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Financial Frictions in Mexico: Evidence from the Credit Spread and its Components

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Financial Frictions in Mexico: Evidence from the Credit Spread and its Components*

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Abstract: We investigate the relationship between financial market frictions and economic activity in Mexico by constructing and decomposing a credit spread index from bonds issued by non-financial corporations in domestic markets, following Gilchrist and Zakrajsek (2012). We show that the credit spread is significantly informative about the evolution of economic activity and financial aggregates in Mexico. Moreover, the excess bond premium (EBP), which tracks the relationship between firms' default risk and their credit spread, is found to be the main driver of this relationship. We show evidence that negative shocks on financial conditions, identified as a sudden increase of EBP, prompt a contraction in economic activity and credit aggregates. Finally, we find evidence of non-linear effects on the responses of economic activity in response to the shock.
Keywords: Credit spread, economic activity, credit aggregates
JEL Classification: E32, E44

Resumen: Este artículo investiga la relación entre las fricciones en los mercados financieros y la actividad económica en México, para lo cual se construye y descompone un diferencial de tasas para los bonos emitidos por empresas privadas no financieras en el mercado interno, basado en Gilchrist y Zakrajsek (2012). Se muestra que el diferencial contiene información significativa sobre la evolución de la actividad económica y de los agregados crediticios. Además, se encuentra que la prima excedente de los bonos (PEB), cuya dinámica describe la relación entre la probabilidad de impago de las empresas y su diferencial de tasas, es el componente con mayor poder predictivo. Se muestra que choques negativos en las condiciones financieras, identificados como innovaciones en PEB, generan una desaceleración en la actividad económica y en el financiamiento. Finalmente, se encuentra evidencia de efectos no lineales en la respuesta de la actividad económica ante este choque.
Palabras Clave: Diferencial de tasa, actividad económica, agregados crediticios

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1 Introduction

The role of financial markets in propagating and generating business cycles fluctuations has been a long-standing query in macroeconomics. The seminal works of Bernanke, Gertler and Gilchrist (1996, 1999) formalized this type of analysis. In particular, these authors developed a new strand in the macroeconomic literature focused on studying the mechanism known as the credit channels, that operates within financial markets to initiate, propagate and amplify shocks to the economy.[1] There are two main types of mechanisms related to financial frictions: (i) the balance-sheet channel, which posits that adverse shocks on the aggregate economy cause a decline in expected profits and in the net worth of economic agents that weakens households' and firms' financial position, constraining their access to credit markets; and, (ii) the lending channel, which concentrates on the drop in the financial intermediaries' risk bearing capacity or willingness to lend as a result of shocks. While the source of the shocks that could affect any of the credit channels may be diverse,[2] when they happen, the two mechanisms reinforce each other and create a feedback loop between the financial and non-financial private (NFP) sector that is translated into asset price fluctuations and a deterioration of economic fundamentals.

There is extensive empirical literature that has examined and quantified the feedback effects between the financial and NFP sector at times of financial stress. The strategy has been mainly to assess the way that fluctuations on asset prices translate to the business cycle and to test for their forecasting power on real variables. Among them, studies that use corporate bond credit spreads —i.e. the yield difference between private non-financial corporate debt instruments and sovereign securities of comparable maturity—have received special attention in recent dates, as these are thought to carry substantial predictive content for economic

[1] Known as the "financial accelerator" mechanisms, these theories were initially focused on studying the way financial markets propagate and amplify shocks that are initiated in other sectors of the economy, mainly monetary policy shocks. More recent literature has argued that the financial sector may act as a source of economic fluctuations on its own and not just as a propagating force of other type of shocks. See, for example, Gertler and Karadi (2011) and Jermann and Quadrini (2012).

[2] Some sources of shocks could be monetary shocks, exchange rate shocks, supply shocks, country risk shocks, or shocks that are generated in the banking sector itself, among others.

activity (Philippon, 2009). In their seminal work, Gilchrist and Zakrajšek (2012), henceforth GZ12, employed a new methodology for computing the credit spread, known as the "GZ credit spread" and, additionally, decomposed it into two main components: the risk premium and the excess bond premium (EBP henceforth). They showed that the EBP component accounts for most of the explanatory power of the credit spread on macroeconomic variables, as it is strongly linked to the supply of credit in the economy, and therefore, it is a useful indicator for the amplification effect of both credit channels. They find that sudden increases of the EBP that are orthogonal to the state of the economy lead to economically and statistically significant declines on real variables.

This paper aims to investigate the relationship between financial market frictions and macroeconomic aggregates in Mexico by means of a credit spread index constructed from data on non-financial domestic firms bond issuance. We intend to show that the credit spread is a useful indicator to investigate the way that credit channels operate in the Mexican economy. Therefore, following closely GZ12, we first compute, and further decompose, a credit spread from domestically issued bonds using a novel cross-sectional dataset containing bonds issued by Mexican non-financial corporations from January 2003 to February 2020. With the credit spread and its components at hand, we then aim to investigate if the former holds a significant relationship with macroeconomic aggregates, and if so, if there is a specific component of it that drives such relationship. We are interested in learning if the credit spread —and which of its components especially—has forecasting power on macroeconomic aggregates like economic activity and financing. Finding such evidence could be specifically challenging for an emerging economy like Mexico, in which not only the financial market is highly bank dependent, but that domestic corporate debt markets are relatively young and, in some cases, poorly liquid.

Nevertheless, after applying an in-sample forecasting Bayesian-estimated linear regression model using data from January 2004 to February 2020, we find that the constructed credit spread has a significant marginal effect in forecasting economic and credit aggregates. Moreover, we find that the EBP component is the primary carrier of information related to the

strains of financial markets as it bears a stronger relationship and higher forecasting power with the variables of interest at different forecasting horizons than the credit spread itself, and the risk premium.

We next confirm these results by estimating three different Bayesian vector autoregressive (BVAR) models and performing out-of-sample forecasts, each one with the same specifications but including alternatively the credit spread, the risk premium, and the EBP. The models are estimated by means of the Gibbs sampling algorithm and using Minnesota-style priors for a dataset containing the same variables and sample as in the in-sample forecast. By computing the root mean squared error distributions for forecasting both economic activity and private domestic financing for each of the models, we find that the error distribution is significantly lower for the model that includes the EBP.

Having found evidence that the EBP is the component that carries more information on financial conditions, we then use a BVAR framework to analyze how the credit channel transmission mechanism operates and affects aggregate variables. The model includes an exogenous block of U.S. variables, yearly growth on IGAE[3], annual core inflation, annual growth on private domestic financing, the short-term interest rate, the EBP, the slope of the yield curve and the currency depreciation *vis-a-vis* the U.S. dollar. The model is estimated with monthly data from January 2004 to February 2020. We provide evidence that orthogonal negative innovations on financial conditions, identified by a sudden increase of the EBP through a Cholesky decomposition, are translated into a slump on total private financing, a decrease in the slope of the yield curve, sluggish economic activity, as well as lower inflation and nominal interest rate in a persistent manner. We also find evidence that the responses on economic activity are different when taking different aggregates from the supply and demand side. From the supply side, a shock on the EBP generates a deeper drop in the growth of industrial activity compared to the also negatively significant response on services. From the demand side, although the response on consumption is significant and negative after a surge

[3]IGAE, thus named by its acronym in the Spanish language, measures the monthly evolution of economic activity in Mexico. This indicator uses the conceptual framework and the methodology of the national accounts, in particular the gross domestic product (GDP).

in the EBP, the response on investment is significantly larger and more persistent. Finally, we perform a linear projection exercise *á la* Jorda (2005) in order to further investigate the effect of shocks on the EBP on economic activity. We present evidence of non-linear effects operating through the credit channel in Mexico as the responses on economic activity to financial shocks are stronger when financial conditions deteriorate, while the effects of positive shocks on financial conditions, when conditions improve, take more time to be reflected on economic activity and can be less informative.

This paper is, to the best of our knowledge, the first to explore the relationship between credit spreads in domestically issued securities and other macroeconomic aggregates for Mexico, and for emerging markets in general. Furthermore, it is the first one to extract the unobserved component from the credit spread that carries the main information content on financial conditions and can therefore be a useful indicator for studying the credit channels in Mexico.

The main contribution of the paper, therefore, is the construction of a novel indicator or instrument which can be used as a proxy for financial frictions in Mexico and that can therefore be employed, empirically or theoretically, for analyzing the credit channel as an amplifier of shocks in the economy. In particular, using this indicator can contribute to previous literature focused on analyzing the monetary transmission mechanism through the credit channel in Mexico. Specifically, it can be employed as an alternative or complementary variable to be included in models as the ones presented in Sidaoui and Ramos-Francia (2008), Ibarra (2016) or Cantú, Lobato, López, and López-Gallo (2019). It could also help to complement studies on the international monetary policy transmission mechanism of the credit channels, as in Morais, Peydró, Roldán-Peña and Ruiz (2017). Studying the credit channel is of special interest for a central bank as it allows to generate priors on how monetary policy actions can propagate to inflation and economic activity through the transmission mechanism of monetary policy to financial markets. Likewise, it may help to design a better monetary policy response to other exogenous shocks that may affect the credit channels.

Although the Mexican case may differ in some respects to other emerging economies, we believe that results derived from this analysis may provide useful insights to those interested in understanding the relationship between financial markets and the macroeconomy in emerging-market economies. In this sense, our findings may be useful to further investigate how financial frictions propagate to credit and business cycles in Mexico and other economies alike. Some topics are beyond the scope of our analysis and can be met in future research. For example, our study focuses only on the effects of credit spread and its components on aggregate financing, but further analysis can explore the different responses on other credit aggregates, such as like households' or firm's financing, as in Sidaoui and Ramos-Francia (2008) or Ibarra (2016). Likewise, the cross-sectional nature of the dataset could be used to examine if the credit channel works differently by separating firms by size or any other characteristic, like in Cantú, Lobato, López, and López-Gallo (2019).

The rest of the paper is organized in six further sections. Section 2 briefly reviews the literature on the credit spread and its role as a measure for identifying financial stress periods. Section 3 describes the main trends of financing in Mexico and presents some stylized facts of the market from which we will be extracting the credit spreads. The methodology used for calculating the credit spreads and its decomposition, together with a description of the datasets, are presented in Section 4. Section 5 studies the forecasting power of the aggregate credit spread and its components with some key macroeconomic variables in Mexico by the means of in-sample and out-of-sample forecasting exercises. Section 6 applies a Bayesian VAR to assess the implications that orthogonal shocks on the EBP —the component of the credit spread with the strongest relationship with macroeconomic variables —have on economic activity and credit aggregates. We also look for non-linear effects on these responses by applying a linear projection approach. Finally, Section 7 presents the conclusions.

2 Literature review

One of the main strategies in empirical studies that is used to find evidence on the way that credit channels operate in the economy has been to assess how asset price fluctuations propagate to economic fundamentals and to test their forecasting ability. Fama (1981), for example, used stock prices, and Harvey (1988) used the term premium, while Gertler and Lown (1999) and Mody and Taylor (2004) performed their analysis using the spread between high yield bonds over government debt or AAA-rated corporate bonds. Stock and Watson (2003), for instance, presented a systematic evaluation of the information contained in asset prices for forecasting macroeconomic variables.

More recently, Gilchrist, Yankov and Zakrajšek (2009) rely on corporate bond credit spreads to find evidence on the effect of asset price fluctuations on economic activity. They employed a new approach to compute corporate credit spread indexes for U.S. non-financial firms constructed from bond-level data that are not distorted by embedded options or non-liquid bonds. In order to assess the information content of the corporate credit spread for economic activity, they controlled for both the maturity structure and the credit risk of the issuer, by constructing 20 monthly credit spreads indexes for different maturities and credit risk categories. They find that credit spreads contain substantial predictive power for economic activity, specially for longer maturity bonds and middle and high credit-quality. They also conducted a FAVAR analysis for showing evidence that orthogonal increases in bond spreads cause large and persistent contractions in economic activity, and that shocks emanating from the corporate bond market account for more than 30 percent of the forecast-error variance in economic activity at the two-to-four-year horizon. The advantage of including the corporate credit spread in forecasting models was also documented by Faust, Gilchrist, Wright and Zakrajšek (2013), which provided a thorough evaluation of the marginal information content of credit spreads in real-time economic forecasting. In turn, Gilchrist and Zakrajšek (2012) use a new methodology concentrated on the careful selection of the benchmark yield employed to calculate bond spreads in order to avoid biases induced by mismatched maturities

or coupon schedules. They did so by constructing a synthetic benchmark bond that mimics the coupon payment structure of every security in the sample. For deriving the benchmark yield, they calculated the price of the benchmark bond using the U.S. Treasury yield to compute the discount factor at each time frame. This credit spread index is now known as the "GZ credit spread". Additionally, they presented a methodology to decompose the GZ credit spread into two main components: the risk premium and the EBP. The decomposition stems from the "credit-spread puzzle" in corporate finance, which states that only a fraction of the variations on the spread can be accounted by the issuer's risk. In other words, bond spreads contain a fundamental component that reflects bond-specific factors and the credit risk of the issuer, but also an unpredictable component —the EBP—that reflects changes in investors' risk preferences, signaled by shifts in the effective supply of funds offered by financial intermediaries. GZ12 showed that it is actually the EBP component that accounts for most of the explanatory power of the credit spread on macroeconomic variables and analyzed the consequences that orthogonal innovations on it have on macroeconomic dynamics. Furthermore, Favara, Gilchrist, Lewis and Zakrajšek (2016), found that the EBP can predict the likelihood of a recession in the U.S. over the following 12 months by applying a probit regression. They give evidence that the EBP provides a timely and useful leading indicator for economic downturns. The main mechanism behind this result, they argue, is related to the supply of credit.

The literature on the credit spread in the U.S. motivated a corresponding analysis for the Euro Area and Great Britain, the largest bond markets besides the U.S. Bleaney, Mizen and Veleanu (2015) replicate the GZ credit spread methodology and study its predictive ability over macroeconomic variables for markets different than the U.S. They did so despite the fact that bank lending dominated the debt financing market in Europe and comprised around 75% of all corporate debt outstanding at the time the study took place. They constructed corporate bond spreads indices for eight European countries and analyzed their predictive ability over macroeconomic variables. As in the U.S. case, they showed that the credit spreads have significant predictive ability over main macroeconomic variables for European countries and

argued that there is empirical evidence for heterogeneity in the predictive power of the spread among them. Finally, they computed the credit spread decomposition and showed that the predictive performance of GDP growth can be explained by the spread required by investors beyond the compensations of expected defaults, i.e., the EBP. The fact that Bleaney, Mizen and Veleanu (2015) constructed the synthetic bond benchmark using the Euro Bloomberg Benchmark without differentiating within countries, raised the debate of whether the EBP, calculated following GZ12, will remain with information concerning country-specific systematic risk, which may be actually driving its predictability of economic activity. Therefore, De Santis (2016) also computed the credit spread for the Euro Area, but applied a different methodology for calculating the EBP by controlling by both observable credit and systematic risk. The estimated unobserved systematic components are therefore employed to construct the "relative excess bond premium", which is tested to have considerable predictive power for economic activity. Okimoto and Takaoka (2017) suggested that the term spread of corporate credit spreads in Japan has significant predictability for the business cycle.

Even though these studies have mostly focused on advanced economies, particularly on the U.S. and the Eurozone, there is considerable amount of research that has tried to analyze the way financial stress propagates into emerging market economies when international borrowing is constrained.[4] Most of these studies have emphasized the role of financial frictions in international capital markets, by analyzing the relationship of sovereign external credit spreads —i.e. the spread between sovereign bonds issued in U.S. dollars in international markets and the Treasury benchmark —and economic outcomes on emerging economies. However, malfunctioning of domestic banks and domestic lending has received less attention and few studies have assessed the interactions between the domestic financial sector and the real sector during times of financial stress for developing markets. A theoretical reference among them is Hwang (2012), who through a small-open economy model calibrated for Korea, investigates the role of financial frictions in an emerging economy. Empirical studies include Auel and Ferreira (2011) and Stona, Morais and Triches (2018), who analyzed

[4]Some examples are Blanchard, Das and Faruqee (2010), Akinci (2013), Brei and Buzaushina (2015), Ben Zeev (2019) and Epstain, Finkelstein-Shapiro, Gonzáles-Gómez (2019).

the way that domestic credit market conditions propagate and amplify shocks, affecting economic dynamics in Brazil. In turn, Kara, Hacihasanoglu and Unalmis (2019) argued that the feedback loop between banking and non-financial sectors during financial stress episodes is stronger for emerging markets with high net foreign currency indebtedness like Turkey.

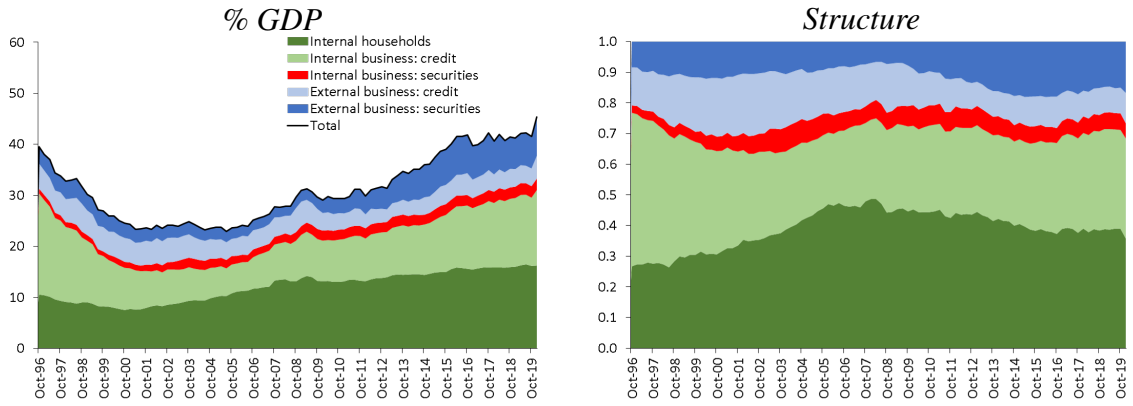
As a proxy for identifying the financial stress episodes, these studies have used either aggregate macroeconomic indices or financial stress indices constructed by means of a state-space Dynamic Factor Model. None of these studies, however, have analyzed the consequences that frictions in domestic financial markets may have on macroeconomic fundamentals in an emerging economy using domestic credit spreads, and its components, as in GZ12. Some key exceptions are Wang, Nie, and Wang (2019) who computed a domestic credit spread between state-owned and private companies in China and analyzed its predictive ability with macroeconomic variables. And, Barnea and Menashe (2015), who followed closely GZ12 and computed a non-financial sector credit spread index for the Israeli economy and decompose it in order to test for its informative content as leading indicators for business cycle fluctuations.

More recent papers related to the literature have started to study theoretical and empirical non-linearities on the financial accelerator mechanism, mainly for advanced economies. For instance, Akinci and Queralto (2017) proposed a dynamic stochastic model in which banks' leverage constrains are occasionally binding. When the constrains bind, the economy enters a financial crisis mode and, as a consequence of the non-linearity induced by the leverage constrain, an amplification mechanism takes place via the financial accelerator, strengthening the link between credit spreads and the real economy. Similarly, Stein (2014) reported evidence of asymmetries on the responses on U.S. economic variables to hikes or declines on the EBP: while upwards moves on the EBP are very informative about the evolution of the real economy, declines on it have no significant effects. Finally, for the case of Mexico, Ibarra (2016) studied the asymmetries of the transmission mechanism of monetary policy through the credit channel.

3 Stylized facts on Financing in Mexico

In this section, we present some stylized facts on firm financing in Mexico and how it has evolved over time. The purpose of this section is to show the evolution of the market from which we extract our indicators and how it is compared with other sources of financing. During the last 30 years, the Mexican economy experienced a deep transformation that allowed to achieve macroeconomic stability, the restoration of banks' financial health, and improved conditions to access financing for households and non-financial firms through different sources (Sidaoui and Ramos-Francia, 2008).

Figure 1: Total Financing for Non-Financial Private Sector in Mexico and its Structure



Source:Banco de México (CF297, click for link)

Nevertheless, the level of financial deepness has been historically low relative to other economies. For instance, while in Mexico total private financing to non-financial sector represents around 45% of GDP as of March 2020 (Figure 1), the same figures for 2019 for the U.S., Chile and Brazil were 150%, 148% and 71%, respectively. Private financing to non-financing sector dropped steadily in GDP terms from the period after the Tequila Crisis until around the year 2000, mainly as a response of the deleveraging process of domestic credit embraced by firms. Financing levels remained subdued and hovered around 23-24% of GDP until 2006, when mainly domestic financing through banking credit to businesses started to

reactivate. During these years, internal bond markets started to develop. The shift to an explicit inflation targeting framework in 2003 together with fiscal discipline translated into a sharp decline of inflation, its expectations and its volatility, as documented by Chiquiar, Noriega and Ramos-Francia (2007). The latter allowed the emergence of medium and long-term financial instruments and the development of both sovereign and corporate domestic bond markets (Banco de Mexico (2019a)). Finally, as documented by Carabarín, de la Garza and Moreno (2015), in the aftermath of the 2008 Global Financial Crisis, we observed a spike on the issuance of debt securities in international financial markets under significantly deeper and more liquid financial conditions. This occurred in the context of the inclusion of Mexican sovereign bonds in the FTSE Russell World Government Bond Index[5] (WGBI) in 2010, which fostered the purchases of Mexican government debt by foreign investors, as part of their exposure strategy to the global sovereign fixed income market.

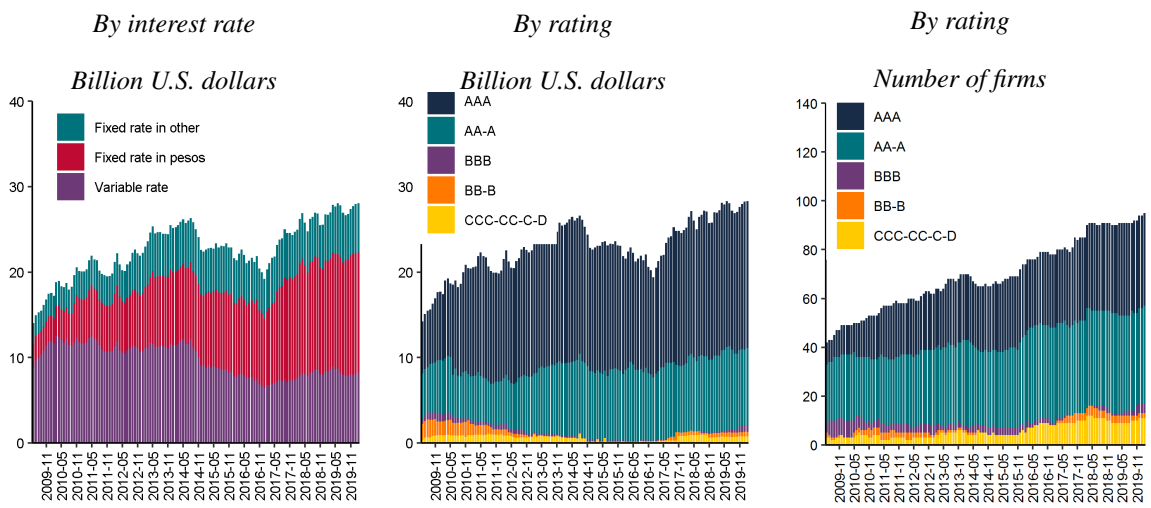
Focusing on domestic business financing through securities, the actual source from which we will be extracting our indicators, it is worth noticing that it has more than doubled in size and represents around 2% of GDP as of March 2020. The right and left panel of Figure 2 show that in the last 20 years, this market has doubled in size, reaching an outstanding amount of around $28 billion as of March 2020. For instance, in the left panel of Figure 2 we can witness that while by the end of 2009 only a small part of the bonds were in Mexican pesos and at a fixed coupon rate, by 2020 this type of securities represented the main share of the market. The latter is related with the previously mentioned development of fixed-income markets that benefited from low and stable levels of inflation. From the quality of the issuers, the center panel of Figure 2 shows that the market has been concentrated in highly rated firms, although it has gradually become more heterogeneous.

On a firm level, the right panel of Figure 2 shows that the number of firms in the domestic debt market has increased from around 40 firms to close to 100 firms, demonstrating that not

[5]The FTSE World Government Bond Index (WGBI) is broad index providing exposure to the global sovereign fixed income market, the index measures the performance of fixed-rate, local currency, investment-grade sovereign bonds. It comprises sovereign debt from over 20 countries, denominated in a variety of currencies.

only the size of the market has grown (in terms of amount outstanding) but also new firms have entered the market. The market has been dominated by high quality firms, although it is more evenly shared among firms with AAA and AA or A ratings (see center panel of Figure 2). Simultaneously, firms with CCC or below ratings have increased their market share, showing that not only more firms, but also more diverse firms have entered the market. Despite these developments, however, our sample is still dominated by a large portion of high-quality firms, contrasting with the dataset of GZ12 which shows a median credit rating of BBB1 and, in general, a wider distribution of credit ratings, from D to AAA.

Figure 2: NFP Sector Internal Securities Issuance



Note: Left and middle panels show quantities in U.S. dollars, transformed from original Mexican peso quantities using the monthly average exchange rate in each month.

Source: Banco de México (CF297, click for link)

Although, as shown, the market has evolved at a relevant pace, it is still significantly young and small compared to other financing sources in Mexico. For example, as for December 2019, bank credit and non-domestic debt issuance represented 73.3% of total long-term liabilities stock for private firms. Similarly, compared to a total of 129 firms in our sample, GZ12 reported a total of 1,112 firms in their sample. The latter represents a challenge to what is to be achieved in this paper, as the size of the market from which we want to extract

information, which we will later try to relate to total financing and business cycles, is admittedly a very small fraction of total financing. Nevertheless, other countries that have actually calculated the credit spread and have attempted to extract conclusions from it, have faced similar challenges. For instance, Bleaney, Mizen and Veleanu (2015) pointed out that even for countries where firms are more heavily bank-dependent, such as Germany, bond spreads offer a signal of tightening in credit conditions more broadly.

4 The Credit Spread and its Decomposition

In this section we introduce the methodology applied for the construction and decomposition of the credit spread for corporate securities issued in Mexican markets.

4.1 Credit Spread

The construction of credit spreads involves the use of a benchmark interest rate, commonly regarded as a baseline for all interest rates in an economy or a specific market. When calculating credit spreads, the benchmark rate is used to extract the fluctuations derived from the benchmark itself from other interest rates, leaving only the fluctuations that can be attributed to shifts on the perceived risk of the issuer, the specific conditions of the security itself or the general conditions of the market in which the security is being traded. Therefore, when calculating the credit spread of a security, a common approach is to take as a benchmark the yield of a security perceived as more liquid and safer, and with identical characteristics than the private security —i.e. type, currency, remaining maturity and coupon rate. It is commonplace within the credit spread literature to use government bond yields as benchmarks to calculate corporate bond spreads.

As previously stated, for the construction of the credit spread for Mexican non-financial corporations we build on the work of GZ12, in that we use prices of individual corporate bonds traded in the secondary market to construct a synthetic minimum-risk security that

mimics the cash flows of each corporate debt instrument in our database. By using this methodology, we avoid the "duration mismatch" problem that emerges when simply subtracting the yield of the benchmark with similar maturity from the observed corporate yield. This mismatch emerges as it is unlikely to find a benchmark with the exact characteristics as the bond of interest, for example, with the same remaining maturity or coupon rate.

The price P of corporate bond k issued by firm i, and with a set of cash flows $\{C(s) : s = 1, 2, ..., S\}$, corresponding to a fixed coupon payment for $s = 1, ..., S-1$, and the sum of the coupon and principal payments when matured, is defined as:

$$P_{it}[k] = \sum_{s=1}^{S} C(s)D(t_s) \tag{1}$$

Where $D(t_s) = e^{-r_{ts}t}$ is the discount factor in period t for cash flow s. Therefore, the benchmark price, $P_t^b[k]$, for bond k at time t, is obtained through the sum of the remaining cash flow payments, each one discounted with the corresponding interest rate extracted from the compounded zero-coupon government yield curve with the same time profile as the cash flow. In particular, the discount factor for each cash flow s is: $e^{-r_{ts}} = e^{\left[\left(\frac{r_{tj}}{100}\right)\left(\frac{T_s}{360}\right)\right]}$, where T_s is the remaining maturity of the specific cash flow s; r_{tj} is the interest rate chosen from the government yield curve (expressed in annualized terms) according to the remaining maturity of the cash flow s at time t. The rate r_{ts} is, therefore, the rate expressed in terms of the maturity of the cash flow.

Once the price of the synthetic benchmark is obtained, we can find the benchmark yield, $y_{i,t}^b[k]$. This is the yield that the government would pay for a hypothetical bond with the exact same characteristics as the corporate bond in question. Once the benchmark yield is annualized, the credit spread is calculated by simply subtracting the synthetic bond yield from the observed rate of the corporate security:

$$s_{it}[k] = y_{it}[k] - y_{it}^b[k] \tag{2}$$

Where $s_{it}[k]$ is the credit spread at time t, of the bond k, issued by corporate i.

Using data from Indeval, Valmer, PiP and the Mexican Stock Exchange, we construct a micro-level dataset for the securities of Mexican non-financial corporations issued in the local market. The dataset contains monthly information from January 2004 to February 2020. The securities contained in the dataset fulfil the following characteristics: (i) coupon bonds with an original maturity of more than one year; (ii) issued at a fixed coupon rate; (iii) with a remaining maturity of more than one year and less than 30 years; and (iv) issued in Mexican pesos. Discount rates used for the synthetic bonds prices computation come from the continuously compounded zero-coupon yield curve of fixed rate sovereign bonds (*BonosM*).

As opposed to the U.S. dataset used by GZ12, in which about two-thirds of the securities are callable —that is, the issuer has the right to call or redeem the bond issue prior to its maturity under certain prespecified conditions—, in our data less than 5% of the bonds have this feature for certain months. Therefore, we follow Bleaney, Mizen and Veleanu (2015) and exclude callable bonds from our data. By doing so, and with only a small loss in the number of observations, we avoid incorporating in our analysis movements in corporate bond yields and credit spreads of callable bonds that vary as consequence of changes in the value of the embedded call option and, additionally, we avoid working with bonds whose prices are more sensitive to uncertainty regarding the future course of interest rates and less sensitive to changes in default risk, given their shorter duration.

The micro-level dataset allows us to compute a credit spread for each bond at any given moment in time. The selection criteria result in a credit spread database with 4,909 individual securities. Table 1 contains summary statistics on the resulting credit spread dataset.

The average firm in our sample has close to three securities trading in any given month, with a positive skew, as some firms may have up to seven issues trading. The distribution of the nominal total amount outstanding per security is also positively skewed, with a range

running from \$9.09 million to \$740.25 million dollars.[6] The average bond has a maturity at issue of little less than 11 years, an average remaining maturity of 7.4 years, and a duration of 5.3 years. The coupon rate and the yield distributions are approximately symmetric, centered at around 8.6% and 7.9%, respectively. In terms of default risk, our database contrasts with the GZ12 U.S. sample, as for Mexico the markets' lower rating is BB, whereas in the U.S. sample is D. The latter is also reflected by the narrow range of the credit spread. As can be seen in Table 3, the standard deviation of the spread is of 68 basis points and it goes from a range of 1 basis points to 472. In contrast, GZ12 reported a standard deviation of the GZ credit spread of 281 basis points, and a range that goes from 5 to 3,499 basis points.

Finally, to obtain an aggregate index of the credit spreads, following GZ12 and similar studies, we take the arithmetic average of the individual credit spreads for any given month. Left panel of Figure 3 shows the dynamics of the average credit spread (to be described next).

Table 1: **Credit Spread Bond Level Database**

Variable	Mean	S.d.	Min	Q10	Median	Q90	Max
Bonds per firm-month	2.65	1.42	1.00	1.00	2.00	5.00	7.00
Issued amount (U.S. dollar)	156.01	132.97	9.09	36.24	114.76	390.03	740.25
Maturity at issue (years)	10.92	5.35	4.73	6.98	9.97	14.96	29.92
Duration (years)	5.26	2.29	1.03	2.17	5.29	8.14	12.44
Term to maturity (years)	7.37	5.28	1.05	2.27	6.45	13.44	29.90
Coupon rate(%, in pesos)	8.56	1.29	5.46	6.83	8.53	10.25	12.70
Nominal yield (%, in pesos)	7.93	1.54	3.35	5.87	8.03	9.90	12.77
Credit rating (S&P)	-	-	BB	AA-	AAA	AAA	AAA

Note: Our database goes from January 2004 to February 2020. The issued amount is shown in nominal, millions of dollars, while the maturities and duration are shown in years.

Source: Indeval, PiP, Mexican Stock Exchange, Banco de México.

[6]Figures are shown in U.S. dollars, transformed from original Mexican peso quantities using the monthly average exchange rate in each month.

4.2 Measuring the Risk Premium

By constructing the credit spread, we isolate the fluctuations on corporate interest rates associated with movements on the benchmark rate. However, at this point, fluctuations on the credit spread may still be reflecting shifts in a mixture of elements. For example, they may be associated with a shift in the perceived quality of the issuer, or may reflect alterations on the supply of funds offered by financial intermediaries, which, in the presence of financial frictions, may reduce their willingness to lend. In order to filter these components from the credit spread, we build a dynamic indicator of expected default risk for each firm in our database. For this, we employ the distance to default (DD) framework based on the extensions that Moody's/KMV Corporation made to the model developed by Merton (1974). According to this theory, DD_{it} index, for firm i at time t, depends upon the interaction of three main elements: (i) the firm's assets value $V_{A_{it}}$, (ii) the volatility of its assets value $\sigma_{V_{A_{it}}}$, and (iii) the value of its debt D_{it}. In this context, a default event occurs when the firm's net value —the value of its assets minus the value of its debt—is less or equal to zero. The DD_{it} indicator takes this net value and scales it by the volatility of the firm's assets value in order to get a measure of the distance to default —i.e. the distance between $V_{A_{it}}$ and D_{it}—in standardized units. The latter idea is consistent with the intuition that a firm with high volatility has a higher chance to get its value of assets below its value of debt (negative net value). In this context, the firm's value of assets, the volatility of its assets, and the firm's liabilities can be used to compute the DD_{it} index of individual firms as follows:

$$DD_{it} = \frac{V_{A_{it}} - D_{it}}{V_{A_{it}} * \sigma_{V_{A_{it}}}} \tag{3}$$

Given that the net value of assets is normalized when dividing by a risk measure —i.e., the volatility of firm's value of assets—DD_{it} is interpreted as the number of standard deviations that the firm's net value deviates from the default point. Therefore, the probability of default shows an inverse relationship with DD_{it}.

However, neither the firm's value of assets nor its volatility are directly observable in practice; those values must be estimated from observed data of each firm. Based on Merton (1974), individual firms capital structure consists of two elements: debt (senior claim) and equity (junior claim). If at any point in time, the firm's value of assets were insufficient to meet the firm's debt commitments, firm's default would occur, shareholders pay-off would be zero, and debt holders would receive the remaining value of assets. Conversely, if at any point in time, the firm's value of assets is enough to pay debt holders, shareholders would receive the remaining value of assets, and firm operations would continue. Given that the shareholders pay-off depends upon the firm's value of assets, we can employ the contingent claim approach to denote this pay-off —i.e the firm's equity E_{it}—as a call option on the underlying value of the firm $V_{A_{it}}$ with a strike price equal to the face value of firm's debt D_{it}. We use this approach to estimate the unobserved firm's value of assets and its volatility by applying the Black-Scholes-Merton option pricing framework. Finally, we compute the probability of default by using a stochastic process which computes the probability that, in one year's time, the value of the assets of the firm drops below the threshold set by the liabilities of the firm.[7]

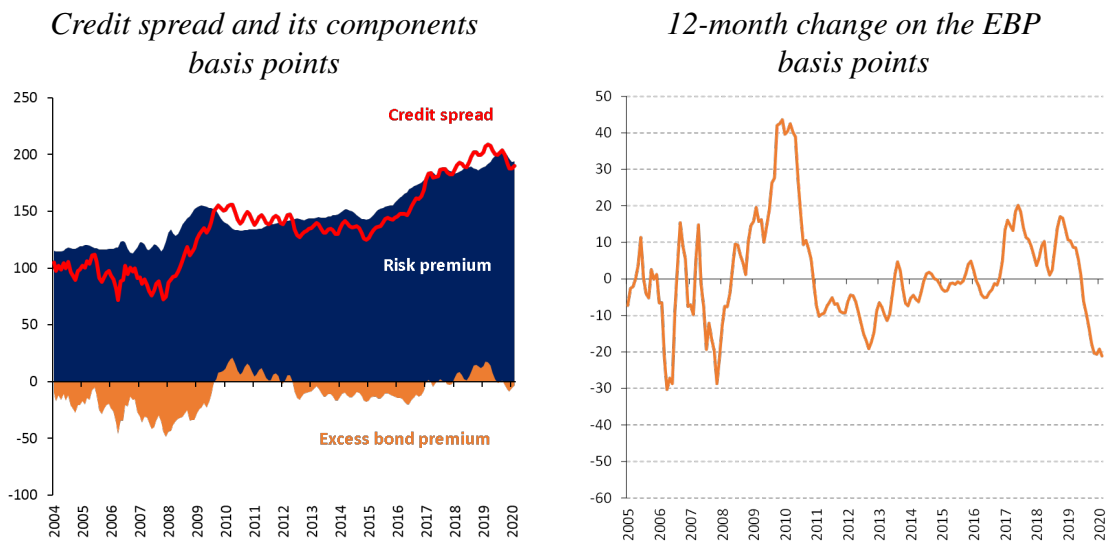
Using data from the Mexican Stock Exchange for firms' market value and liabilities, we compute the distance to default and the probability of default for all firms in our dataset at every moment in time. The computation has as main inputs a monthly dataset, from January 2003 to February 2020, containing the observed data of firms' market value and liabilities, as well as a monthly dataset, covering the same time window, of the annualized daily-stock-returns volatility, computed through the standard deviation of a 1-year moving window of the firms' stock prices logarithmic returns. The final dataset contains monthly information from January 2004 to February 2020 for 116 Mexican non-financial firms.[8]

Table 3 shows some key statistics on the distance to default obtained by the aforementioned method. On average, firms in Mexico have a distance to default of 9.6 units and have

[7] See Merton (1974) and Gilchrist and Zakrajšek (2012) for more details.
[8] We also use data of short-term government interest rate from Banco de Mexico.

a wide range that goes from -3 to 36 units. This means that, on average, firm's net values are more than 9 standard deviations away from their default point. We find that the distance to default series in our dataset have, on average, a higher level than those obtained by GZ12, who report a median distance to default of around 6 standard deviations, with an interquartile range never below zero and rarely surpassing 12 standard deviations. This is not surprising considering that Mexican equity and stock markets continue to be dominated by high quality firms, which show high distance to default series. In fact, in our dataset, only a small portion of Mexican firms faced a high probability of a default event at some point in time, with only 1.4% of the observations showing a distance to default below zero.

Figure 3: Credit Spread, Risk Premium and the Excess Bond Premium for Mexican Corporations



Note: left side figure shows the aggregated credit spread, risk premium and EBP time series. Each series is presented in 3-month moving average. The right panel shows 12-month difference on the aggregated EBP. Source: own calculations using data from Indeval, PiP, Mexican Stock Exchange, Banco de México.

4.3 Credit Spread Decomposition

With the credit spread and the risk premium at hand for every security in our dataset, the final step is to decompose it into the predicted spread (the risk premium) and the EBP. Following GZ12 and Bleaney, Mizen and Veleanu (2015), we let the predicted spread of each bond

account for its issuer's credit risk as well as for the bond's liquidity risk.

We leave, therefore, the EBP to represent the share of the bond spread that is not explained by default or liquidity risks. We then proceed to run a regression of the individual credit spreads on a group of specific variables that account for the risks that we want to control for.

We assume that the natural logarithm of the credit spread on bond k, issued by firm i at time t, $ln(s_{it}[k])$, is related linearly to DD_{it}, which expresses the default risk of issuer i, and a vector of bond-specific characteristics $Z_{it}[k]$, that capture the term and liquidity premia (these variables are mentioned below). We also incorporate industry level and credit-rating fixed effects, as in GZ12 and Bleaney, Mizen and Veleanu (2015), so that we have:

$$\ln(s_{it}[k]) = \beta_1(DD_{it}) + \beta_2^T Z_{it}[k] + \varepsilon_{it}[k] \tag{4}$$

Where the zero-mean disturbance $\varepsilon_{it}[k]$ represents a pricing error, and β_2^T represents the transpose vector of the regression parameters associated to the variables contained in $Z_{it}[k]$.

Assuming normally distributed errors, the predicted value of the credit spread for bond k of firm i at time t is given by:

$$\hat{s}_{it}[k] = exp\left[\hat{\beta}_1 DD_{it} + \hat{\beta}_2{}^T Z_{it}[k] + \frac{\hat{\sigma}_\varepsilon^2}{2}\right]$$

Where $\hat{\sigma}_\varepsilon^2$ is the estimated variance of the model residuals and $\hat{s}_{it}[k]$ is the estimated credit spread (fitted values) of bond k, which we interpret as the risk premium. Consequently, the EBP of bond k issued by firm i at time t is computed as the remaining share of the observed credit spread and its risk premium:

$$EBP_{it}[k] = s_{it}[k] - \hat{s}_{it}[k] \tag{5}$$

Table 2 reports the results of the model following equation 4. As mentioned before, the

dataset contains monthly information from January 2004 to February 2020.

Column (1) includes the base model presented by GZ12, in which the vector of variables controlling for term and liquidity premia, $Z_{it}[k]$, includes the bond duration $DUR_{it}[k]$[9], the fixed coupon rate $CPN_i[k]$, the amount outstanding $AMT_{it}[k]$, and the age of the bond $AGE_{it}[k]$[10]. A second regression in column (2) adds the square of the distance to default in order to allow for a quadratic relationship between the credit spread and default risk, as in Bleaney, Mizen and Veleanu (2015).

The measure of default risk is a statistically significant predictor of the logarithm of the credit spread for each of the two regressions, and reflects that the higher the DD_{it} is (and hence lower the probability of default), the lower the credit spread. Column (2) suggests that an increase of one unit in DD_{it} relates to a decrease of 3.6% in the credit spread, this result is consistent with the findings of previous literature in which an increase of one unit in DD_it has a negative impact of less than 10% in the credit spread. The square of the DD_{it} is also highly significant, suggesting a non-linear relationship between the distance to default and the credit spread. This means that the less risky a firm is, the higher the marginal effect on the credit spread is. This result, in line with Bleaney, Mizen and Veleanu (2015), suggests that investors punish (or reward) extreme values of the default risk more intensively. The duration is also significant and is positively related to the credit spread. The coupon rate, however, appears to have non-significant relation on the credit spread. Finally, the age and amount outstanding appear to have a positive significant correlation with the credit spread. The fixed effects for rating and sector are significant. This may show that we are not able to fully characterize the firm-specific default risk by only using the DD_{it}, and therefore the credit ratings are still necessary. Likewise, it could mean that liquidity risk may be different between industries.

[9]The modified duration is an adjusted version of the Macaulay duration, which is calculated as a weighted average term to maturity of all cash flows from a bond, where the weight of each cash flow is determined by dividing the present value of the cash flow by the price of the bond. The Macaulay and modified duration were computed using Indeval, Valmer and Bloomberg information.

[10]The age of the bond is defined as the time that the bond has been in circulation.

The regressions give a fit of around 31%, as suggested by the R^2 and the $adjusted - R^2$. Regression (2) gives a marginally better fit considering both measurements and, therefore, this is the one we keep for our following analysis. The goodness of fit of our model is, therefore, in the interval reported by De Santis (2016), who registered that on average distance to default and bond characteristics can explain about 25-50% of the credit spread. For most of these models, the goodness of fit remains below 50%, suggesting that there are other variables that play a role in the dynamics of the credit spread that may not be firm or bond related.

Table 3 shows the descriptive statistics of our main inputs and results in the credit spread decomposition process. For the distance to default we observe a very disperse distribution. While there is a firm for which assets are projected to be 2.99 standards deviations below the threshold in a year time, there is a firm with a distance to default of 36 standard deviations. For the yields of the synthetic bonds constructed as benchmark for each of the securities at the sample, we observe a symmetric distribution with a mean of 6.4% and a median of 6.5%. The distribution of the difference between the observed yields and the benchmark yields for each of the securities, i.e. the credit spread, depicts also a relative symmetric distribution with a mean of 1.6% and a standard deviation of 0.68%. The risk premium, i.e., the share of the credit spread that is estimated to account for the risk, term and liquidity premia has a right skewed distribution with a minimum value of 0.9% and a maximum of 4.5%. Finally, the EBP, which accounts for the difference between the credit spread and risk premium has a mean value of -0.04% and a standard deviation of 0.52%.

Table 2: Decomposition for Domestic Market

	Dependent variable:	
	$lnS_{it}[k]$	
	(1)	(2)
DD_{it}	-0.0101***	-0.0366***
	(0.0017)	(0.0047)
DD_{it}^2		0.0012***
		(0.0002)
$ln(Dur_{it}[k])$	0.0629***	0.0510***
	(0.0154)	(0.0154)
$ln(CPN_i[k])$	-0.0220	-0.0801
	(0.0511)	(0.0518)
$ln(AGE_{it}[k])$	0.0128*	0.0130*
	(0.0067)	(0.0067)
$ln(AMT_{it}[k])$	0.0302***	0.0274***
	(0.0103)	(0.0102)
Observations	4,909	4,909
R^2	0.3031	0.3082
Adjusted R^2	0.3011	0.3061

Note: *p<0.1; **p<0.05; ***p<0.01.

The linear regression model is estimated by OLS from a dataset containing monthly information from January 2004 to February 2020.

Source: own calculations using data from Indeval, PiP, Mexican Stock Exchange, Banco de México.

Similar to all of the related literature, we compute an aggregate credit spread, risk premium and EBP by simply calculating an arithmetic average of the monthly individual observations. Left panel of Figure 3 shows the averages for the credit spread, the risk premium and the EBP. The right panel shows the 12-month absolute change on the EBP as a way of showing the dynamics of financial conditions. As can be seen, by the last quarter of 2008, the credit spread, the risk premium and the EBP started to rally, reflecting the strains in the financial conditions and the difficulties that private companies faced as the financial and economic crisis unfolded. During the financial crisis, the EBP started to increase abruptly, as shown in the right panel, evidencing the sharp contraction and tightening on financial conditions.

After the policy response, both in Mexico and abroad, the EBP started to decrease by the end of 2009 and during 2010. Around the beginning of 2013 and specially after 2015, a new contraction cycle on financial conditions started. The latter coincides with the taper tantrum episode in 2013, and with the normalization on U.S. monetary policy that started in 2016 and the restrictive monetary policy cycle that followed in Mexico. After this date, and in line with the change in policy that the Federal Reserve and other major central banks undertook at the beginning of 2019, financial conditions became less restrictive. By the beginning of 2020, therefore, the EBP hovered around zero.

Table 3: **Domestic Corporate Bond Characteristics (DD, CS and EBP)**

Variable	Mean	S.d	Min	Q10	Median	Q90	Max
Distance to default	9.62	4.62	-2.99	4.53	9.02	16.07	36.30
Benchmark yield (%, in pesos)	6.37	1.32	2.35	4.62	6.48	7.95	10.39
Credit spread (%, in pesos)	1.56	0.68	0.01	0.85	1.45	2.36	4.72
Risk premium (%)	1.60	0.51	0.92	1.12	1.41	2.12	4.52
Excess bond premium (%)	-0.04	0.52	-2.17	-0.65	-0.09	0.64	2.38

Note: the table shows descriptive statistics for the results of the process of calculating and decomposing the credit spread. Data sample goes from January 2003 to February 2020.

Source: own calculations using data from Indeval, PiP, Mexican Stock Exchange, Banco de México.

5 Predictive content of the Credit Spread and its Components on Aggregate Macroeconomic Variables

With the credit spread and its components at hand, we now aim to test for their forecasting power and ability to predict macroeconomic aggregates. To do so, we follow the methodology largely applied in similar studies by computing an in-sample forecast technique as in Gilchrist, Yankov and Zakrajšek (2009), GZ12, and all the subsequent studies. We also add an out-of-sample forecast using a Bayesian VAR and computing the RMSE for a rolling out-of-sample window.

5.1 In-Sample Forecast

To assess the predictive ability of the credit spread for economic activity and credit we estimate the following forecasting specification:

$$\nabla^h Y_{t+h} = \alpha + \beta_1 CS_t + \beta_2 TS_t + \beta_3 R_t + \beta_4 ExR_t + \beta_5 USIP_t + \beta_6 TS_{US,t} + \sum_{i=1}^{p} \omega_i \nabla Y_{t-i} + \varepsilon_{t+h} \tag{6}$$

Where Y is the variable we want to forecast for different horizons; $\nabla^h Y_{t+h} = \frac{1200}{1+h} ln(\frac{Y_{t+h}}{Y_{t-1}})$, $h \geq 0$ is the forecast horizon, which we set at 3-,6-, and 12-months ahead. We settle alternatively Y to be economic activity represented by $IGAE$ and domestic private financing to non-financial sector. CS_t is the credit spread obtained in Section 4. As control variables, we use: the slope of the yield curve or term spread, TS_t, defined as the difference between the yield on the 10-year Mexican Government nominal bond (M10) and the rate in the 3-month bill (Cetes91); the real short-term interest rate, R_t (in annual % terms), defined as the 28-day inter-bank equilibrium interest rate (TIIE-28) minus the annual inflation; the annual rate of depreciation of the peso against the dollar, ExR_t; the annual growth rate in the U.S. industrial production, $USIP_t$; and the slope of the U.S. Government yield curve, TS_{US}, defined as the 10-year Treasury bond and the 3-month Treasury bill rate. For the model with domestic financing as dependent variable, we also control for the lag effects of economic activity. We add this control because we are interested in knowing how financial conditions, represented by the credit spread, affect lending and financing. Therefore, we need to isolate the effect of lagged economic activity. On the other hand, in the model with economic activity as dependent variable, we do not control for financing because that is precisely the channel we want to explore: how credit conditions affect production.

The framework, therefore, examines the marginal information contained in the credit spread controlling for the slope of the yield curve and the real interest rate—two key indicators of the monetary policy stance—, along with the exchange rate, industrial production and the term spread in the U.S., —in order to control for possible external effects, as Mexico is

a highly open economy with significant links to U.S. activity. The dataset contains monthly observations from January 2004 to February 2020. The dynamics, source and specification of each of the time series in the model can be consulted in Appendix A.

Regression 6 is estimated by a Bayesian linear regression model with normally distributed priors and applying the Gibbs sampling algorithm to approximate the marginal posterior distributions.[11] To set the prior coefficients distributions, we distinguish between the model forecasting economic growth and financing growth. For the model with economic activity growth as dependent variable, we incorporate in the prior distribution that the credit spread and the real interest rate should have an expected negative effect on economic activity growth by centering its distributions at -1. This expected marginal effect is consistent with the literature and economic theory. For instance, the expected negative relationship of the credit spread to economic activity has been highly documented in the main references of this paper: Gilchrist, Yankov and Zakrajšek (2009), Gilchrist and Zakrajšek (2012), Faust, Gilchrist, Wright and Zakrajšek (2013), Bleaney, Mizen and Veleanu (2015), De Santis (2016) and Favara, Gilchrist, Lewis and Zakrajšek (2016). The real interest rate, on the other side, represents the cost of capital and therefore, a higher rate is expected to be associated to lower output growth. For the U.S. annual growth in industrial production we incorporate in the prior distribution an expected positive relationship with the dependent variable by centering its distribution at 1, as Mexico's economic performance is highly linked to U.S. economic cycle, mainly in manufacturing activities. Less clear it is the effect we could define for the exchange rate depreciation; therefore, we center the prior distribution for this specific coefficient at zero. Likewise, for the difference between the 10-year yield and the 3-month interest rate, we do not incorporate any specific relationship on the prior distribution, following Ibarra (2021) findings that the relationship between the yield curve slope and economic activity in Mexico, although positive in a linear model, depicts significant non-linear behaviour and depends on the level of the term premium.[12] Following Ibarra (2021), we also do not set any

[11] The model is estimated 20,000 times keeping the last 2,000 iterations to form the posterior distributions.

[12] Specifically, Ibarra (2021) finds that the positive relationship between the slope of the yield curve and economic activity in Mexico holds only when the term premium is above a specific threshold.

specific prior expected effect of the U.S. term spread on economic activity as evidence has suggested that this effect depends heavily on the forecast horizon. For the model with private financing growth as dependent variable, we set very similar priors, with the only difference that we center at zero the prior distribution of the coefficient of industrial production in the U.S., as the effect of it on credit is less obvious. For the coefficient of the lag effect of economic activity, we center its prior distribution at zero. All the other priors are set identically as in the model forecasting IGAE.

Finally, we set a loose variance for the distribution of each of these prior normal distributions in order to let the model learn from the data. More importantly, we set the same variance for each of the coefficients' priors in order not to affect *a-priori* its forecasting marginal effect.

Table 4 details the results on the predictive power of the credit spread for 3-, 6- and 12-month ahead on economic activity and total private domestic financing. We show percentiles 16, 50 and 84 of the coefficient's distributions of the explanatory variables, as it is common in Bayesian models. It is worth mentioning that, for each of the models and horizons, we compute some convergence test in order to ensure that Gibbs sampling is converging and that posterior distributions are correctly approximated.[13]

Coefficients for the credit spread are negatively significant for each forecast horizon and for both economic activity and domestic financing. For instance, an increase of 100 basis points in the credit spread is expected to reduce the 3-month (annualized) growth of IGAE between 0.13 and 0.6 percentage points. For the 12-month ahead forecast horizon, a 100 basis points increase in the credit spread is expected to have a median effect of -0.36 in the expected 12-month growth of IGAE. Our results are in line with the findings of GZ12, given that, for the 3-month and 12-month forecasting horizons, our coefficient's intervals of the

[13]Following Blake and Mumtaz (2017), we perform some empirical tests for convergence. Specifically, we plot the sequence, the recursive means and the autocorrelation functions of the retained draws for each of the parameters of the model. The first two show, for all parameters, a random fluctuation around a stationary mean and do not display a trend, while the third shows close to zero autocorrelations of the parameters.

effect of the credit spread on economic activity contains the point estimates they report for the effects of the credit spread on GDP in the U.S. The effect of the term spread on economic activity is positive and in line with Ibarra (2021), who documented a positive relationship between the slope of the yield curve and economic activity.

Table 4: **In-Sample Forecasting Results: Credit Spread**

	3 months			*6 months*			*12 months*		
	16	50	84	16	50	84	16	50	84
					IGAE				
CS	−0.5961	−0.3573	−0.1273	−0.5419	−0.3343	−0.1406	−0.5381	−0.3612	−0.1819
TS	0.1611	0.2707	0.3858	0.1249	0.2228	0.3267	0.0848	0.1648	0.2482
R	−0.9084	−0.8453	−0.7797	−0.9201	−0.8688	−0.8066	−0.9623	−0.9166	−0.8671
ER	0.0061	0.0183	0.0301	0.0128	0.0234	0.0335	0.0088	0.0173	0.0251
I.P. U.SA	0.8586	0.8953	0.9319	0.8591	0.8894	0.9219	0.8910	0.9165	0.9427
T.S. U.S.	0.0551	0.1663	0.2756	0.0762	0.1741	0.2722	0.1000	0.1763	0.2562
					Domestic Financing				
CS	−0.7789	−0.5971	−0.4317	−0.7399	−0.5957	−0.4511	−0.6995	−0.5656	−0.4337
TS	−0.0110	0.0762	0.1652	0.0254	0.0950	0.1684	0.0377	0.1023	0.1646
R	−0.9063	−0.8616	−0.8147	−0.9322	−0.8916	−0.8516	−0.9596	−0.9269	−0.8942
ER	−0.0155	−0.0069	0.0014	−0.0113	−0.0042	0.0028	−0.0073	−0.0015	0.0048
I.P. U.SA	0.0178	0.0442	0.0693	0.0169	0.0383	0.0584	0.0062	0.0236	0.0405
T.S. U.S.	−0.1075	−0.0257	0.0550	−0.0490	0.0209	0.0902	0.0125	0.0718	0.1291
IGAE_{t-3}	0.0727	0.1245	0.1755	0.0614	0.1073	0.1552	0.0370	0.0766	0.1149

CS: credit spread; *TS*: Term spread; *R*: real interest rate; *ER*: Exchange rate depreciation; *I.P. USA*: 12-month growth on U.S industrial production; *T.S. U.S.*: the slope of the yield curve in the U.S.; $IGAE_{t-3}$: 3-month lagged IGAE. Models are estimated using a Bayesian linear regression approach by means of the Gibbs sampling algorithm and with normal distributed priors. Dataset goes from January 2004 to February 2020. Columns show percentiles 16, 50 and 84 of the coefficients' distribution for each forecasting horizon (3-,6-,12-month ahead).

These results are also supported by GZ12 who found that a flat or inverted yield curve signals a deterioration in economic activity indicators. It is worth noting that other previous studies have obtained a non-significant or even a negative relationship between the term spread and economic activity indicators. For instance, the work of Bleaney, Mizen and Veleanu (2015) shows that an increase in the slope of the yield curve adversely affects the real GDP growth rate. The latter could be associated with the findings of Ibarra (2021), who

documented that the predicted power of the term spread on economic activity is weak when the term premium is located at low levels, a condition that has been persistent in Europe. The coefficients for the real interest rate and U.S industrial production show the expected sign and are highly significant. For the exchange rate depreciation, we see a positive effect on economic activity that could be related to an increase in foreign demand of Mexican goods as the peso depreciates, although coefficients are barely significant. For the term spread in U.S. we see a slightly positive effect. The latter relationship may be a result of the link between the U.S. yield curve slope and the U.S. output as many studies for the U.S., documented in Ibarra (2021), have found.

Similar figures are shown for the model with private domestic financing as dependent variable: an increase of 100 basis points on the credit spread is translated into an expected decrease of between 0.4 and 0.7 percentage points on the 12-month growth of private domestic financing, signaling that an increase on the credit spread reflects a tightening of domestic financial conditions. Lagged economic activity affects domestic financing significantly and positively for all forecasting horizons, a result that could be related with an increase on the demand of credit as economic activity fares well. The relationship of the term spread for shorter horizons, on the other side, shows a non-significant effect on financing, neither for the domestic yield curve slope nor the U.S term spread. For longer horizons, effects become positive and significant, result in line with the forward-looking nature of the term spread with economic activity and the alluded relationship of the latter with financing. As in the model for economic activity, real interest rate has a significant relationship with private domestic financing growth, as it affects the opportunity cost of capital accumulation. Finally, the U.S. industrial production shows a positive forecasting power to domestic financing for all forecasting horizons, in line with the relationship with economic activity and financing. This effect, though, becomes less significant with longer horizons.

Although our purpose is to study the marginal contributions of the credit spread and its components to forecasting economic activity and financing, and not precisely to propose a methodology for doing so, it is important to know the fit of the models estimated. Appendix

B shows the fitted values and the mean squared errors (MSE) of the models estimated. For instance, Figure 9 shows the fit of the models represented by the upper panel of Table 4 for forecasting economic activity 3-,6- and 12-month ahead. Similarly, Figure 10 show the fit of the models with domestic financing as dependent variable, i.e., the lower panel of Table 4. We can see that the models follow relatively well both dependent variables and more importantly that the models do not consistently over or underestimate the dependent variables.

Once we know that the credit spread has significant predictive power for economic activity and domestic private financing, we now allow for the two components of the credit spread to enter the forecasting regression instead of the credit spread. The models are estimated exactly as before, but we just interchange the CS with both of its components. More importantly, the same prior that we gave for the coefficient of the credit spread, we now give for the priors of the coefficients of the risk premium and the EBP. The priors for the other coefficients are left as in Model 6, both when forecasting economic activity and financing.

$$\nabla^h Y_{t+h} = \alpha + \beta_1 EBP_t + \beta_2 RP_t + \beta_3 TS_t + \beta_4 R_t + \beta_5 ExR_t + \beta_6 USIP_t + \beta_7 TS_{US,t} + \sum_{i=1}^{p} \omega_i \nabla Y_{t-i} + \varepsilon_{t+h} \tag{7}$$

The upper panel of Table 5 shows the forecasting power of the credit spread components on economic activity. According to the estimates, only the EBP contain significant independent explanatory power for economic activity; furthermore, coefficient for the EBP are significantly higher (in absolute values) than the marginal effects reported from the credit spread on economic activity in Table 4.[14] For instance, Table 5 shows that a 100 basis points increase in the EBP is associated with a median decrease of around 1.8, 1.7 and 1.4 percentage points in economic growth for the 3-, 6-, 12-month horizons, respectively. This also reflects a marginally decreasing effect as the forecasting horizon expands. Our findings regarding the coefficient associated to the EBP are closer to those obtained by Bleaney, Mizen and Veleanu (2015) who, similar to us, conclude that when forecasting economic activity, the predicted part of the credit spread is no significant at all horizons, but find that the EBP has a consis-

[14] As before, for each of the models and horizons, we compute some convergence test in order to ensure that Gibbs sampling is converging and that posterior distributions are correctly approximated.

tently negative and significant sign, as well as a magnitude close to our results. Particularly, they estimate that a 100 basis points increase in the EBP is associated with a median decrease of around or above 1.0 percentage points for most of the countries they analyze. As before, the slope of the yield curve holds a positive forecasting power with economic activity that seems to be higher at shorter terms, a result in line with Ibarra (2021). The real interest rate also holds the expected relationship with economic activity as in Table 4 and coefficients are highly significant. Regarding U.S. control variables, industrial production holds its positive forecasting power as expected, whereas the term spread is now only significant for longer horizons, a result also in line with Ibarra (2021).

Table 5: **In-Sample Forecasting Results: Credit Spread Components**

	3 months			*6 months*			*12 months*		
	16	50	84	16	50	84	16	50	84
					IGAE				
EBP	−2.5507	−1.8228	−1.1630	−2.2024	−1.6563	−1.1024	−1.7982	−1.4020	−0.9763
RP	−0.6424	−0.2250	0.1695	−0.4459	−0.1235	0.2172	−0.3039	−0.0428	0.2265
TS	0.0882	0.2102	0.3275	0.04084	0.1480	0.2469	0.0279	0.1017	0.1750
R	−0.9645	−0.8987	−0.8348	−0.9694	−0.9181	−0.8645	−0.9991	−0.9551	−0.9157
ER	0.0022	0.0145	0.0263	0.0102	0.0198	0.0295	0.0065	0.0142	0.0214
I.P. U.S.	0.8607	0.8987	0.9345	0.8628	0.8945	0.9258	0.9013	0.9246	0.9478
T.S. U.S.	−0.0650	0.0479	0.1623	−0.0371	0.0636	0.1561	0.0124	0.0821	0.1596
					Domestic Financing				
EBP	−1.8185	−1.2832	−0.7101	−1.6344	−1.1766	−0.7392	−1.4899	−1.1281	−0.7541
RP	−0.6598	−0.3600	−0.0657	−0.4906	−0.2396	0.0056	−0.2947	−0.0745	0.1522
TS	−0.0732	0.0138	0.1033	−0.0411	0.0297	0.1047	−0.0054	0.0567	0.1193
R	−0.9215	−0.8754	−0.8264	−0.9387	−0.8973	−0.8601	−0.9589	−0.9252	−0.8923
ER	−0.0166	−0.0084	0.0002	−0.0126	−0.0058	0.0011	−0.0088	−0.0029	0.0028
IP U.SA	0.0234	0.0498	0.0747	0.0233	0.0436	0.0640	0.0109	0.0295	0.0463
T.S. U.S.	−0.1980	−0.1065	−0.0195	−0.1368	−0.0649	0.0084	−0.0548	0.0013	0.0602
IGAE_{t-3}	0.0700	0.1236	0.1791	0.0633	0.1071	0.1527	0.0382	0.0751	0.1130

EBP: excess bond premium; *RP*: risk premium; *TS*: Term spread; *R*: real interest rate; *ER*: Exchange rate depreciation; *I.P. USA*:12-month growth on U.S industrial production; *T.S. U.S.*: the slope of the yield curve in the U.S.; $IGAE_{t-3}$: 3-month lagged IGAE. Models are estimated using a Bayesian linear regression approach by means of the Gibbs sampling algorithm and with normal distributed priors. Dataset goes from January 2004 to February 2020. Columns show percentiles 16, 50 and 84 of the coefficients' distribution for each forecasting horizon (3-,6-,12-month ahead).

The lower panel of Table 5 shows the marginal contribution of the variables for forecasting domestic private financing. Coefficients for both of the components are statically different than zero for the 3-month horizons, while coefficients for the risk premium at higher horizons turn non-significant. As in the model for economic activity, coefficients of the EBP for forecasting domestic financing are significantly higher that the credit spread coefficients reported in Table 4 for all horizons. As before, lagged economic activity affects domestic financing significantly and positively for all forecasting horizons. The effect of the term spread on financing is non-significant, neither for the domestic yield curve slope nor the U.S term spread. As in the model for economic activity, real interest rate has a significant relationship with private domestic financing growth, as it affects the opportunity cost of capital accumulation.

Finally, the U.S. industrial production shows a positive forecasting power to domestic financing for all forecasting horizons, in line with the relationship with economic activity and financing. This effect also becomes less significant as horizon increases as in the previous model. These findings suggest that, as all related studies on the subject referred in Section 2 have found, the EBP is the main carrier of information related to macroeconomic aggregates.[15]

5.2 Out-of-Sample Forecast

In order to further investigate the predictive power of the credit spread and its components, we estimate different models that separately and alternatively include the credit spread, the risk premium, and the EBP. Next, we perform an out-of-sample forecast for economic activity and private domestic financing with a rolling forecast window. We rely on a Bayesian Vector

[15] As in the case of the models with the credit spread, Appendix B shows the fitted values and MSE of the models introducing the components of the credit spread into the regression. Figure 11 shows the fit of the models represented by the upper panel of Table 5 for forecasting economic activity 3-,6- and 12-month ahead. Similarly, Figure 12 shows the fit of the models with domestic financing as dependent variable, i.e., the lower panel of Table 5. As before, the models follow relatively well both dependent variables and that the models do not consistently over or underestimate dependent variables. More importantly, the set of models containing the EBP and risk premium show lower MSE for any of the forecasting horizons relative to the models when the credit spread, and not its components, is introduced in the regression.

Autoregressor (BVAR) framework, estimated by means of the Gibbs sampling algorithm. The VAR specification, in its reduced form representation, is as follows:

$$Y_t = c + \sum_{i=1}^{p} \phi_i Y_{t-i} + \varepsilon_t \tag{8}$$

Where c represents a vector of constants; ϕ_i is the matrix of persistence factors and controls the lagged effect (for each lag i) of each variable on itself and the others; ε_t is the vector of residuals with covariance matrix Σ.

Using the lag operator, the model can be written as:

$$Y_t = c + \Phi(L) Y_t + \varepsilon_t \tag{9}$$

Where $\Phi(L)$ is a matrix of polynomial in the lag operator. Y_t includes the following variables: (i) annual growth in industrial production in the United States; (ii) an average of the shadow rates for the Federal Funds Rate[16]; (iii) the term spread of the U.S government yield curve, calculated as the difference between the yield on the 10-year Treasury bond and the 3-month Treasury bill; (iv) annual growth in IGAE; (v) the short-term real interest rate; (vi) annual growth in total private financing; (vii) the credit spread/risk premium/RBP; $(viii)$ the term spread defined as the difference between 10-year and 3-month maturity Mexican peso denominated government yield; and, (ix) the yearly percentage rate of depreciation in the Mexican peso with respect to the U.S. dollar.[17]

The model is estimated using monthly data from January 2004 to February 2020. We apply a Bayesian approach using the Gibbs sample algorithm and a Minnesota-type prior scheme for the VAR's coefficients. The model is estimated 30,000 times and we keep the last 1,000 estimations to form the empirical posterior distributions. Furthermore, we formulate as prior that U.S. variables are block-exogenous, this is, the first three variables of the model

[16] A shadow federal funds rate is an instrument created to quantify the actual monetary policy stance of unconventional policies when the federal funds rate sits at or near zero. We compute a simple average of two shadow rate measures: Wu-Xia and Leo Krippner. More information in Appendix A.

[17] The specifications, source and dynamics of the time series in the model can be consulted in Appendix A.

do not respond to shocks on the Mexican variables. We also set long-run level priors to the variables; specifically, we set a long-run level of the Federal Funds rate at 2.5% according to the June 2020 median "longer-run" projection published by the FOMC. For the level of the short-term real interest rate, we set a long-run prior level centered at 2.6%, in line with the Central Bank's latest studies on the neutral nominal interest rate (Banco de Mexico (2019b)). Finally, for the model containing the EBP, we impose as a prior the fact that in steady state it should converge to zero. For the rest of the variables, we use their sample mean as the prior for convergence.

For each of the three models estimated, containing the credit spread, the risk premium or the EBP, respectively, we compute a model selection criteria procedure in order to choose for the lags, the hyper-parameter that control the standard deviation of the prior on its own lags (λ_1), and the parameter that controls the standard deviation of the prior on other variables (λ_2). In a more general manner, the parameter that controls the degree to which coefficients on lags higher than one are likely to be zero (λ_3) is set to 2 for all the models; the parameter that controls the relevance of the constant term (λ_4) is set to 10^5; while a tight prior for the steady state variables is imposed for all the models ($\lambda_0 = 0.1$). The selection criteria consist on running each model for different lags, and a window of plausible values for λ_1 and λ_2 for each lag selection. We then calculate the marginal likelihood of each of the models and compute the Bayes factors. As a result of this selection criteria, the lags for each of the models are set as follows: $p = 3$ for the model containing the credit spread; $p = 2$ for the model containing the risk premium; and, $p = 2$ for the model with the EBP. For the hyper-parameters, and within the optimal lag selection for each model, the selection criteria give a similar outcome for λ_1 in the vicinity of $[0.4, 0.7]$, and in the vicinity of $[0.2, 0.6]$ for λ_2. Therefore, we follow the standard recommendation contained in Blake and Mumtaz (2017), and set $\lambda_1 = 0.5$ and $\lambda_2 = 0.3$ for the three models alike.

For each model selected, we calculate the distribution of the root mean squared errors for 12-month growth in economic activity and private financing after a rolling out-of-sample forecast for the next six months ($h = 6$) for the last two years of the sample. The models

are estimated 30,000 times ($j = 30,000$) and we keep the last 1,000 observations to form the posterior distribution. The algorithm in detail works as follows:

1. We limit the database from January 2004 to February 2018 (24 months before the full sample).

2. We compute the first six forecasts for each variable; i.e. a forecast of the annual growth on the variables of interest for the next six months. With these forecasts, we calculate the root squared error for every forecast $h = 1, ..., 6$ and every variable of interest i. For each iteration j, and variable, i, we then compute and average of the root squared errors as:

$$RSE_{i,j} = \sqrt{\frac{\sum_h [\hat{y}_{i,j} - y_i]^2}{h}}$$

   With all the $RSE_{i,j}$ we then form a distribution of the root squared error over the iterations j.

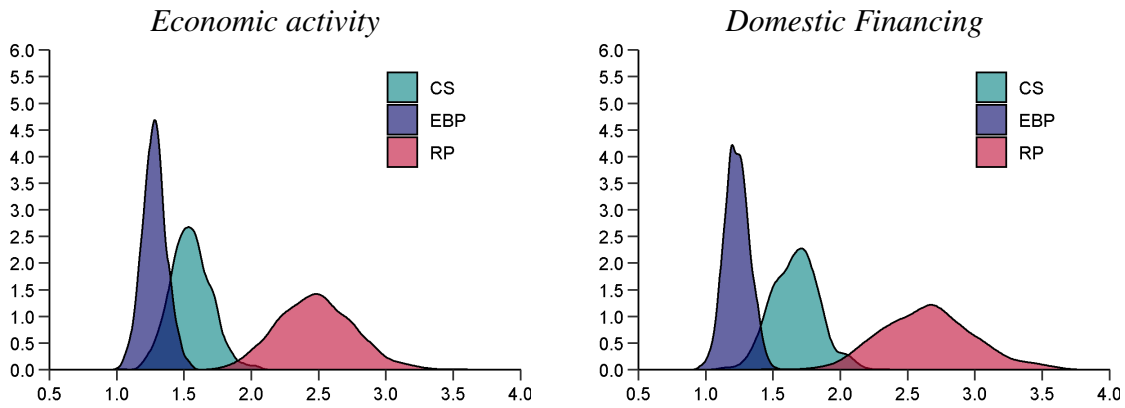
3. We move the rolling window of forecasting by adding one more month to the sample and repeat the steps until the last rolling window (h months before the end of the complete sample).

4. We are then left with a distribution of RSE for each variable at each rolling window. We take the mean across the 24 distributions, so that we get one root mean squared error (RMSE) distribution for each variable.

Figure 4 shows the RMSE distribution for economic activity and domestic financing for each of the models. The results show that, in forecasting economic activity and aggregate private financing, the model with the EBP performs the best, i.e., has the closest to zero RMSE distribution among any of the other models. The latter confirms our in-sample result.

In conclusion, from the in-sample and out-of-sample exercises, we conclude that the credit spread holds a significant forecasting power for economic and financing cycles that is mainly driven by the EBP. This is quite surprising given that, although we are extracting the index from a small fraction of the total financing in Mexico (as exposed in Section 3), the

Figure 4: RMSE Distributions for a Six Months Ahead Forecast of Economic Activity and Financing



Note: Each plot depicts the distribution of the RMSE for forecasting economic activity and financing, respectively, with the three different version of Model 10: one containing the credit spread, one containing the risk premium and one containing the EBP. For completeness, we also ran a model containing the risk premium and the EBP in the same VAR specification. For this model, the distribution of the RMSE for forecasting both variables of interest locate in between the RMSE distributions of the model containing the credit spread and the one with only the risk premium.

credit spread and its components appear to contain signals on the economic cycle and the financial strains of the aggregate economy. Admittedly, this issue is no different as in other countries where the credit spread has been computed. As an example, Bleaney, Mizen and Veleanu (2015) states that even for countries where firms are more heavily bank-dependent, such as Germany, bond spreads offer a signal of tightening in credit conditions more broadly.

6 The Excess Bond Premium and the Macroeconomy

Once we learned, as the literature has suggested, that the EBP contains the strongest predictive power and relationship with economic activity and financing, in this last section we examine the consequences that orthogonal innovations on the former can have on key macroeconomic variables and assess if these responses are symmetric depending on the dynamics of the financial shock.

6.1 Bayesian VAR

In order to analyse the credit channel, and relying on the information content on the EBP, we estimate a VAR model containing key macroeconomic variables for Mexico. VAR models provide a systematic framework that allows to capture the dynamics and co-movements for a set of time series. The VAR specification in its reduced form representation is as follows:

$$Y_t = c + \sum_{i=1}^{2} \phi_i Y_{t-i} + \varepsilon_t \tag{10}$$

Where c represents a vector of constants; ϕ_i is the matrix of persistence factors and controls the lagged effect (for each lag i) of each variable on itself and the others; ε_t is the vector of residuals with covariance matrix Σ.

Using the lag operator the model can be written as:

$$Y_t = c + \Phi(L) Y_t + \varepsilon_t \tag{11}$$

Where $\Phi(L)$ is a matrix of polynomial in the lag operator. Y_t includes the following variables, and in the following order: (i) annual growth in industrial production in the United States; (ii) an average of the shadow rates for the Federal Funds Rate as in Section 5.1; (iii) the term spread of the U.S government yield curve, calculated as the difference between the yield on the 10-year Treasury bond and the 3-month Treasury bill; (iv) annual growth in IGAE; (v) annual growth in the core consumer price index; (vi) the short-term nominal interest rate; (vii) annual growth in total private domestic financing; $(viii)$ the EBP; (ix) the term spread defined as the difference between 10-year and 3-month maturity Mexican peso denominated government yield; and, (x) the yearly percentage rate of depreciation in the Mexican peso with respect to the U.S. dollar.[18]

As in Section 5.2, the model is estimated using monthly data from January 2004 to

[18]The specifications, source and dynamics of the time series in the model can be consulted in Appendix A.

February 2020. We apply a Bayesian approach using the Gibbs sample algorithm and a Minnesota-type prior scheme for the VAR's coefficients. As before, the model is estimated 30,000 times and we keep the last 1,000 estimations to form the posterior distributions. Furthermore, and as in the out of sample forecast framework, we formulate as prior that U.S. variables are block-exogenous, this is, the first three variables of the model are not affected by shocks on the Mexican variables. We also set long-run level priors to the variables; specifically, we set a long-run level of the Federal Funds rate at 2.5% according to the June 2020 median "longer-run" projection published by the FOMC. For core inflation in Mexico, we set a long-run prior centered at 3.0%, in line Bank of Mexico's central objective. For the level of the short-term nominal interest rate, we set a long-run prior level centered at 5.6%, in line with the Central Bank's latest studies on the neutral nominal interest rate (Banco de Mexico (2019b)). Finally, for the EBP, we impose as a prior the fact that in steady state it should converge to zero. For the rest of the variables, we use their mean as priors for convergence. The hyper-parameter that controls the standard deviation of the prior on its own lags (λ_1), and the hyper-parameter that controls the standard deviation of the prior on other variables (λ_2), are set as the model selection criteria explained in Section 5.2 suggests.

In order to recover the structure of the model and break the correlation between the different shocks, we orthogonalized the residuals in the reduced form, ε_t, using a Cholesky decomposition of the variance covariance matix Σ, in order to get the structural innovations, e_t. This is:

$$Ce_t = \varepsilon_t$$

where C is the Cholesky lower triangular matrix.

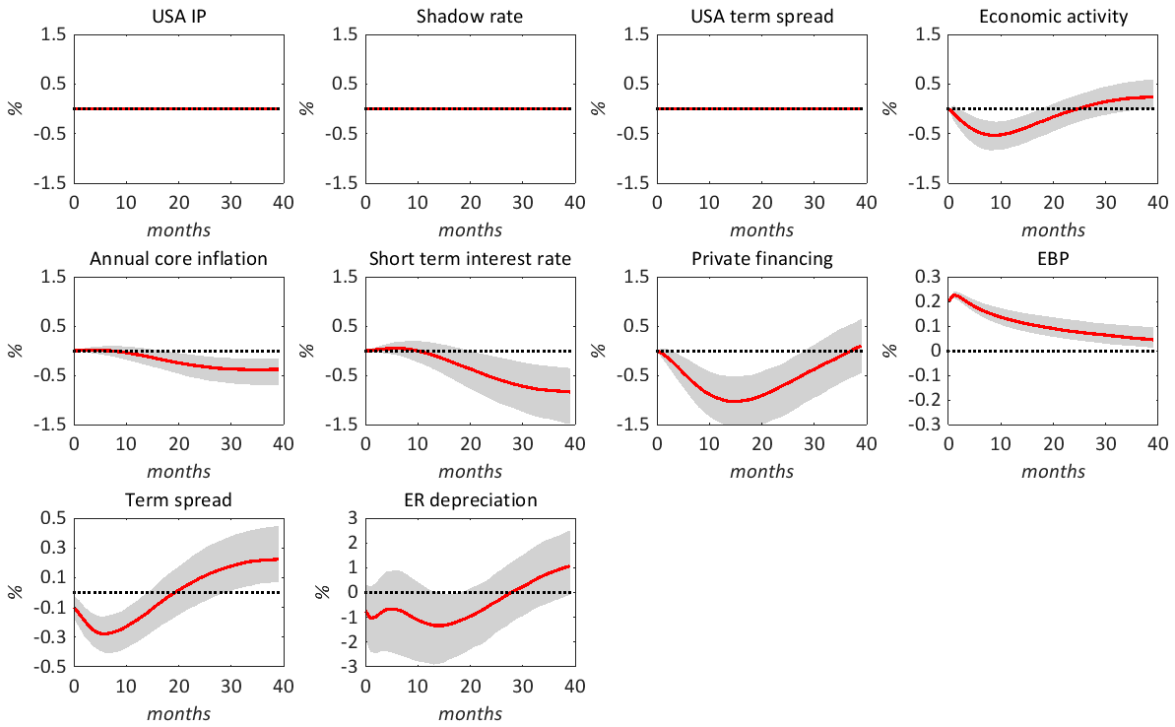
Given the recursive nature of the identification mechanism, the identifying assumption implied by the ordering and the prior specifications of our model is that orthogonal shocks on the EBP do not affect the exogenous variables neither contemporaneously nor with a lag; it may affect inflation, economic activity, short-term interest rate and private financing with a lag; and that the shock can affect contemporaneously the term spread, and the exchange rate.

The ordering of the variables is influenced by Ibarra (2016) as short-term interest rate is order after economic activity and inflation. This means that monetary authorities take into account the current state of output and inflation, hence short-term interest rate can respond contemporaneously to shocks on output and prices, but there is a lag in the opposite direction. Likewise, the interest rate is placed before credit in order to allow for the traditional interest-rate-channel of monetary policy to work together with the credit channel and translate immediately to credit. Finally, given the forward-looking nature for forecasting macroeconomic variables of the EBP and the term spread, they are placed after output, inflation, short-term rate and financing. The exchange rate is left at the end, with the intention for it to operate as the shock-absorber of any innovation. This order is also in line with GZ12 as the identifying assumption is that shocks to the EBP affect macroeconomic variables with a lag, while market variables can react contemporaneously.

Figure 5 depicts the response of the variables to an orthogonal shock on the EBP. A 20 basis points innovation of the EBP derives in a significant negative deviation of economic activity. This deviation achieves its highest impact 8-12 months after the shock and its effects persist until close to 2 years. For instance, the 20 basis point shock on the EBP, is translated into an expected decline in economic activity growth close to 0.5% after 12 months. This result coincides with GZ12, for which a shock of about to 20 basis points in the EBP translates into a 0.5% decrease in GDP three to four quarters after the shock. The shock also derives in a non-significant decline of inflation that gets significant over a long horizon, a result similar to what GZ12 find. The response on the short-term rate appears to be intuitive, as after a shock on the financial conditions, the model estimates a non-significant response on the short-term rate that becomes negative with time, possibly after a policy response. As with economic activity the effect on private financing is negatively significant. In this case, however, the effect appears to be more lagged and stronger as the EBP innovation derives into a maximum response of -1% in domestic private financing growth around 15 months after impact. Likewise, consistent with the sluggish economy, the term spread plunges but recovers around 12 months after, possibly as the central bank responds with a decrease in the

short-term rate. Finally, after the financial shock identified by the EBP, the model suggests a non-significant response on the exchange rate depreciation.[19]

Figure 5: Business Cycle Implications of a Shock in the Excess Bond Premium



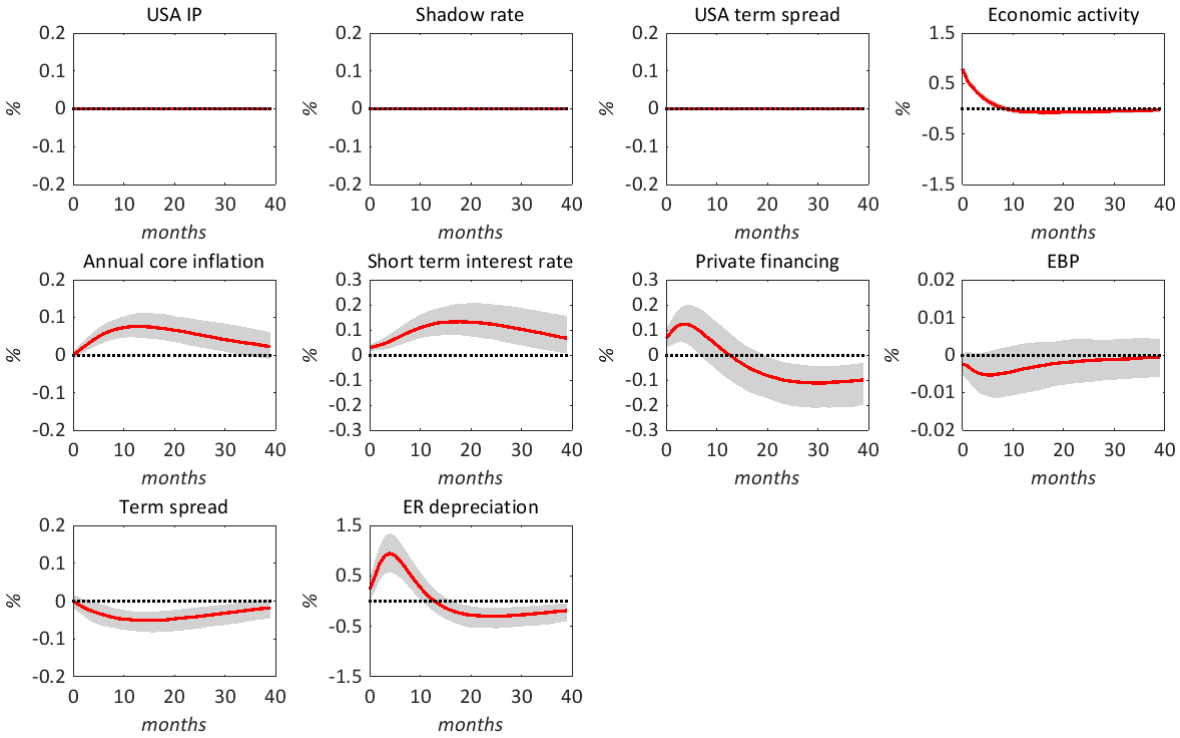
Note: Figure shows the Impulse Response Functions of variables in model represented by Equation 10 after a normalized 20 basis points shock increase in the EBP. Model is estimated using monthly data from January 2004 to February 2020.

Figure 6 shows the sets of IRF for all variables after a shock on output. This is important in order to analyze if output shocks can also affect the supply of credit, represented in this case by the EBP. The responses of inflation, short-term interest rate and domestic financing

[19] As robustness exercises, we ran the previous model incorporating financial volatility variables. Specifically, we include EMBI index between the EBP and the term spread, maintaining all the other features of the model. Responses remain very similar as in the baseline model. Furthermore, we ran a second robustness check model with annual growth in Mexican GDP instead of IGAE and quarterly transformed data for the other variables. Results show very similar IRFs. Specifically, results still show a negative response in GDP after a 20 basis point increase in the EBP that reaches its maximum effect around 4 quarters after the shock. Likewise, the response of domestic financing shows a stronger negative effect on financial conditions, with a maximum effect around six quarters after the shock.

are significant and show that, after a positive shock on economic activity, credit increases, prices rise and monetary authorities respond with rate hikes. Although the EBP decreases, its response is not significant. The latter may reflect that an output shock may come from very different sources and may not necessarily affect the risk-bearing capacity of lenders. This suggests that the positive response on domestic financing must be explained by demand rather than by supply factors.

Figure 6: Business Cycle Implications of a Shock in Output



Note: Figure shows the Impulse Response Functions of variables in model represented by Equation 10 after a one standard deviation positive shock in economic activity. Model is estimated using monthly data from January 2004 to February 2020.

The forecast error variance decompositions of previous model are shown in Figure 13 in Appendix C. We show the forecast error variance decomposition for economic activity, private domestic financing and the EBP. We aggregate the decomposed shocks of the first three variables as "External", and we keep unaltered the shocks on economic activity, private do-

mestic financing and the EBP. We group all the remaining shocks as "Others". For economic activity, external shocks account for a large proportion of the forecast error variance. Respectively, both for the forecast error variance of private domestic financing and the EBP, the shock to the variable itself explains the main proportion of the deviation. More importantly, Figure 14 shows the proportion of the deviations, both for forecasting economic activity and financing, that is due to shocks to the EBP. It shows that, around the 10-month horizon, innovations to the EBP explains up to 7% of the forecast error variance of economic activity. Although slightly lower, our results are in line with findings of GZ12, who outline a forecast error variance decomposition of a 20 basis points orthogonalized shock to the EBP of around 10% to economic activity after 4 quarters. Accordingly, around the 15-month horizon, innovations to the EBP explains around 15% of the forecast error variance of private domestic financing.

Finally, before moving to the analysis of non-linear effects of the shocks of financial conditions, we present evidence that shocks to the EBP also affect differently narrower aggregates of economic activity. For instance, we estimate Model 10, presented in this section, with the exact same specifications but opening economic activity into its main components both from the supply and demand side. That is, we estimate two new models in which we substitute IGAE with its components, both from the supply and demand side. From the supply side, we introduce industry and services, and from the demand side we introduce consumption and investment. Figure 15 in Appendix D shows the responses of the model with economic activity from the supply side. While all of the other variables responses remain closely similar to the ones in Figure 5, we observe a small, though statistically significant, negative response on services after a sudden hike on the EBP. On the other side, we see a stronger, more immediate and more persistent response on industry. Very similar conclusions are extracted from Figure 16, also in Appendix D, which shows the responses of the demand side of economic activity. Consumption reacts with a lag and shows only a slightly negative significant response after the shock, while investment shows an acute negative reaction. As with industry, this response is more immediate and persistent. The latter results are in line

with insights presented by GZ12, who also report a significantly negative but transitory response on consumption, but a strong and persistent reaction on investment after shocks on financial conditions represented by positive innovations on the EBP.

6.2 Non-Linear effects of shocks on Financial Conditions

Our final exercise will analyze the more recent non-linearity theories assessed by Akinci and Queralto (2017) and remarked by Stein (2014) on the effect of shocks on the EBP on economic activity. For instance, we will look for empirical evidence of differentiated responses on economic activity depending on the behavior dynamics of the excess bond premium.

We apply a local projection methodology *á la* Jorda (2005). The baseline model for the local projection of a vector of variables $\mathbf{w}_{t+h}$, for different horizon $h = 0, 1, ..., s$, onto the linear space $(\mathbf{w}_{t-1}, \mathbf{w}_{t-2}, ..., \mathbf{w}_{t-p})$ is:

$$\mathbf{w}_{t+h} = \alpha^h + \mathbf{B}_1^{s+1}\mathbf{w}_{t-1} + \mathbf{B}_2^{s+1}\mathbf{w}_{t-2} + ... + \mathbf{B}_p^{s+1}\mathbf{w}_{t-p} + \mathbf{e}_{t+h}^h \tag{12}$$

Where α^h is a vector of constants; $\mathbf{w}$ is a vector of time series that include the exact same variables as in the BVAR model of Equation 10 in Section 6, and in the exact same order, with the only exception that EBP is replaced by the 12-month change on the EBP: ΔEBP; finally, $\mathbf{B}_i^h$ are a matrices of coefficients for each lag and horizon. For different horizons h, the model is estimated by linear Bayesian methods using normally distributed priors and Gibbs sampling in order to approximate posterior distributions at each horizon. Our dataset, as in previous section, includes data from January 2004 to February 2020. We set as a prior that all coefficients' distributions $\mathbf{B}_i^h$ are centered at zero for each regression, given a different h. We initiate with a loose variance for the prior distributions, in order for the model to learn from the data, however, as h increases, we gradually increase the prior tightness in a similar way as in a Minnesota prior.

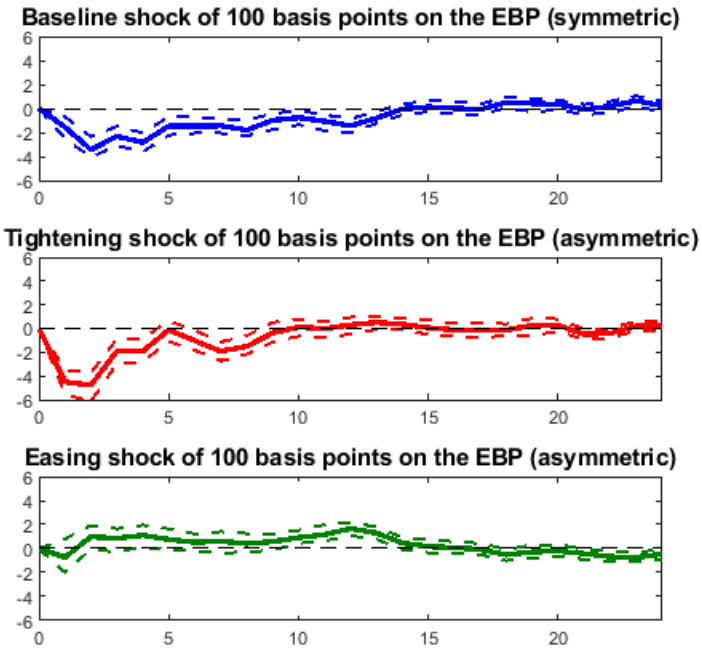
The impulse responses of $\mathbf{w}_{t+h}$ to a structural shock λ are given by: $IR(t,h,\lambda) = \mathbf{B}_1^h$ for

$h = 0, 1, ..., s$. Notice that λ is a $nx1$ vector containing the responses of $\mathbf{w}_t$ to the structural shock of interest, i.e. to the EBP, at the impact period. To compute λ, we rely on the Cholesky decomposition of the variance-covariance matrix of the reduced-form residuals $\mathbf{e}_t^0$, this is, $E\{\mathbf{e}_t^0 \mathbf{e}_t^{0^T}\} = \Omega$. The order implied by the variables is the same as in the model of Equation 10 in Section 6.

We are interested in the impulse response function of $IGAE$ after a structural shock on the EBP. An alternative model to the baseline will replace the EBP with the following two variables: $\Delta EBP_t^+ = d_t^+ \times \Delta EBP_t$ and $\Delta EBP_t^- = d_t^- \times \Delta EBP_t$. Where $d_t^+ = 1$ if $\Delta EBP_t > 0$ and zero otherwise; and $d_t^- = 1$ if $\Delta EBP_t < 0$ and zero otherwise.

Responses for the baseline model are shown in the top panel of Figure 7. We confirm a significant drop in total economic activity after a shock on the EBP as in Section 6.1. A 100 basis point increase on the EBP derives in a negative and significant response on the 12-month growth of IGAE of close to four percentage points, relatively equivalent to the response shown in Section 6.1, in which a 20 basis point shock on the EBP derives into a maximum response of close to one percentage points on the 12-month growth of IGAE. Although the timing and persistence of the response in this model is not precisely as in the BVAR exercise, this is not entirely surprising as the models are different by construction. The relevant outcome is that the relationship holds. Finally, in order to assess if the effects on economic activity are different depending on the dynamics of the EBP, the meddle and lower panel of Figure 7 show the alternative model responses of IGAE to shocks on each of the variables of interest. The meddle panel show the response after a tightening shock on financial conditions (positive innovation on the EBP) when conditions are already tight. We observe that the negative effect on economic activity is stronger at impact that in the baseline case, though the effect is less persistent. The lower panel of Figure 7 shows the asymmetric response of economic activity after an easing shock in financial conditions when conditions are already getting looser. We find evidence of a non-significant effect on economic activity at the moment of the shock, while there is a slightly positive and significant effect around a year after the shock.

Figure 7: Symmetric and asymmetric responses of economic activity after shocks on the EBP



Note: The IRFs in the upper panel show the response of economic activity after a shock on the EBP without differentiating its behaviour. In the middle and lower panels, IRFs show the asymmetric effect of a shock on financial conditions. Responses are estimated by applying a linear projection approach. Sample includes data form January 2004 to February 2020.

Results are in line with findings of Akinci and Queralto (2017), who reported that the relationship between credit spreads and activity is highly asymmetric. Stein (2014) also noted these asymmetries by highlighting that upward moves of the EBP are normally more informative about the evolution about future economic real activity. Likewise, results are line with the findings of Ibarra (2016), who presented evidence that the monetary transmission mechanism through the credit channel has stronger effects on economic activity when conditions are tightening than when conditions are easing.

7 Concluding remarks

A common stance in the literature is that a widening of corporate credit spreads may reflect two different kinds of shocks: i) idiosyncratic shocks on the net worth of firms that limit

the willingness of financial intermediaries to lend, or ii) shocks that emanate directly from financial intermediaries, affecting the availability of credit. The significance of credit spreads as predictors of economic activity for advanced economies demonstrates the relevance of these theoretical channels and raises the importance for research on the matter for emerging economies. Additionally, literature has found empirical evidence that a specific component of the credit spread carries the strongest linkages with the business and credit cycles. This specific component, therefore, can be used as a better proxy for identifying financial frictions, as it is closely linked to the supply of credit in the economy. The latter is the excess bond premium (EBP): a measure of firms' borrowing cost that is more directly linked to financial market frictions, as it excludes default premia and is orthogonal to firms' and bond fundamentals.

In this paper we constructed a credit spread of domestically issued bonds for the Mexican non-financial corporations and decomposed it into a risk premium and an EBP, following closely Gilchrist and Zakrajšek (2012). We find that the aggregate credit spread for the Mexican economy has a significant contribution for forecasting both economic activity and private domestic financing at different horizons, and that the EBP component is the main driver of this relationship. Both from an in-sample and out-of-sample forecasting techniques, we find that the EBP has a significantly higher predictive content for economic and financial aggregates than the risk premium. The latter suggests that the inclusion of the credit spread or the EBP can improve forecasting and nowcasting models for the Mexican economy.

In addition, we show that orthogonal negative shocks on financial conditions, identified as a sudden increase in the EBP, generate a slump on total private financing, a decrease in the term premium, a sluggish economy and persistent lower inflation. The responses on economic activity are also different when taking different aggregates from the supply and demand side. From the supply side, a shock on the EBP derives in a deeper drop in the growth of industrial activity compared to the also negatively significant response on services. From the demand side, although the response on consumption is negatively significant after positive innovations on the EBP, the response on investment is significantly larger. These results, in turn, underline

the relevance of frequently monitoring the credit spread and its components, as it may have properties of a leading indicator for financial frictions and, therefore, may generate additional priors on the expected behaviour of inflation and economic activity, both from the demand and supply sides, which are key variables for the monetary policy design and implementation.

Finally, we find evidence of non-linear effects on the responses of economic activity to shocks on the EBP, as the responses are stronger for tightening shocks in financial conditions when financial conditions are already getting tighter, while the effects of an easing shock on financial conditions when conditions are getting loose, are less informative on the response of economic activity. The latter may contribute to the studies of asymmetries in the transmission mechanism of monetary policy in Mexico, introduced by Ibarra (2016), as it may suggest that monetary policy actions affecting financial conditions may have stronger effects in times of financial stress.

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A Appendix 1

This Appendix shows the source and specifications of the variables used in the paper.

Annual growth rate in the U.S. industrial production, USIP $(USIP)$: This is an economic indicator that measures real output for all facilities located in the United States manufacturing, mining, and electric, and gas utilities. The index is compiled on a monthly basis to bring attention to short- term changes in industrial production. Annual growth in the production index is an indicator of growth in the industry. Data retrieved from FRED, Federal Reserve Bank of St. Louis https://fred.stlouisfed.org/series/INDPRO.

Average shadow rate for the Federal Funds Rate: When the federal funds rate hovers near zero, which is common during recessions in developed economies, unconventional monetary policy is usually deployed. A shadow federal funds rate is an instrument created to quantify the stance of these unconventional policies even when the federal funds rate sits at or near zero. We compute average shadow rate as a simple average of two shadow rates obtained by different methodologies: Wu-Xia and Leo Krippner. The former is constructed with underlying input data for Gurkaynak, Sack, and Wright yield curve estimates and is reported by the Federal Reserve Bank of Atlanta https://www.atlantafed.org/cqer/research/wu-xia-shadow-federal-funds-rate. The latter is the Shadow Short Rate for the United States computed by and Leo Krippner, available in the Reserve Bank of New Zealand https://www.rbnz.govt.nz/research-and-publications/research-programme/additional-research/measures-of-the-stance-of-united-states-monetary-policy/comparison-of-international-monetary-policy-measures.

Slope of the U.S. Government yield curve (TS_{US}): The US term spread, measured as the difference between the daily 10-year Treasury bond rate and the 3-month Treasury bill rate. To compute monthly figures we take monthly average.

Annual growth of Global Economic Activity Indicator (IGAE, for its Spanish acronym): Shows the evolution of the economic activity on a monthly basis using the methodology and

conceptual framework of national accounts. We use the seasonally adjusted IGAE from INEGI https://www.inegi.org.mx/temas/igae/.

General and core annual inflation: We calculate the annual percentage change on monthly figures of the Consumer price index, both core and general, from INEGI.

Nominal short-term interest rate: It is defined as the 28-day inter-bank equilibrium annualized interest rate (TIIE-28 for its Spanish acronym). https://www.banxico.org.mx/SieInternet/consultarDirectorioInternetAction.do?accion=consultarCuadro&idCuadro=CF117&locale=es.

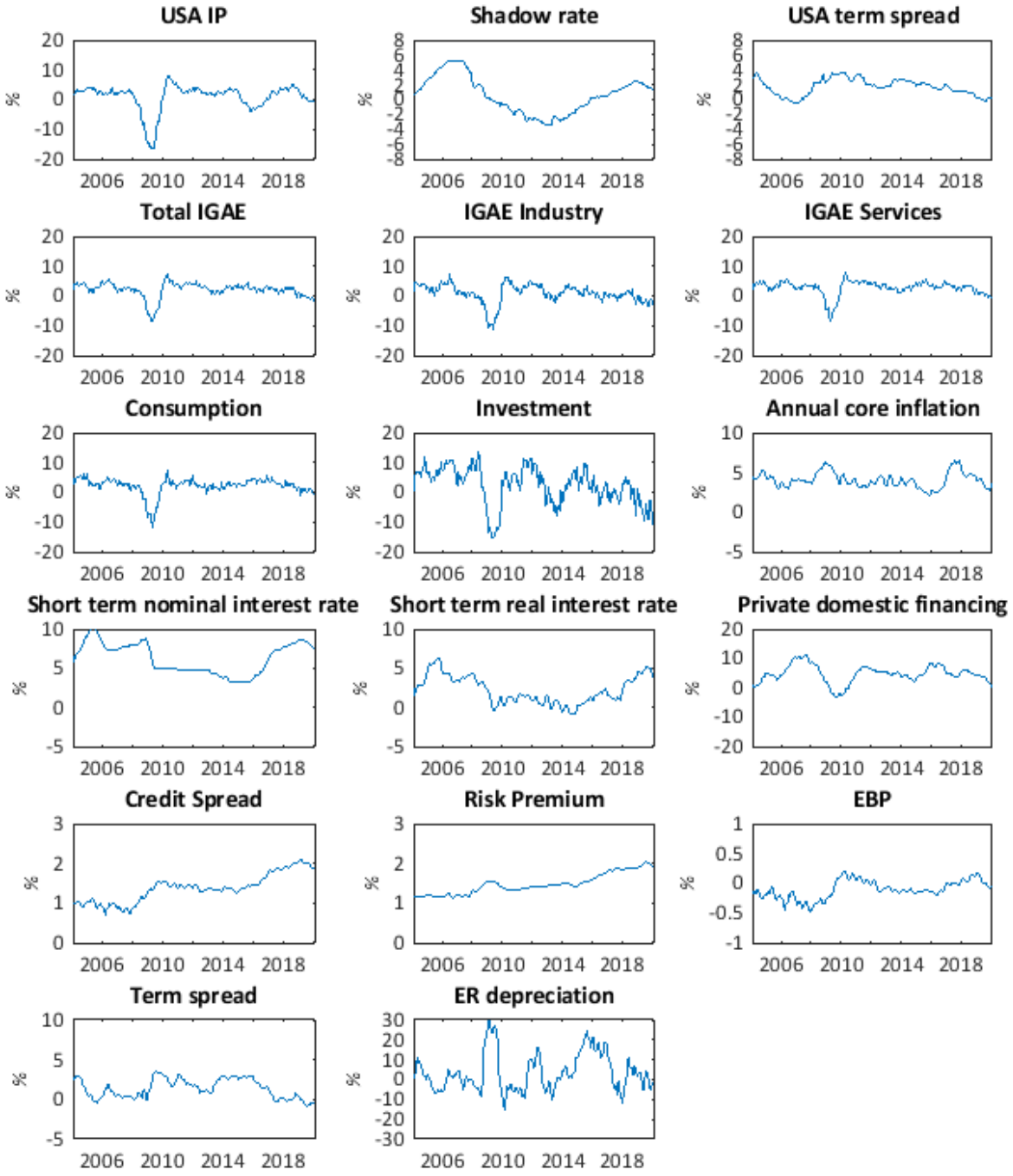
Real short-term interest rate: Defined as the nominal short-term interest rate minus the annual inflation.

Annual growth of private domestic financing: Monthly series of total domestic private financing, obtained through own calculations from quarterly statistics of Total Funding of the Mexican Economy (Sources and Uses). Data retrieved from Banco de México CF297. https://www.banxico.org.mx/SieInternet/consultarDirectorioInternetAction.do?sector=19&idCuadro=CF297&accion=consultarCuadro&locale=en.

Term spread or slope of the yield curve (TS): We calculate the daily difference between the 10-year Mexican government bond yield (M10) and the 3-month interest rate on Mexican Treasury bill (Cetes91). To compute monthly figures we take monthly average.

Annual rate of depreciation of the peso against the dollar (ExR): Computed as the annual percentage change of monthly exchange rate series, which was obtained through the average of daily date-of-determination (FIX) exchange rate series for each month. Data retrieved from Banco de Mexico https://www.banxico.org.mx/SieInternet/consultarDirectorioInternetAction.do?accion=consultarCuadro&idCuadro=CF86&locale=es.

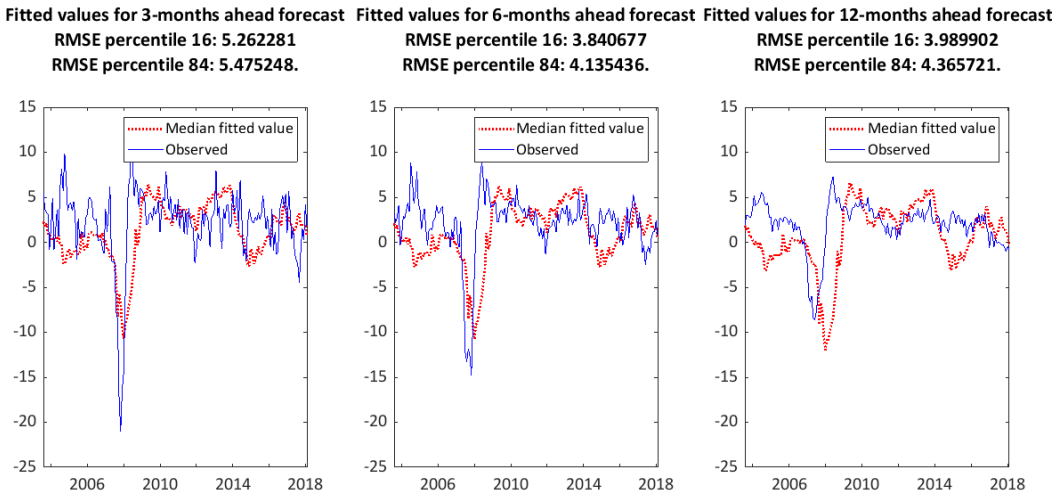
Figure 8: Dynamics of Variables used in the Models



Note: Figure shows all the variables included in the models. Data is monthly and goes from January 2004 to February 2020.

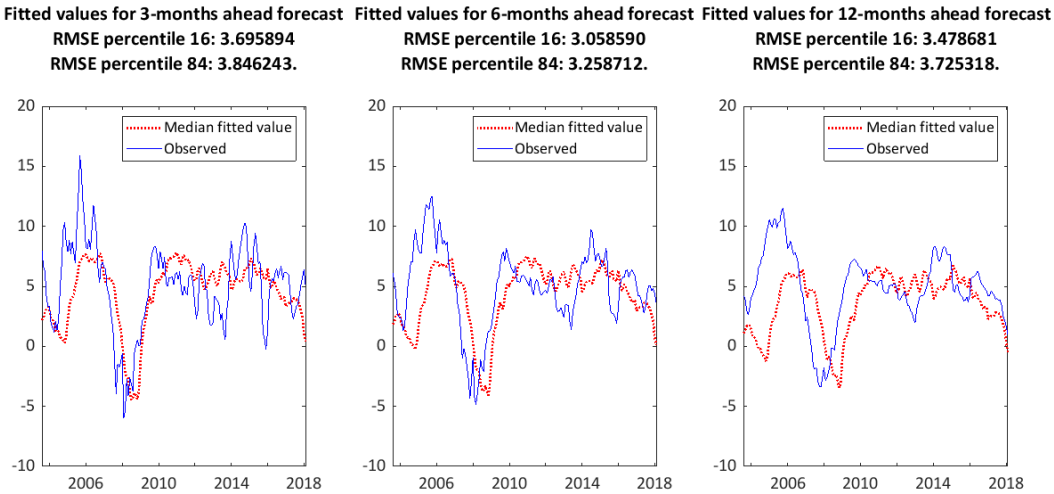
B Appendix 2: In-sample model fit

Figure 9: Credit Spread model: IGAE as dependent variable



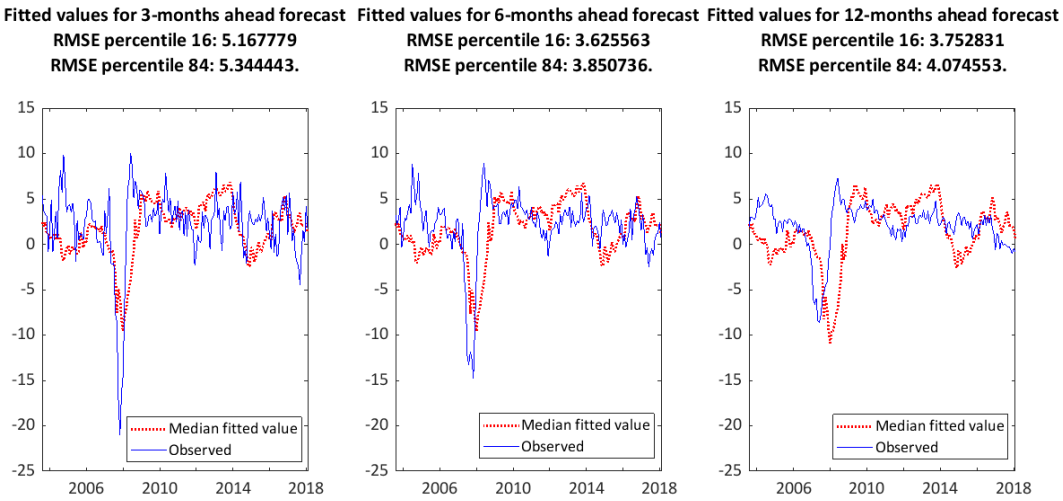
Note: Figure shows the actual and fitted values of IGAE extracted from Model in equation 6 and upper panel of Table 4.

Figure 10: Credit Spread model: Domestic financing as dependent variable



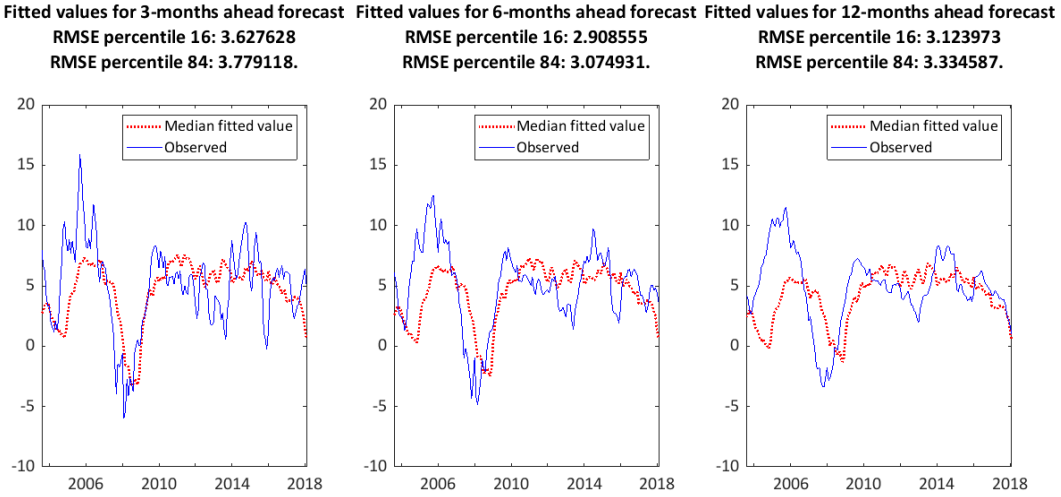
Note: Figure shows the actual and fitted values of IGAE extracted from Model in equation 6 and lower panel of Table 4.

Figure 11: Risk Premium and EBP In-sample model: IGAE as dependent variable



Note: Figure shows the actual and fitted values from Model in equation 7 and upper panel of Table 5.

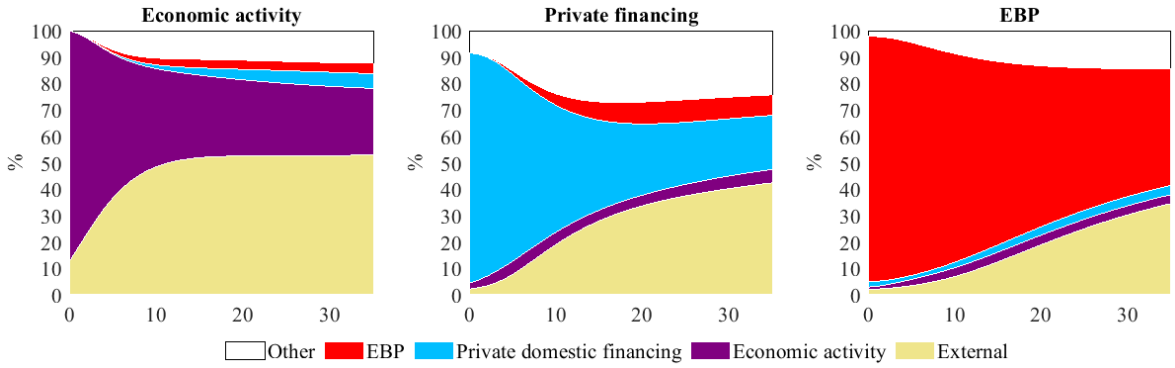
Figure 12: Risk Premium and EBP In-sample model: Domestic financing as dependent variable



Note: Figure shows the actual and fitted values from Model in equation 7 and lower panel of Table 5.

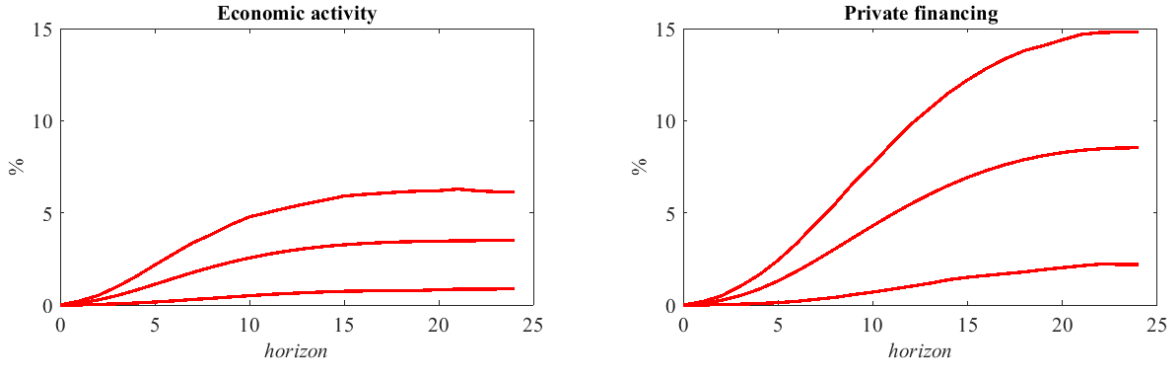
C Appendix 3: Variance decomposition

Figure 13: Forecast error variance decomposition



Note: Figure shows the forecast error variance decomposition for Economic activity, Private Financing and the EBP explained from the shocks identified in the Model of Section 6.1.

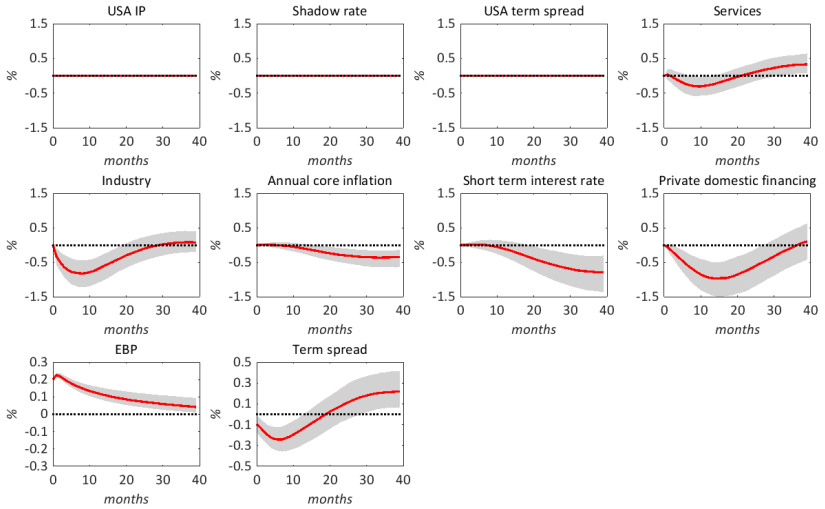
Figure 14: Proportion explained by the EBP shock on the forecast error variance of Economic activity and financing



Note: Figure shows the forecast error variance for Economic activity and Private Financing explained by shocks on the EBP in Model of Section 6.1.

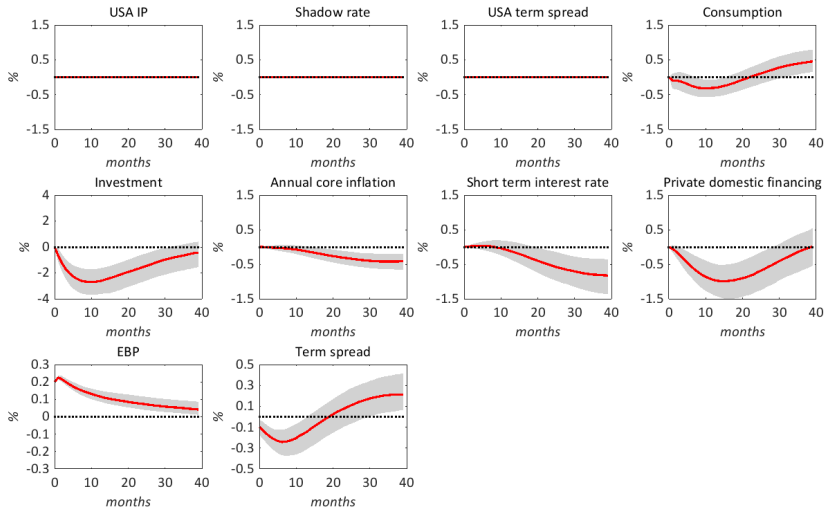
D Appendix 4: IRF for different economic aggregates

Figure 15: Business Cycle Implications of a Shock in the EBP: from the supply side



Note: Figure shows the IRFs of the extended version of model in Equation 10 after a normalized 20 basis points shock increase in the EBP. Model is estimated using monthly data from January 2004 to February 2020.

Figure 16: Business Cycle Implications of a Shock in the EBP: from the demand side



Note: Figure shows the IRFs of the extended version of model in Equation 10 after a normalized 20 basis points shock increase in the EBP. Model is estimated using monthly data from January 2004 to February 2020.