-0.141
(t-stat)	(9.663)	(5.256)	(3.481)	(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	0.699	0.681	0.653	0.715	0.670	0.639	0.680	0.639	0.604	0.510	0.566	0.585
variables in $t-2$												
r	-0.102	-0.671	-1.093	-0.187	-0.833	-1.069	-0.253	-0.896	-1.267	-0.476	-0.207	-0.280
(t-stat)	(0.490)	(2.177)	(2.267)	(0.727)	(1.852)	(2.118)	(0.888)	(1.781)	(1.740)	(1.505)	(0.959)	(1.194)
term	0.693	0.305	0.293	0.788	0.322	0.315	0.713	0.286	0.182	0.864	1.503	0.235
(t-stat)	(2.469)	(0.889)	(0.762)	(2.448)	(0.760)	(0.786)	(1.985)	(0.607)	(0.338)	(2.458)	(2.937)	(0.654)
lag	0.264	0.107	0.010	0.191	0.121	0.032	0.180	0.157	0.152	0.439	0.000	0.526
(t-stat)	(4.523)	(0.798)	(0.044)	(1.231)	(0.525)	(0.139)	(0.909)	(0.675)	(0.630)	(2.778)	(0.000)	(5.339)
variable	-10.980	-8.317	-7.993	-15.654	-12.178	-8.245	-17.831	-13.406	-10.142	-2.343	-1.929	-0.300

	IBOR-OIS spread (SFS)			3-month FFS ($F^{(x)}_{3m,3m}$)			12-month FFS ($F^{(x)}_{12m,12m}$)			CDS spread	GZ spread	Goldberg var.
Tenor x	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$			
(t-stat)	(8.196)	(5.721)	(3.425)	(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	0.669	0.627	0.596	0.691	0.634	0.578	0.649	0.585	0.526	0.413	0.470	0.476
variables in $t-4$												
r	-0.670	-1.559	-2.197	-0.823	-1.823	-2.195	-0.948	-1.938	-2.487	-1.353	-1.027	-0.823
(t-stat)	(1.015)	(1.894)	(2.006)	(1.018)	(1.677)	(1.964)	(1.106)	(1.639)	(1.624)	(1.464)	(1.159)	(1.236)
term	1.694	1.018	0.873	1.778	1.006	0.926	1.645	0.988	0.778	2.392	2.597	1.163
(t-stat)	(2.141)	(1.079)	(0.785)	(1.902)	(0.869)	(0.813)	(1.596)	(0.793)	(0.553)	(2.900)	(3.146)	(1.428)
lag	0.202	0.101	0.030	0.163	0.104	0.031	0.132	0.112	0.105	0.290	-0.053	0.431
(t-stat)	(2.699)	(1.018)	(0.205)	(1.443)	(0.667)	(0.202)	(0.914)	(0.658)	(0.548)	(1.603)	(0.245)	(3.377)
variable	-17.471	-12.492	-11.250	-23.489	-18.088	-12.078	-27.543	-20.566	-14.891	-5.238	-2.967	-0.563
(t-stat)	(4.631)	(5.071)	(4.048)	(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	0.601	0.569	0.520	0.597	0.558	0.522	0.577	0.526	0.457	0.433	0.435	0.456
Panel D: Unemployment rate change												
variables in $t-1$												
r	0.011	0.054	0.092	0.018	0.067	0.090	0.024	0.072	0.104	0.032	0.016	0.024
(t-stat)	(0.923)	(3.934)	(5.469)	(1.210)	(3.712)	(4.676)	(1.407)	(3.406)	(3.354)	(2.426)	(0.871)	(1.725)
term	-0.010	0.021	0.024	-0.014	0.023	0.023	-0.008	0.024	0.031	-0.014	-0.091	0.014
(t-stat)	(0.661)	(1.487)	(1.608)	(0.925)	(1.208)	(1.382)	(0.412)	(1.071)	(1.181)	(0.612)	(2.049)	(0.630)
lag	0.496	0.318	0.180	0.409	0.327	0.218	0.380	0.357	0.336	0.675	0.093	0.735
(t-stat)	(5.067)	(4.281)	(2.263)	(6.508)	(3.826)	(2.601)	(4.823)	(3.732)	(3.363)	(5.394)	(0.359)	(6.882)
variable	0.766	0.657	0.690	1.104	0.908	0.696	1.314	1.020	0.829	0.109	0.192	1.120
(t-stat)	(10.245)	(10.288)	(7.800)	(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	0.763	0.774	0.775	0.760	0.735	0.756	0.745	0.715	0.698	0.592	0.701	0.593
variables in $t-2$												
r	0.031	0.129	0.217	0.050	0.164	0.210	0.064	0.178	0.253	0.093	0.062	0.046
(t-stat)	(1.235)	(4.309)	(4.524)	(1.456)	(3.041)	(3.947)	(1.644)	(2.823)	(2.551)	(2.119)	(1.421)	(1.428)
term	-0.052	0.027	0.048	-0.055	0.032	0.040	-0.038	0.038	0.061	-0.086	-0.193	-0.012
(t-stat)	(1.700)	(0.910)	(1.233)	(1.892)	(0.671)	(0.935)	(0.978)	(0.640)	(0.805)	(1.554)	(3.010)	(0.298)
lag	0.428	0.243	0.080	0.323	0.217	0.116	0.277	0.237	0.208	0.560	-0.075	0.715
(t-stat)	(6.950)	(4.412)	(0.825)	(6.319)	(1.810)	(0.997)	(3.066)	(1.681)	(1.156)	(3.525)	(0.246)	(5.431)
variable	1.735	1.396	1.440	2.531	2.083	1.474	3.033	2.369	1.879	0.382	0.417	4.244
(t-stat)	(10.718)	(11.647)	(7.185)	(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	0.806	0.798	0.781	0.821	0.787	0.764	0.800	0.751	0.703	0.574	0.670	0.612
variables in $t-4$												
r	0.155	0.354	0.525	0.197	0.424	0.516	0.235	0.464	0.628	0.320	0.259	0.168
(t-stat)	(1.727)	(3.206)	(3.489)	(1.599)	(2.575)	(3.386)	(1.778)	(2.532)	(2.535)	(1.975)	(1.764)	(1.581)
term	-0.148	0.027	0.100	-0.142	0.047	0.079	-0.094	0.063	0.137	-0.267	-0.285	-0.106
(t-stat)	(1.924)	(0.255)	(0.706)	(1.318)	(0.291)	(0.534)	(0.691)	(0.339)	(0.591)	(2.133)	(2.779)	(1.184)
lag	0.263	0.106	-0.039	0.185	0.078	-0.021	0.113	0.062	0.007	0.290	-0.141	0.547
(t-stat)	(3.980)	(2.191)	(0.454)	(3.071)	(0.716)	(0.223)	(1.209)	(0.486)	(0.048)	(1.602)	(0.800)	(3.555)
variable	3.467	2.626	2.562	4.825	3.922	2.713	5.907	4.646	3.693	1.105	0.681	9.667
(t-stat)	(5.210)	(6.303)	(6.310)	(6.801)	(5.188)	(6.051)	(5.313)	(4.244)	(3.661)	(1.816)	(4.356)	(3.472)

	IBOR-OIS spread (SFS)			3-month FFS ($F^{(x)}_{3m,3m}$)			12-month FFS ($F^{(x)}_{12m,12m}$)			CDS spread	GZ spread	Goldberg var.
Tenor x	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$			
variable												-2.339
(t-stat)												(0.818)
Adj. R^2	0.688	0.686	0.664	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 1 quarter, 2 quarters, and 4 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 OA3. Predicting U.S. Bank Lending Variables using Funding and Credit Spreads

	IBOR-OIS spread (SFS)			3-month FFS ($F^{(x)}_{3m,3m}$)			12-month FFS ($F^{(x)}_{12m,12m}$)			CDS spread	GZ spread	Goldberg var.
Tenor x	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$			
Panel A: Bank lending growth												
variables in $t-1$												
r	0.050	0.021	-0.012	0.042	0.006	-0.015	0.046	-0.006	-0.061	0.010	0.072	0.004
(t-stat)	(0.531)	(0.222)	(0.122)	(0.446)	(0.068)	(0.147)	(0.489)	(0.067)	(0.580)	(0.102)	(0.653)	(0.039)
$term$	-0.281	-0.287	-0.280	-0.296	-0.317	-0.282	-0.292	-0.317	-0.319	-0.309	-0.195	-0.348
(t-stat)	(1.663)	(1.941)	(1.975)	(1.710)	(2.113)	(2.029)	(1.851)	(2.320)	(2.528)	(1.616)	(1.121)	(2.053)
lag	0.219	0.222	0.203	0.186	0.177	0.197	0.176	0.170	0.162	0.147	0.167	0.217
(t-stat)	(1.366)	(1.622)	(1.678)	(1.248)	(1.329)	(1.684)	(1.353)	(1.444)	(1.532)	(1.066)	(1.304)	(1.359)
variable	-0.794	-0.779	-0.837	-0.867	-0.885	-0.916	-1.316	-1.334	-1.348	-0.195	-0.176	-0.027
(t-stat)	(1.336)	(2.137)	(2.380)	(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	0.265	0.289	0.311	0.260	0.273	0.315	0.272	0.290	0.315	0.252	0.286	0.252
variables in $t-2$												
r	0.105	0.051	-0.038	0.110	0.007	-0.043	0.117	-0.028	-0.180	-0.003	0.209	0.020
(t-stat)	(0.526)	(0.274)	(0.204)	(0.576)	(0.035)	(0.227)	(0.626)	(0.151)	(0.926)	(0.015)	(0.883)	(0.094)
$term$	-0.549	-0.493	-0.454	-0.524	-0.555	-0.453	-0.521	-0.578	-0.592	-0.403	-0.149	-0.736
(t-stat)	(1.342)	(1.418)	(1.405)	(1.398)	(1.753)	(1.442)	(1.536)	(1.997)	(2.257)	(1.017)	(0.353)	(1.711)
lag	0.156	0.205	0.199	0.141	0.147	0.191	0.123	0.125	0.118	0.104	0.171	0.059
(t-stat)	(0.791)	(1.208)	(1.354)	(0.813)	(0.977)	(1.386)	(0.808)	(0.932)	(0.973)	(0.646)	(1.017)	(0.260)
variable	-1.650	-2.004	-2.246	-2.623	-2.832	-2.474	-3.735	-3.775	-3.704	-1.129	-0.532	0.025
(t-stat)	(1.861)	(2.855)	(3.342)	(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	0.335	0.407	0.472	0.353	0.405	0.483	0.380	0.431	0.493	0.385	0.434	0.290
variables in $t-4$												
r	0.321	0.096	-0.134	0.330	-0.016	-0.133	0.333	-0.086	-0.446	-0.008	0.504	0.059
(t-stat)	(0.981)	(0.306)	(0.495)	(1.013)	(0.052)	(0.496)	(1.043)	(0.294)	(1.838)	(0.021)	(1.329)	(0.160)
$term$	-0.575	-0.565	-0.448	-0.530	-0.731	-0.468	-0.590	-0.812	-0.845	-0.416	0.380	-1.157
(t-stat)	(0.959)	(1.162)	(1.069)	(1.033)	(1.648)	(1.145)	(1.228)	(1.901)	(2.440)	(0.589)	(0.609)	(1.606)
lag	0.285	0.328	0.344	0.243	0.239	0.320	0.197	0.191	0.198	0.156	0.323	0.183
(t-stat)	(1.973)	(2.992)	(3.902)	(1.977)	(2.136)	(3.620)	(1.687)	(1.773)	(2.228)	(0.947)	(2.272)	(0.944)
variable	-6.190	-5.481	-5.649	-9.237	-8.063	-6.054	-11.675	-10.089	-9.055	-2.789	-1.343	-0.071
(t-stat)	(6.004)	(7.239)	(9.255)	(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	0.551	0.665	0.760	0.614	0.682	0.766	0.658	0.714	0.792	0.561	0.671	0.366
Panel B: Consumer loan growth												
variables in $t-1$												
r	-0.367	-0.207	-0.182	-0.277	-0.194	-0.182	-0.224	-0.185	-0.196	-0.187	-0.115	-0.221
(t-stat)	(2.055)	(1.282)	(1.138)	(1.769)	(1.309)	(1.129)	(1.553)	(1.196)	(1.149)	(1.151)	(0.661)	(1.181)
$term$	-0.797	-0.545	-0.474	-0.662	-0.522	-0.469	-0.567	-0.488	-0.455	-0.473	-0.323	-0.556
(t-stat)	(2.698)	(2.315)	(2.159)	(2.686)	(2.643)	(2.137)	(2.656)	(2.469)	(2.234)	(2.495)	(1.350)	(2.111)
lag	0.173	0.351	0.408	0.285	0.370	0.411	0.346	0.397	0.424	0.395	0.450	0.289
(t-stat)	(1.031)	(2.450)	(3.079)	(2.190)	(3.384)	(3.080)	(3.051)	(3.516)	(3.480)	(3.426)	(3.293)	(1.558)
variable	1.771	0.244	-0.112	1.303	0.222	-0.148	0.738	-0.103	-0.455	-0.073	-0.135	0.048
(t-stat)	(2.140)	(0.452)	(0.245)	(1.096)	(0.247)	(0.303)	(0.535)	(0.107)	(0.657)	(0.214)	(1.190)	(1.122)
variable												-0.052

	IBOR-OIS spread (SFS)			3-month FFS ($F^{(x)}_{3m,3m}$)			12-month FFS ($F^{(x)}_{12m,12m}$)			CDS spread	GZ spread	Goldberg var.
Tenor x	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$			
(t-stat)												(1.512)
Adj. R^2	0.404	0.367	0.366	0.380	0.366	0.366	0.369	0.365	0.369	0.366	0.378	0.385
variables in $t-2$												
r	-0.433	-0.146	-0.195	-0.349	-0.287	-0.211	-0.294	-0.304	-0.399	-0.387	0.120	-0.524
(t-stat)	(0.983)	(0.470)	(0.667)	(1.003)	(1.027)	(0.688)	(1.003)	(1.035)	(1.243)	(1.129)	(0.432)	(1.248)
$term$	-1.224	-0.636	-0.497	-1.079	-0.862	-0.530	-0.978	-0.840	-0.744	-0.971	-0.007	-1.354
(t-stat)	(1.515)	(1.240)	(1.283)	(1.579)	(1.813)	(1.335)	(1.769)	(1.982)	(1.936)	(1.897)	(0.021)	(2.002)
lag	0.282	0.537	0.583	0.334	0.434	0.567	0.369	0.444	0.492	0.335	0.576	0.185
(t-stat)	(1.006)	(2.931)	(4.264)	(1.419)	(2.538)	(4.080)	(1.912)	(3.039)	(3.882)	(1.941)	(4.809)	(0.800)
variable	0.169	-2.121	-2.472	-0.740	-2.055	-2.534	-1.791	-2.898	-3.342	-0.556	-0.734	0.085
(t-stat)	(0.091)	(2.679)	(4.085)	(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	0.402	0.432	0.462	0.404	0.419	0.458	0.408	0.429	0.459	0.412	0.489	0.411
variables in $t-4$												
r	-1.035	-0.719	-0.681	-0.781	-0.824	-0.747	-0.708	-0.888	-1.115	-1.058	0.173	-1.266
(t-stat)	(1.013)	(0.771)	(0.831)	(0.816)	(0.960)	(0.894)	(0.793)	(1.053)	(1.408)	(1.248)	(0.219)	(1.552)
$term$	-3.095	-2.372	-1.753	-2.629	-2.385	-1.925	-2.484	-2.395	-2.168	-2.535	-0.343	-3.323
(t-stat)	(1.793)	(1.486)	(1.365)	(1.613)	(1.690)	(1.501)	(1.705)	(1.827)	(1.886)	(2.217)	(0.321)	(2.581)
lag	0.124	0.308	0.452	0.210	0.299	0.403	0.237	0.294	0.366	0.161	0.489	0.047
(t-stat)	(0.430)	(1.132)	(1.993)	(0.802)	(1.257)	(1.806)	(0.992)	(1.318)	(1.770)	(0.821)	(2.222)	(0.210)
variable	-0.905	-3.795	-5.594	-4.821	-6.112	-5.323	-7.255	-7.683	-8.293	-1.847	-1.802	0.164
(t-stat)	(0.327)	(1.952)	(4.007)	(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	0.492	0.529	0.589	0.513	0.546	0.572	0.528	0.555	0.602	0.526	0.650	0.513
Panel C: Real estate loan growth												
variables in $t-1$												
r	0.031	0.020	0.010	0.019	0.019	0.005	0.029	0.010	-0.017	0.020	0.013	0.007
(t-stat)	(0.226)	(0.156)	(0.073)	(0.138)	(0.148)	(0.040)	(0.215)	(0.074)	(0.123)	(0.148)	(0.095)	(0.051)
$term$	-0.454	-0.456	-0.452	-0.489	-0.480	-0.443	-0.462	-0.463	-0.458	-0.476	-0.511	-0.475
(t-stat)	(1.706)	(1.870)	(1.883)	(1.704)	(1.944)	(1.923)	(1.779)	(2.106)	(2.207)	(1.764)	(1.579)	(2.247)
lag	0.312	0.316	0.315	0.288	0.293	0.319	0.300	0.303	0.307	0.290	0.282	0.326
(t-stat)	(1.266)	(1.330)	(1.379)	(1.164)	(1.271)	(1.477)	(1.367)	(1.492)	(1.567)	(1.494)	(1.190)	(1.574)
variable	-0.284	-0.258	-0.267	0.053	-0.076	-0.387	-0.411	-0.582	-0.641	-0.033	0.025	-0.015
(t-stat)	(0.316)	(0.420)	(0.476)	(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	0.420	0.422	0.423	0.419	0.419	0.426	0.421	0.424	0.428	0.419	0.419	0.414
variables in $t-2$												
r	-0.011	-0.016	-0.063	-0.007	-0.028	-0.070	0.016	-0.050	-0.146	-0.038	0.060	-0.014
(t-stat)	(0.046)	(0.067)	(0.270)	(0.026)	(0.120)	(0.302)	(0.066)	(0.213)	(0.595)	(0.162)	(0.237)	(0.058)
$term$	-0.762	-0.676	-0.617	-0.747	-0.702	-0.602	-0.692	-0.687	-0.668	-0.553	-0.442	-0.792
(t-stat)	(1.610)	(1.606)	(1.581)	(1.553)	(1.713)	(1.620)	(1.587)	(1.891)	(2.042)	(1.341)	(0.895)	(1.919)
lag	0.406	0.443	0.464	0.409	0.426	0.464	0.417	0.426	0.438	0.404	0.470	0.368
(t-stat)	(1.817)	(2.056)	(2.250)	(1.860)	(2.087)	(2.415)	(2.106)	(2.334)	(2.505)	(2.249)	(2.194)	(1.647)
variable	-0.068	-0.796	-1.119	-0.282	-1.066	-1.397	-1.410	-1.998	-2.208	-0.822	-0.265	0.060
(t-stat)	(0.062)	(0.886)	(1.272)	(0.147)	(0.662)	(1.511)	(0.585)	(1.090)	(1.567)	(1.604)	(1.235)	(1.812)
variable												-0.016

	IBOR-OIS spread (SFS)			3-month FFS ($F^{(x)}_{3m,3m}$)			12-month FFS ($F^{(x)}_{12m,12m}$)			CDS spread	GZ spread	Goldberg var.
Tenor x	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$			
(t-stat)												(0.211)
Adj. R^2	0.529	0.537	0.549	0.529	0.536	0.558	0.534	0.547	0.563	0.552	0.544	0.531
variables in $t-4$												
r	-0.345	-0.479	-0.685	-0.327	-0.520	-0.667	-0.289	-0.565	-0.891	-0.477	-0.200	-0.452
(t-stat)	(0.757)	(1.118)	(1.702)	(0.725)	(1.217)	(1.670)	(0.666)	(1.360)	(2.285)	(1.076)	(0.470)	(0.975)
term	-1.267	-1.155	-0.939	-1.216	-1.240	-0.970	-1.161	-1.248	-1.179	-0.966	0.015	-1.514
(t-stat)	(1.140)	(1.162)	(1.086)	(1.167)	(1.337)	(1.139)	(1.226)	(1.457)	(1.578)	(1.070)	(0.019)	(1.509)
lag	0.521	0.564	0.612	0.512	0.528	0.589	0.506	0.514	0.546	0.464	0.669	0.475
(t-stat)	(2.502)	(3.188)	(4.352)	(2.721)	(3.248)	(4.475)	(3.041)	(3.550)	(4.623)	(2.687)	(4.496)	(2.202)
variable	-2.865	-3.336	-4.178	-4.558	-4.978	-4.539	-7.143	-7.010	-7.144	-2.226	-1.186	0.065
(t-stat)	(1.770)	(2.674)	(3.437)	(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	0.665	0.697	0.741	0.674	0.701	0.747	0.696	0.722	0.764	0.702	0.742	0.644
Panel D: C&I loan growth												
variables in $t-1$												
r	0.380	0.233	0.123	0.331	0.172	0.118	0.308	0.139	0.009	0.181	0.395	0.215
(t-stat)	(3.639)	(2.197)	(1.058)	(3.107)	(1.604)	(0.952)	(2.607)	(1.166)	(0.067)	(1.312)	(3.391)	(1.997)
term	0.357	0.237	0.198	0.297	0.148	0.190	0.241	0.118	0.069	0.238	0.530	0.096
(t-stat)	(2.712)	(1.971)	(1.597)	(1.842)	(0.932)	(1.540)	(1.475)	(0.712)	(0.402)	(1.001)	(4.438)	(0.523)
lag	0.913	0.872	0.817	0.861	0.824	0.814	0.831	0.806	0.774	0.816	0.744	0.929
(t-stat)	(11.54)	(13.94)	(15.47)	(11.03)	(12.24)	(15.06)	(11.72)	(12.28)	(12.37)	(11.51)	(15.54)	(10.05)
variable	-3.636	-2.736	-2.452	-3.955	-3.107	-2.570	-4.486	-3.749	-3.260	-0.769	-0.653	-0.125
(t-stat)	(6.406)	(7.082)	(6.559)	(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	0.794	0.817	0.819	0.768	0.772	0.814	0.765	0.773	0.782	0.722	0.814	0.749
variables in $t-2$												
r	1.108	0.770	0.414	1.059	0.567	0.409	0.991	0.440	-0.013	0.552	1.282	0.624
(t-stat)	(3.328)	(2.502)	(1.372)	(3.147)	(1.779)	(1.240)	(2.697)	(1.253)	(0.036)	(1.195)	(4.343)	(1.429)
term	0.958	0.819	0.725	0.996	0.622	0.737	0.847	0.468	0.257	1.118	1.900	0.136
(t-stat)	(1.758)	(1.968)	(2.066)	(1.877)	(1.309)	(2.072)	(1.610)	(0.946)	(0.560)	(1.705)	(5.591)	(0.152)
lag	0.811	0.805	0.739	0.782	0.746	0.740	0.740	0.707	0.652	0.734	0.654	0.732
(t-stat)	(7.762)	(7.794)	(8.747)	(6.491)	(6.798)	(8.562)	(6.617)	(6.844)	(7.260)	(8.701)	(11.049)	(5.659)
variable	-9.077	-7.876	-7.477	-12.384	-10.483	-7.926	-14.488	-12.263	-10.590	-3.432	-2.101	-0.143
(t-stat)	(11.466)	(7.809)	(7.942)	(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	0.675	0.775	0.816	0.694	0.735	0.809	0.697	0.727	0.757	0.633	0.847	0.533
variables in $t-4$												
r	2.152	1.382	0.498	2.145	0.798	0.502	1.968	0.431	-0.812	0.690	2.830	0.560
(t-stat)	(1.988)	(1.668)	(0.704)	(2.337)	(0.956)	(0.643)	(2.006)	(0.465)	(0.920)	(0.473)	(4.138)	(0.366)
term	0.390	0.317	0.336	0.800	-0.141	0.374	0.471	-0.572	-1.120	0.741	3.690	-2.326
(t-stat)	(0.178)	(0.228)	(0.372)	(0.502)	(0.111)	(0.402)	(0.322)	(0.431)	(1.021)	(0.336)	(4.111)	(0.741)
lag	0.390	0.427	0.390	0.387	0.357	0.386	0.335	0.293	0.234	0.290	0.337	0.191
(t-stat)	(3.323)	(4.081)	(4.295)	(3.853)	(3.383)	(4.133)	(3.616)	(3.007)	(2.573)	(2.319)	(4.093)	(0.972)
variable	-23.618	-20.181	-19.610	-34.528	-28.842	-20.605	-40.960	-33.598	-28.601	-8.539	-5.379	-0.215
(t-stat)	(7.471)	(9.828)	(11.95)	(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)

	IBOR-OIS spread (SFS)			3-month FFS ($F^{(x)}_{3m,3m}$)			12-month FFS ($F^{(x)}_{12m,12m}$)			CDS spread	GZ spread	Goldberg var.
Tenor x	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$			
Adj. R^2	0.507	0.671	0.773	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 1, 2, and 4 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 OA4. Predicting Euro Area Real Activity Variables using Funding and Credit Spreads

	IBOR-OIS spread (SFS)			3-month FFS ($F^{(x)}_{3m,3m}$)			12-month FFS ($F^{(x)}_{12m,12m}$)			CDS spread	GM spread
Tenor x	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$		
Panel A: Real GDP growth											
variables in $t-1$											
r	0.198	0.204	0.179	0.139	0.141	0.129	0.136	0.155	0.111	-0.032	-0.083
(t-stat)	(3.458)	(3.100)	(3.011)	(3.510)	(3.953)	(3.067)	(3.248)	(3.984)	(3.184)	(0.805)	(1.231)
$term$	0.131	0.188	0.270	0.130	0.196	0.268	0.178	0.269	0.358	0.182	0.257
(t-stat)	(1.973)	(2.351)	(2.553)	(2.703)	(3.151)	(2.817)	(3.326)	(3.300)	(3.095)	(1.612)	(1.761)
lag	0.185	0.116	0.126	0.183	0.188	0.063	0.034	0.177	0.188	0.583	0.372
(t-stat)	(0.885)	(0.554)	(0.691)	(1.007)	(1.184)	(0.353)	(0.153)	(1.072)	(1.223)	(3.411)	(2.281)
variable	-2.688	-1.770	-1.567	-3.806	-2.222	-1.676	-5.175	-2.860	-2.413	-0.173	-0.499
(t-stat)	(3.021)	(2.971)	(3.056)	(3.008)	(3.759)	(3.405)	(3.371)	(3.641)	(3.276)	(2.253)	(2.327)
Adj. R^2	0.597	0.630	0.655	0.596	0.615	0.683	0.663	0.619	0.632	0.385	0.462
Variables in $t-2$											
r	0.386	0.419	0.377	0.330	0.343	0.280	0.296	0.372	0.272	-0.021	-0.110
(t-stat)	(4.343)	(4.038)	(3.667)	(3.959)	(4.555)	(3.551)	(3.573)	(4.655)	(3.653)	(0.250)	(1.094)
$term$	0.348	0.428	0.580	0.320	0.471	0.563	0.401	0.636	0.815	0.525	0.613
(t-stat)	(1.569)	(2.269)	(2.636)	(2.576)	(3.793)	(2.812)	(3.093)	(4.053)	(3.543)	(1.517)	(1.714)
lag	0.211	0.058	0.066	0.033	0.004	-0.003	-0.046	0.020	0.063	0.484	0.249
(t-stat)	(1.272)	(0.379)	(0.483)	(0.183)	(0.024)	(0.022)	(0.273)	(0.126)	(0.467)	(2.390)	(1.351)
variable	-4.262	-3.222	-2.861	-8.421	-5.109	-3.042	-9.949	-6.353	-5.067	-0.414	-1.007
(t-stat)	(8.549)	(6.004)	(5.137)	(4.027)	(5.061)	(6.188)	(5.745)	(5.261)	(4.614)	(2.029)	(2.865)
Adj. R^2	0.475	0.573	0.598	0.674	0.726	0.623	0.679	0.712	0.676	0.303	0.378
Variables in $t-4$											
r	0.655	0.662	0.563	0.505	0.502	0.379	0.413	0.560	0.379	-0.233	-0.384
(t-stat)	(3.980)	(4.049)	(3.569)	(3.571)	(3.676)	(2.654)	(2.384)	(3.990)	(2.599)	(0.953)	(2.224)
$term$	0.588	0.638	0.889	0.504	0.708	0.827	0.597	1.011	1.320	1.006	1.021
(t-stat)	(1.186)	(1.637)	(2.032)	(1.944)	(2.782)	(1.990)	(2.010)	(3.346)	(3.168)	(1.217)	(1.360)
lag	0.008	-0.167	-0.162	-0.116	-0.185	-0.224	-0.180	-0.174	-0.162	0.185	-0.073
(t-stat)	(0.066)	(1.562)	(1.533)	(0.966)	(1.514)	(2.158)	(1.505)	(1.430)	(1.529)	(0.886)	(0.494)
variable	-8.087	-5.910	-5.114	-14.994	-9.084	-5.341	-16.539	-11.330	-9.125	-1.016	-2.088
(t-stat)	(4.497)	(5.605)	(5.425)	(5.721)	(7.863)	(5.526)	(5.471)	(7.664)	(6.676)	(2.069)	(4.259)
Adj. R^2	0.393	0.532	0.520	0.658	0.703	0.555	0.605	0.683	0.619	0.150	0.268
Panel B: Real consumption growth											
variables in $t-1$											
r	0.086	0.102	0.092	0.081	0.087	0.068	0.069	0.094	0.066	-0.038	-0.043
(t-stat)	(3.201)	(4.079)	(3.707)	(3.437)	(3.851)	(2.785)	(2.642)	(4.156)	(2.916)	(1.310)	(1.566)
$term$	-0.021	0.000	0.036	-0.031	0.005	0.031	-0.009	0.045	0.090	0.028	0.048
(t-stat)	(0.438)	(0.001)	(0.872)	(1.009)	(0.195)	(0.774)	(0.274)	(1.668)	(2.325)	(0.458)	(0.740)
lag	0.191	0.066	0.057	0.013	-0.032	0.035	0.035	-0.028	0.006	0.390	0.222
(t-stat)	(0.808)	(0.306)	(0.271)	(0.053)	(0.147)	(0.169)	(0.146)	(0.127)	(0.030)	(1.602)	(0.880)
variable	-1.038	-0.797	-0.711	-2.017	-1.270	-0.723	-2.139	-1.599	-1.287	-0.125	-0.265
(t-stat)	(3.295)	(4.625)	(4.674)	(3.632)	(5.269)	(4.988)	(3.975)	(5.265)	(5.246)	(2.030)	(2.720)
Adj. R^2	0.400	0.476	0.485	0.489	0.538	0.491	0.464	0.534	0.520	0.313	0.364
Variables in $t-2$											
r	0.121	0.145	0.133	0.126	0.138	0.101	0.102	0.147	0.107	-0.033	-0.012
(t-stat)	(2.767)	(3.160)	(2.931)	(2.866)	(2.843)	(2.143)	(1.993)	(3.090)	(2.308)	(0.580)	(0.189)
$term$	0.077	0.090	0.133	0.038	0.082	0.124	0.078	0.142	0.208	0.156	0.145
(t-stat)	(0.734)	(1.030)	(1.586)	(0.567)	(1.545)	(1.426)	(0.993)	(2.606)	(2.900)	(1.295)	(1.176)
lag	0.569	0.447	0.433	0.358	0.288	0.423	0.434	0.299	0.341	0.695	0.624
(t-stat)	(3.571)	(3.615)	(3.963)	(2.256)	(2.230)	(3.558)	(3.155)	(2.485)	(3.280)	(4.159)	(3.313)

	IBOR-OIS spread (SFS)			3-month FFS ($F^{(x)}_{3m,3m}$)			12-month FFS ($F^{(x)}_{12m,12m}$)			CDS spread	GM spread
Tenor x	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$		
variable	-1.227	-0.997	-0.901	-2.874	-1.873	-0.883	-2.633	-2.319	-1.808	-0.171	-0.239
(t-stat)	(1.934)	(3.095)	(3.604)	(4.181)	(6.972)	(3.386)	(3.418)	(6.743)	(6.389)	(1.769)	(1.768)
Adj. R^2	0.599	0.638	0.644	0.680	0.714	0.634	0.630	0.705	0.684	0.572	0.556
Variables in $t-4$											
r	0.271	0.302	0.264	0.226	0.241	0.188	0.188	0.266	0.182	-0.112	-0.101
(t-stat)	(2.106)	(2.089)	(1.907)	(1.654)	(1.632)	(1.330)	(1.206)	(1.817)	(1.347)	(0.656)	(0.636)
$term$	0.123	0.123	0.223	-0.009	0.073	0.186	0.097	0.215	0.365	0.340	0.288
(t-stat)	(0.389)	(0.463)	(0.883)	(0.037)	(0.370)	(0.703)	(0.377)	(1.169)	(1.822)	(0.887)	(0.741)
lag	0.320	0.172	0.159	0.103	0.028	0.125	0.177	0.043	0.062	0.497	0.322
(t-stat)	(1.563)	(0.906)	(0.858)	(0.530)	(0.146)	(0.662)	(0.887)	(0.229)	(0.331)	(1.798)	(1.074)
variable	-3.310	-2.460	-2.184	-6.633	-4.165	-2.167	-6.294	-5.186	-4.174	-0.414	-0.708
(t-stat)	(2.328)	(3.228)	(3.584)	(5.082)	(5.794)	(3.564)	(3.406)	(5.357)	(5.427)	(1.556)	(2.147)
Adj. R^2	0.418	0.479	0.483	0.545	0.586	0.464	0.458	0.576	0.542	0.313	0.311
Panel C: Real investment growth											
variables in $t-1$											
r	0.230	0.251	0.163	0.040	0.052	-0.018	-0.002	0.099	-0.065	-0.707	-0.878
(t-stat)	(1.002)	(1.234)	(0.856)	(0.176)	(0.253)	(0.095)	(0.008)	(0.494)	(0.330)	(1.970)	(2.315)
$term$	-0.342	-0.136	0.131	-0.346	-0.111	0.109	-0.179	0.150	0.460	-0.199	0.204
(t-stat)	(1.577)	(0.766)	(0.713)	(1.871)	(0.636)	(0.677)	(1.053)	(0.858)	(2.513)	(0.560)	(0.565)
lag	-0.527	-0.583	-0.587	-0.556	-0.571	-0.606	-0.601	-0.585	-0.583	-0.385	-0.506
(t-stat)	(3.441)	(4.111)	(4.035)	(3.802)	(3.917)	(4.272)	(4.313)	(4.016)	(3.861)	(1.631)	(2.847)
variable	-9.104	-6.023	-5.318	-13.452	-8.017	-5.422	-16.211	-10.297	-8.662	-0.850	-2.241
(t-stat)	(5.896)	(6.389)	(6.251)	(4.480)	(6.147)	(6.961)	(6.737)	(6.377)	(5.972)	(2.667)	(3.113)
Adj. R^2	0.396	0.459	0.466	0.419	0.442	0.486	0.467	0.447	0.448	0.128	0.301
Variables in $t-2$											
r	0.491	0.506	0.396	0.249	0.261	0.133	0.159	0.328	0.104	-0.601	-0.825
(t-stat)	(1.793)	(1.922)	(1.728)	(0.969)	(1.130)	(0.630)	(0.585)	(1.436)	(0.572)	(2.300)	(3.301)
$term$	0.166	0.320	0.685	0.059	0.364	0.622	0.240	0.745	1.201	0.665	0.885
(t-stat)	(0.329)	(0.822)	(1.675)	(0.189)	(1.467)	(1.670)	(0.799)	(2.653)	(3.208)	(0.846)	(1.173)
lag	0.111	-0.028	-0.044	-0.010	-0.068	-0.082	-0.060	-0.062	-0.051	0.325	0.138
(t-stat)	(0.651)	(0.198)	(0.346)	(0.067)	(0.537)	(0.673)	(0.451)	(0.515)	(0.495)	(1.466)	(0.857)
variable	-11.170	-8.052	-7.275	-19.083	-11.877	-7.430	-22.151	-14.830	-12.354	-1.203	-2.721
(t-stat)	(6.685)	(7.813)	(7.393)	(4.777)	(7.231)	(8.585)	(7.214)	(7.833)	(7.378)	(2.728)	(4.194)
Adj. R^2	0.419	0.521	0.548	0.533	0.592	0.561	0.547	0.575	0.569	0.190	0.315
Variables in $t-4$											
r	0.643	0.616	0.375	0.222	0.172	-0.085	-0.009	0.295	-0.128	-1.585	-1.779
(t-stat)	(1.138)	(1.192)	(0.874)	(0.455)	(0.398)	(0.204)	(0.016)	(0.705)	(0.418)	(2.854)	(4.226)
$term$	0.413	0.440	1.022	0.144	0.489	0.855	0.316	1.167	1.967	1.784	1.673
(t-stat)	(0.308)	(0.423)	(0.969)	(0.186)	(0.784)	(0.836)	(0.379)	(1.730)	(2.251)	(0.858)	(0.888)
lag	0.053	-0.135	-0.147	-0.069	-0.180	-0.194	-0.140	-0.191	-0.177	0.279	0.040
(t-stat)	(0.308)	(0.951)	(1.089)	(0.503)	(1.398)	(1.517)	(1.068)	(1.532)	(1.720)	(1.055)	(0.201)
variable	-19.711	-14.268	-12.593	-34.784	-21.674	-12.763	-38.535	-27.418	-22.346	-2.797	-5.046
(t-stat)	(5.046)	(6.442)	(6.340)	(6.135)	(8.900)	(6.549)	(6.376)	(9.086)	(8.293)	(2.658)	(5.113)
Adj. R^2	0.423	0.563	0.568	0.631	0.701	0.577	0.589	0.691	0.647	0.214	0.321
Panel D: Unemployment rate change											
variables in $t-1$											
r	-0.033	-0.031	-0.023	-0.015	-0.014	-0.007	-0.010	-0.018	-0.006	0.007	0.027
(t-stat)	(3.075)	(2.758)	(2.381)	(1.465)	(1.531)	(0.769)	(0.761)	(1.971)	(0.757)	(0.762)	(1.420)
$term$	-0.002	-0.004	-0.025	0.003	-0.010	-0.020	-0.003	-0.029	-0.052	-0.039	-0.041
(t-stat)	(0.117)	(0.305)	(1.875)	(0.194)	(0.786)	(1.523)	(0.178)	(2.252)	(3.143)	(1.220)	(1.143)

	IBOR-OIS spread (SFS)			3-month FFS ($F^{(x)}_{3m,3m}$)			12-month FFS ($F^{(x)}_{12m,12m}$)			CDS spread	GM spread
Tenor x	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$		
lag	0.549	0.435	0.424	0.534	0.501	0.413	0.466	0.497	0.508	0.869	0.718
(t-stat)	(6.066)	(3.671)	(3.987)	(4.850)	(4.896)	(3.928)	(3.356)	(4.643)	(5.066)	(8.093)	(8.204)
variable	0.723	0.493	0.439	0.962	0.583	0.435	1.225	0.748	0.621	0.029	0.101
(t-stat)	(6.333)	(5.005)	(4.915)	(3.673)	(4.382)	(4.738)	(4.389)	(4.277)	(3.641)	(1.824)	(1.850)
Adj. R^2	0.834	0.840	0.844	0.799	0.805	0.837	0.824	0.808	0.808	0.698	0.720
Variables in $t-2$											
r	-0.097	-0.087	-0.069	-0.055	-0.051	-0.033	-0.043	-0.061	-0.031	0.014	0.055
(t-stat)	(3.775)	(3.067)	(2.672)	(2.326)	(2.198)	(1.426)	(1.457)	(2.776)	(1.612)	(0.356)	(1.661)
$term$	-0.069	-0.058	-0.103	-0.033	-0.058	-0.093	-0.058	-0.113	-0.174	-0.169	-0.157
(t-stat)	(0.825)	(0.850)	(1.538)	(0.710)	(1.257)	(1.329)	(1.124)	(2.481)	(2.947)	(1.348)	(1.225)
lag	0.552	0.380	0.359	0.426	0.349	0.355	0.405	0.361	0.393	0.856	0.656
(t-stat)	(3.888)	(2.792)	(2.890)	(3.644)	(2.730)	(2.876)	(3.179)	(2.872)	(3.097)	(4.028)	(3.489)
variable	1.609	1.125	1.004	2.627	1.612	0.979	2.977	2.021	1.610	0.111	0.278
(t-stat)	(10.472)	(10.283)	(10.224)	(6.548)	(7.145)	(10.465)	(8.947)	(7.246)	(5.687)	(1.822)	(2.716)
Adj. R^2	0.790	0.817	0.820	0.831	0.841	0.805	0.832	0.838	0.810	0.589	0.628
Variables in $t-4$											
r	-0.185	-0.157	-0.107	-0.095	-0.071	-0.033	-0.061	-0.092	-0.017	0.166	0.222
(t-stat)	(2.553)	(1.978)	(1.425)	(1.435)	(1.028)	(0.413)	(0.726)	(1.400)	(0.260)	(1.208)	(2.359)
$term$	-0.176	-0.134	-0.213	-0.095	-0.115	-0.195	-0.145	-0.232	-0.359	-0.396	-0.337
(t-stat)	(0.605)	(0.534)	(0.851)	(0.548)	(0.680)	(0.729)	(0.698)	(1.390)	(1.705)	(0.900)	(0.781)
lag	0.404	0.203	0.169	0.268	0.136	0.165	0.244	0.129	0.145	0.629	0.394
(t-stat)	(1.697)	(0.927)	(0.758)	(1.708)	(0.788)	(0.711)	(1.295)	(0.737)	(0.711)	(1.648)	(1.169)
variable	3.636	2.475	2.169	6.168	3.724	2.109	6.622	4.694	3.726	0.390	0.753
(t-stat)	(5.281)	(7.297)	(8.186)	(10.153)	(13.622)	(8.564)	(7.612)	(11.652)	(9.580)	(2.138)	(4.422)
Adj. R^2	0.625	0.700	0.688	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 1, 2, and 4 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 OA5. Predicting Euro Area Bank Lending Variables using Funding and Credit Spreads

	IBOR-OIS spread (SFS)			3-month FFS ($F^{(x)}_{3m,3m}$)			12-month FFS ($F^{(x)}_{12m,12m}$)			CDS spread	GM spread
Tenor x	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$		
Panel A: Bank lending growth											
variables in $t-1$											
r	0.174	0.174	0.165	0.159	0.158	0.153	0.156	0.164	0.148	0.026	0.041
(t-stat)	(3.421)	(3.605)	(3.429)	(3.406)	(3.527)	(3.314)	(3.520)	(3.605)	(3.209)	(0.346)	(0.681)
$term$	0.047	0.069	0.094	0.048	0.078	0.086	0.060	0.110	0.137	0.067	0.106
(t-stat)	(0.967)	(1.343)	(1.697)	(1.069)	(1.548)	(1.640)	(1.266)	(2.109)	(2.478)	(1.208)	(2.087)
lag	0.851	0.847	0.840	0.842	0.844	0.821	0.826	0.843	0.825	0.745	0.748
(t-stat)	(16.244)	(16.546)	(15.912)	(17.177)	(17.170)	(15.928)	(16.189)	(17.286)	(16.410)	(14.465)	(14.309)
variable	-1.110	-0.682	-0.590	-1.781	-1.012	-0.626	-2.006	-1.287	-1.068	-0.239	-0.389
(t-stat)	(5.504)	(4.475)	(3.915)	(6.058)	(5.812)	(4.826)	(7.394)	(5.833)	(4.629)	(3.594)	(3.271)
Adj. R^2	0.828	0.830	0.829	0.836	0.835	0.834	0.837	0.835	0.835	0.827	0.839
Variables in $t-2$											
r	0.506	0.514	0.482	0.455	0.456	0.437	0.445	0.478	0.424	0.035	0.096
(t-stat)	(3.869)	(4.192)	(4.052)	(3.984)	(4.366)	(3.865)	(4.190)	(4.559)	(4.003)	(0.174)	(0.616)
$term$	0.207	0.293	0.373	0.244	0.342	0.335	0.280	0.457	0.522	0.223	0.356
(t-stat)	(1.333)	(1.695)	(1.972)	(1.874)	(2.200)	(1.843)	(1.927)	(2.792)	(2.880)	(1.410)	(1.997)
lag	0.826	0.824	0.809	0.834	0.831	0.773	0.802	0.829	0.785	0.627	0.653
(t-stat)	(10.797)	(10.925)	(10.509)	(12.438)	(12.001)	(10.349)	(11.515)	(12.348)	(11.341)	(9.008)	(9.136)
variable	-3.715	-2.332	-2.002	-6.348	-3.566	-2.045	-6.929	-4.515	-3.604	-0.755	-1.170
(t-stat)	(5.717)	(5.163)	(4.381)	(5.864)	(6.459)	(4.936)	(7.469)	(6.951)	(5.193)	(3.741)	(3.113)
Adj. R^2	0.806	0.816	0.814	0.845	0.839	0.822	0.843	0.839	0.831	0.802	0.825
Variables in $t-4$											
r	1.399	1.447	1.352	1.198	1.227	1.220	1.184	1.306	1.169	0.039	0.254
(t-stat)	(4.273)	(4.879)	(4.971)	(4.296)	(5.119)	(4.652)	(4.273)	(5.623)	(5.495)	(0.095)	(0.770)
$term$	0.520	0.900	1.129	0.703	1.051	0.998	0.811	1.429	1.611	0.553	0.977
(t-stat)	(1.335)	(2.017)	(2.298)	(2.193)	(2.818)	(2.169)	(2.334)	(3.653)	(3.727)	(1.600)	(2.044)
lag	0.726	0.755	0.722	0.780	0.778	0.662	0.723	0.777	0.688	0.396	0.476
(t-stat)	(5.659)	(6.700)	(6.630)	(7.902)	(8.394)	(6.455)	(7.843)	(9.223)	(8.552)	(3.015)	(4.300)
variable	-11.000	-7.362	-6.299	-19.168	-11.199	-6.268	-20.592	-14.279	-11.320	-2.244	-3.282
(t-stat)	(5.469)	(6.281)	(5.542)	(5.662)	(7.938)	(6.030)	(8.018)	(9.247)	(7.318)	(4.319)	(3.412)
Adj. R^2	0.740	0.787	0.785	0.833	0.844	0.803	0.828	0.848	0.836	0.761	0.791
Panel B: Consumer loan growth											
variables in $t-1$											
r	0.024	0.042	0.038	0.043	0.049	0.027	0.031	0.052	0.031	-0.137	-0.102
(t-stat)	(0.407)	(0.717)	(0.681)	(0.832)	(0.942)	(0.500)	(0.581)	(1.001)	(0.630)	(2.387)	(2.351)
$term$	-0.229	-0.209	-0.191	-0.224	-0.194	-0.197	-0.212	-0.168	-0.145	-0.185	-0.170
(t-stat)	(2.072)	(1.915)	(1.670)	(2.326)	(1.896)	(1.788)	(2.069)	(1.575)	(1.287)	(1.784)	(1.666)
lag	0.617	0.610	0.603	0.588	0.584	0.589	0.595	0.583	0.569	0.503	0.504
(t-stat)	(6.483)	(6.579)	(6.578)	(6.305)	(6.369)	(6.586)	(6.431)	(6.419)	(6.315)	(5.173)	(6.063)
variable	-0.391	-0.411	-0.388	-1.497	-0.971	-0.433	-1.400	-1.187	-0.978	-0.288	-0.397
(t-stat)	(1.070)	(1.855)	(1.893)	(3.023)	(3.825)	(2.086)	(2.649)	(3.693)	(3.187)	(2.456)	(3.053)
Adj. R^2	0.635	0.642	0.644	0.657	0.664	0.647	0.649	0.662	0.660	0.669	0.669
Variables in $t-2$											
r	0.167	0.193	0.164	0.144	0.157	0.109	0.112	0.170	0.107	-0.359	-0.287
(t-stat)	(1.120)	(1.263)	(1.144)	(1.040)	(1.113)	(0.768)	(0.771)	(1.210)	(0.801)	(2.846)	(2.653)
$term$	-0.512	-0.434	-0.370	-0.539	-0.436	-0.413	-0.490	-0.348	-0.275	-0.475	-0.414
(t-stat)	(1.963)	(1.676)	(1.391)	(2.288)	(1.749)	(1.573)	(1.920)	(1.362)	(1.050)	(1.712)	(1.518)
lag	0.519	0.515	0.502	0.477	0.480	0.471	0.484	0.479	0.451	0.365	0.341
(t-stat)	(3.616)	(3.651)	(3.541)	(3.333)	(3.426)	(3.327)	(3.335)	(3.410)	(3.146)	(2.941)	(2.535)

	IBOR-OIS spread (SFS)			3-month FFS ($F^{(x)}_{3m,3m}$)			12-month FFS ($F^{(x)}_{12m,12m}$)			CDS spread	GM spread
Tenor x	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$		
variable	-2.603	-1.848	-1.627	-5.009	-3.055	-1.692	-5.015	-3.759	-3.154	-0.746	-1.143
(t-stat)	(3.642)	(4.268)	(4.058)	(4.387)	(5.610)	(4.158)	(4.666)	(5.847)	(5.095)	(2.953)	(3.539)
Adj. R^2	0.644	0.664	0.664	0.682	0.693	0.670	0.666	0.688	0.685	0.673	0.687
Variables in $t-4$											
r	0.673	0.719	0.621	0.546	0.572	0.458	0.468	0.623	0.443	-0.617	-0.491
(t-stat)	(2.041)	(2.014)	(1.848)	(1.671)	(1.688)	(1.318)	(1.299)	(1.861)	(1.380)	(1.916)	(1.746)
$term$	-0.743	-0.516	-0.345	-0.877	-0.589	-0.514	-0.718	-0.311	-0.149	-0.867	-0.640
(t-stat)	(1.160)	(0.823)	(0.533)	(1.493)	(1.006)	(0.772)	(1.108)	(0.530)	(0.241)	(1.193)	(0.850)
lag	0.490	0.487	0.468	0.423	0.431	0.416	0.433	0.433	0.391	0.298	0.257
(t-stat)	(2.594)	(2.686)	(2.534)	(2.264)	(2.378)	(2.220)	(2.211)	(2.398)	(2.093)	(1.637)	(1.544)
variable	-8.406	-5.479	-4.734	-14.219	-8.388	-4.669	-14.517	-10.541	-8.533	-1.547	-2.634
(t-stat)	(6.099)	(6.900)	(6.652)	(7.496)	(9.119)	(6.394)	(7.516)	(9.884)	(8.187)	(2.884)	(4.667)
Adj. R^2	0.716	0.745	0.741	0.778	0.789	0.738	0.745	0.786	0.767	0.667	0.719
Panel C: Real estate loan growth											
variables in $t-1$											
r	0.064	0.065	0.064	0.069	0.069	0.060	0.066	0.072	0.061	-0.015	-0.002
(t-stat)	(1.545)	(1.487)	(1.458)	(1.767)	(1.670)	(1.480)	(1.686)	(1.670)	(1.490)	(0.451)	(0.052)
$term$	0.028	0.037	0.052	0.027	0.044	0.052	0.038	0.063	0.084	0.057	0.062
(t-stat)	(0.459)	(0.554)	(0.709)	(0.526)	(0.752)	(0.742)	(0.682)	(0.960)	(1.046)	(0.771)	(0.715)
lag	0.831	0.822	0.816	0.796	0.796	0.795	0.791	0.797	0.788	0.803	0.788
(t-stat)	(9.917)	(10.087)	(10.101)	(9.753)	(10.273)	(9.737)	(8.965)	(10.717)	(10.714)	(11.033)	(10.521)
variable	-0.487	-0.309	-0.293	-1.071	-0.608	-0.348	-1.215	-0.764	-0.646	-0.114	-0.168
(t-stat)	(1.915)	(1.876)	(1.771)	(2.368)	(2.532)	(2.115)	(2.804)	(2.448)	(2.045)	(1.762)	(1.312)
Adj. R^2	0.769	0.769	0.771	0.778	0.777	0.773	0.778	0.777	0.776	0.769	0.769
Variables in $t-2$											
r	0.239	0.238	0.218	0.236	0.233	0.199	0.218	0.248	0.208	-0.038	0.008
(t-stat)	(2.069)	(1.830)	(1.690)	(2.106)	(1.937)	(1.657)	(1.877)	(1.985)	(1.740)	(0.469)	(0.091)
$term$	0.168	0.194	0.235	0.158	0.211	0.225	0.189	0.279	0.334	0.237	0.261
(t-stat)	(0.844)	(0.914)	(1.007)	(0.968)	(1.144)	(1.007)	(1.058)	(1.397)	(1.400)	(1.019)	(0.997)
lag	0.756	0.738	0.734	0.710	0.705	0.706	0.703	0.703	0.689	0.706	0.688
(t-stat)	(5.912)	(5.853)	(5.854)	(6.005)	(6.023)	(5.612)	(5.427)	(6.184)	(6.017)	(5.909)	(6.021)
variable	-1.924	-1.139	-0.961	-3.644	-2.009	-1.053	-3.847	-2.586	-2.079	-0.366	-0.535
(t-stat)	(3.629)	(2.809)	(2.259)	(4.057)	(3.668)	(2.608)	(4.200)	(3.498)	(2.630)	(2.121)	(1.990)
Adj. R^2	0.708	0.706	0.703	0.732	0.726	0.706	0.724	0.727	0.719	0.696	0.696
Variables in $t-4$											
r	0.589	0.603	0.542	0.562	0.566	0.486	0.508	0.604	0.504	-0.277	-0.062
(t-stat)	(2.019)	(1.859)	(1.700)	(1.961)	(1.846)	(1.596)	(1.636)	(1.951)	(1.710)	(1.203)	(0.248)
$term$	0.622	0.697	0.794	0.606	0.734	0.758	0.659	0.910	1.047	0.798	0.883
(t-stat)	(1.262)	(1.344)	(1.420)	(1.534)	(1.671)	(1.413)	(1.485)	(1.969)	(1.964)	(1.356)	(1.416)
lag	0.675	0.645	0.633	0.629	0.611	0.598	0.612	0.607	0.578	0.541	0.548
(t-stat)	(4.537)	(4.387)	(4.292)	(4.843)	(4.668)	(4.106)	(4.223)	(4.727)	(4.415)	(4.217)	(4.190)
variable	-5.397	-3.231	-2.689	-9.978	-5.476	-2.854	-9.857	-6.946	-5.613	-1.255	-1.638
(t-stat)	(3.620)	(3.687)	(3.207)	(5.519)	(5.070)	(3.622)	(4.493)	(4.564)	(3.816)	(2.856)	(3.400)
Adj. R^2	0.652	0.650	0.640	0.713	0.697	0.648	0.677	0.696	0.679	0.651	0.641
Panel D: C&I loan growth											
variables in $t-1$											
r	0.133	0.137	0.129	0.105	0.108	0.111	0.106	0.117	0.102	-0.041	-0.048
(t-stat)	(2.627)	(3.134)	(2.805)	(1.960)	(2.129)	(2.421)	(2.116)	(2.310)	(1.932)	(0.409)	(0.627)
$term$	0.012	0.037	0.079	0.019	0.033	0.067	0.035	0.073	0.108	-0.009	0.086
(t-stat)	(0.155)	(0.457)	(0.948)	(0.209)	(0.335)	(0.831)	(0.396)	(0.715)	(1.122)	(0.087)	(1.404)

	IBOR-OIS spread (SFS)			3-month FFS ($F^{(x)}_{3m,3m}$)			12-month FFS ($F^{(x)}_{12m,12m}$)			CDS spread	GM spread
Tenor x	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$	$1m$	$3m$	$6m$		
lag	0.921	0.910	0.903	0.923	0.901	0.884	0.903	0.899	0.875	0.778	0.806
(t-stat)	(16.275)	(19.200)	(21.751)	(17.473)	(18.770)	(23.450)	(18.517)	(19.061)	(21.638)	(12.246)	(15.966)
variable	-1.564	-0.963	-0.877	-2.438	-1.282	-0.925	-2.815	-1.629	-1.407	-0.302	-0.562
(t-stat)	(4.871)	(4.340)	(5.368)	(5.170)	(4.276)	(6.391)	(6.520)	(4.385)	(5.256)	(4.437)	(4.833)
Adj. R^2	0.876	0.879	0.882	0.882	0.878	0.888	0.887	0.878	0.881	0.876	0.898
Variables in $t-2$											
r	0.379	0.393	0.358	0.260	0.282	0.287	0.266	0.318	0.267	-0.147	-0.195
(t-stat)	(2.600)	(3.489)	(3.120)	(1.695)	(2.091)	(2.534)	(1.908)	(2.371)	(1.922)	(0.520)	(0.877)
$term$	0.127	0.283	0.402	0.146	0.244	0.307	0.189	0.404	0.483	-0.115	0.256
(t-stat)	(0.521)	(1.405)	(1.836)	(0.633)	(0.964)	(1.465)	(0.820)	(1.615)	(2.029)	(0.364)	(1.726)
lag	0.951	0.954	0.924	0.956	0.926	0.875	0.911	0.921	0.859	0.643	0.724
(t-stat)	(12.018)	(15.925)	(16.098)	(12.902)	(14.723)	(15.770)	(12.762)	(15.736)	(15.246)	(5.467)	(9.429)
variable	-5.979	-3.825	-3.317	-9.010	-5.019	-3.271	-10.042	-6.374	-5.187	-0.909	-1.712
(t-stat)	(8.668)	(8.557)	(9.348)	(6.533)	(7.506)	(9.637)	(9.162)	(8.339)	(8.836)	(4.155)	(4.306)
Adj. R^2	0.873	0.891	0.895	0.889	0.886	0.903	0.898	0.888	0.890	0.846	0.901
Variables in $t-4$											
r	1.097	1.080	0.954	0.683	0.723	0.762	0.706	0.849	0.707	-0.351	-0.528
(t-stat)	(2.423)	(3.351)	(3.379)	(1.452)	(1.929)	(2.794)	(1.697)	(2.345)	(2.102)	(0.537)	(1.026)
$term$	-0.104	0.850	1.283	0.244	0.824	0.982	0.434	1.376	1.677	-0.480	0.640
(t-stat)	(0.121)	(1.316)	(1.926)	(0.350)	(1.311)	(1.626)	(0.648)	(2.076)	(2.578)	(0.620)	(1.234)
lag	0.787	0.924	0.889	0.883	0.896	0.802	0.823	0.890	0.787	0.354	0.539
(t-stat)	(4.335)	(8.049)	(8.190)	(7.294)	(9.844)	(8.895)	(7.972)	(9.720)	(8.853)	(1.791)	(4.610)
variable	-16.256	-12.212	-10.679	-27.828	-16.771	-10.284	-30.724	-21.346	-17.192	-2.757	-4.833
(t-stat)	(5.720)	(8.996)	(9.594)	(5.920)	(10.505)	(10.413)	(10.118)	(11.908)	(12.015)	(4.369)	(4.466)
Adj. R^2	0.756	0.842	0.858	0.830	0.860	0.875	0.850	0.866	0.876	0.755	0.840

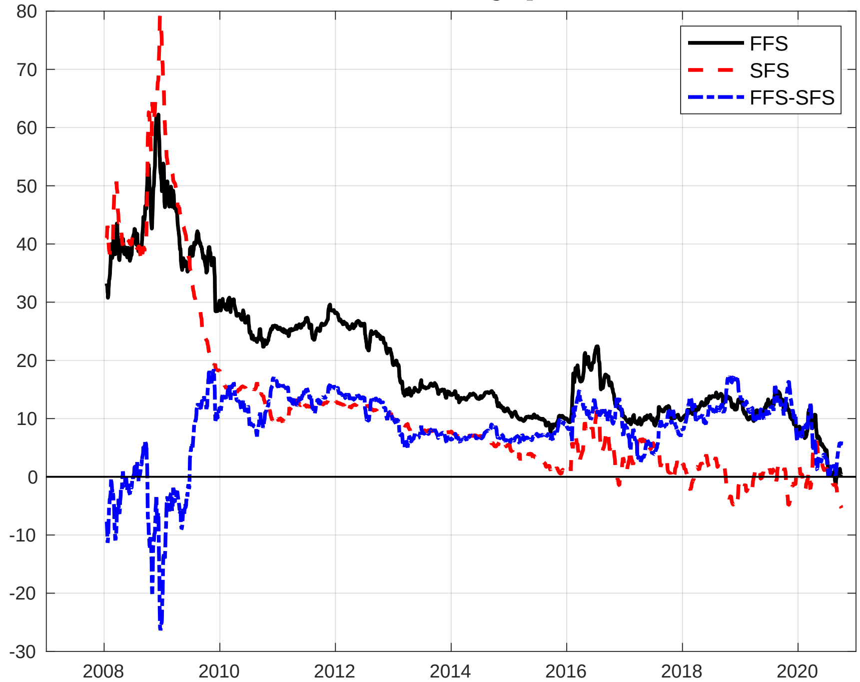
Note: This table reports predictive regressions for euro area bank lending variables. Predictive horizons are 1, 2, and 4 quarters. Presented are the parameter estimates, Newey-West adjusted t-statistics in parentheses, and adjusted R^2 values. The sample period runs from January 2005 to December 2019.

D Data for Japan and the United Kingdom

Figure OA3. Funding Spreads in Japan and Bank of Japan Total Assets

Note: Panel A displays the forward funding spread (FFS), the spot funding spread (SFS), and the difference between the two spreads. Panel B displays the Bank of Japan total assets (in JPY trillion). The spread series are smoothed using a 5-day moving average. The sample periods are January 2007 to September 2020.

Panel A: Funding Spreads



Panel B: Bank of Japan Total Assets

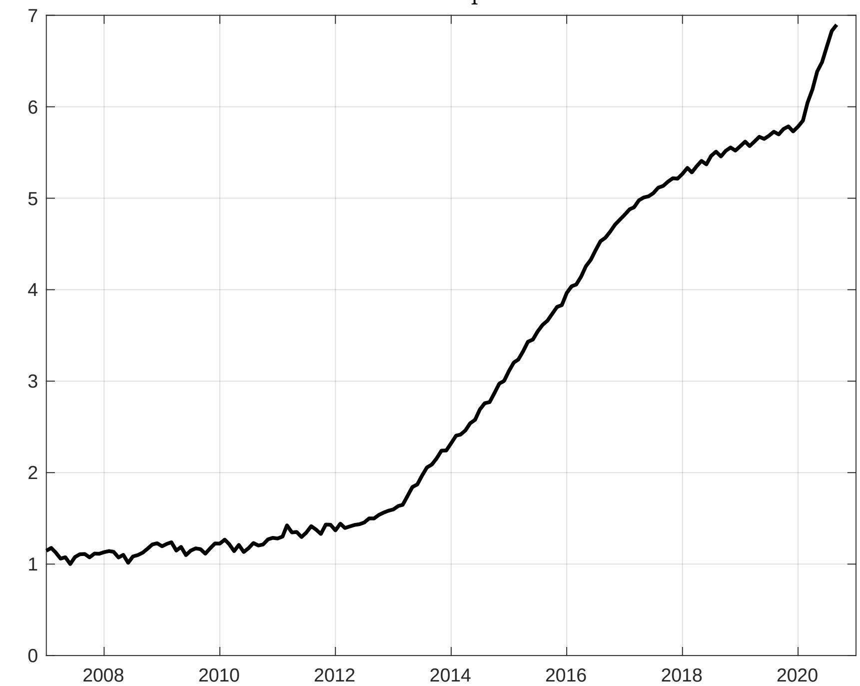
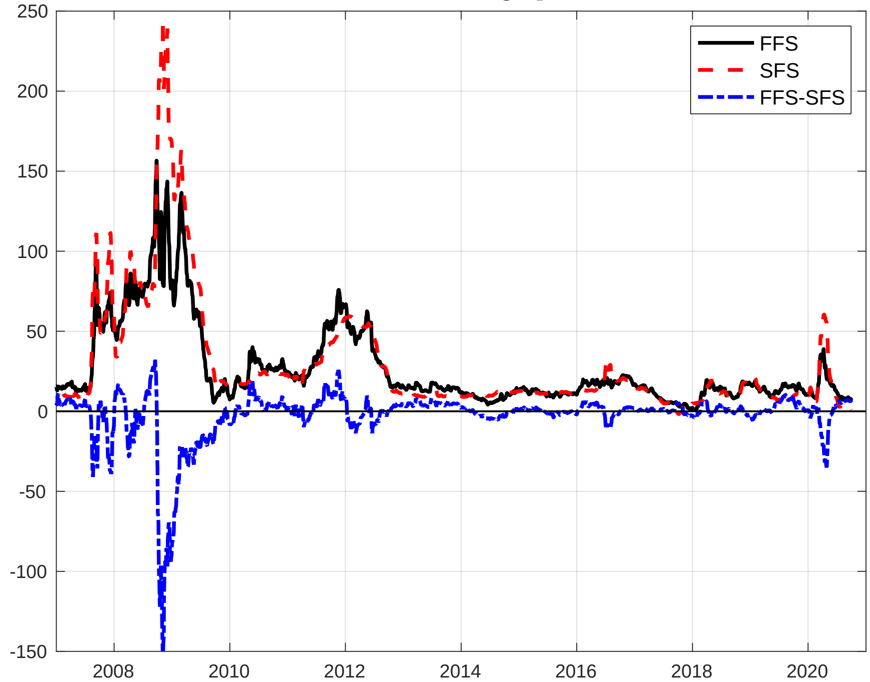


Figure OA4. Funding Spreads in the United Kingdom and Bank of England Total Assets

Note: Panel A displays the forward funding spread (FFS), the spot funding spread (SFS), and the difference between the two spreads. Panel B displays the Bank of England total assets (in GBP trillion). The spread series are smoothed using a 5-day moving average. The sample periods are January 2007 to September 2020.

Panel A: Funding Spreads



Panel B: Bank of England Total Assets

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