High-Frequency Surprises: Uncovering Credit Rating Agency Shocks in an Emerging Market

LORENZO MENNA (BANCO DE MEXICO) AND MARTIN TOBAL (BANCO DE MEXICO)*

Abstract

We argue that the challenges in identifying monetary policy impacts are similar to those in assessing credit rating agencies (CRAs) effects. However, high-frequency models, commonly used in monetary policy analysis, have never been applied to the debated issues surrounding CRAs. We fill this gap using a high-frequency IVLP model to examine the unresolved question of CRA effects. Employing intraday changes in Mexico's sovereign CDS as an instrument to capture "surprises" in CRA announcements, we find that CRAs affect financial markets, influencing both public and private sector variables. These results emphasize the pervasiveness of sovereign risk perceptions in emerging markets.

Keywords: monetary policy, high-frequency methods, financial markets, credit rating agencies

JEL Classification: E44, E52, H63.

1. Introduction

In recent years, high-frequency methods have revolutionized the identification of causal effects in macroeconomics and finance. These methods have been especially pioneering in the study of monetary policy (Gertler and Karadi, 2015; Hanson and Stein, 2015; Nakamura and Steinsson, 2018; Swanson, 2021; Miranda Agrippino

---

* The views expressed in this paper do not reflect Banco de México's opinions. We thank Marco Brianti, Claudio Raddatz and several attendants to the conferences where the paper was presented for useful suggestions. We thank Óscar de Jesús Meneses Covarrubias and Daniel Perez for outstanding research assistance. Please address e-mail correspondence to: martin.tobal@banxico.org.mx.

and Ricco, 2021; Rogers et al, 2018), where they address three key challenges: (i) isolating the impacts of monetary policy from preexisting economic conditions, (ii) distinguishing these effects from market reactions that anticipate central bank decisions, and (iii) identifying the effects of monetary policy statements released alongside rate changes, since central bank communication in general, and these statements in particular, is difficult to quantify. High-frequency methods overcome these empirical challenges by attributing markets reactions within a narrow window around policy announcements to the effects of rate changes and statements.

However, despite the significant advantages these methods have brought to the study of monetary policy, to the best of our knowledge, they have never been applied to explore the highly debated issues surrounding credit rating agencies (CRAs). This is surprising, given that some of these issues have sparked intense discussions in policy circles and the general press (BIS, 2008), and the challenges in identifying their effects are similar to those faced in monetary policy analysis. Like central banks, CRAs respond to preexisting economic conditions; financial markets anticipate their announcements; CRAs rating decisions and statements are released simultaneously; and their communication is difficult to quantify. In this paper, we use a high-frequency instrumental variable-local projection (IVLP) model to identify exogenous variation, also called "surprises" or structural shocks, in CRA actions and analyze their impact on public and private asset markets in Mexico. To isolate these surprises, we use—intraday—changes in Mexico's sovereign Credit Default Swap (CDS) within a narrow window around CRA announcements as an instrument in our IVLP.

Thus, our first contribution is the use of a state-of-the-art identification model, commonly used in monetary policy studies, to address a significant and widely debated but unresolved question. This model, combined with our choice of intraday changes in Mexico's CDS as an instrument, enables us to tackle an empirical challenge that goes beyond monetary policy analysis and arises exclusively in the context of CRAs. Specifically, this instrument allows assessing how CRAs surprise financial markets, even without knowing their expectations before announcements—credible measures of expectations for credit ratings are unavailable, unlike for monetary policy. Our second contribution is focusing on emerging market and developing economies (EMDEs). While most high-frequency studies concentrate on advanced economies (AEs), such as those by Gertler and Karadi (2015), Hanson and Stein (2015), Nakamura and Steinsson (2018), Miranda Agrippino and Ricco (2021) and Swanson (2021) on US monetary policy, or Kanzig (2021), Ottonello and Song (2022), and Balduzzi et al. (2023) on the effects of oil prices, net worth, and political risk in AEs, we focus on Mexico.[1] Among EMDEs, Mexico's financial markets stand out as some of deepest and most liquid around the world. Our third contribution is the subject matter: we investigate how increased sovereign risk perceptions—attributable to CRAs—affect EMDEs, precisely where these perceptions are presumably more pervasive and have stronger impacts on financial markets. To the best of our knowledge, Solis (2023), Pirozhkova et al. (2024), Camara et al. (2024), and De Leo et al. (2024) are the only other high-frequency studies on EMDEs, but they focus on monetary policy.[2] Hence, our paper stands out by addressing a different yet critical topic for EMDEs.

The results indicate that CRA shocks have a statistically significant impact on Mexico's sovereign CDS, the interest rate spread of Mexico's government bonds, and the CDS of a large Mexican state-owned oil company, called Pemex. Additionally, the statistically significant effect of these shocks extends to variables more closely tied to the private sector, such as private bond interest rates, the stock market, and the Mexican peso-USD exchange rate. The effects are relevant in

[1] In an additional contribution, Rogers et al (2018) measure the effect of different types of monetary policy surprises on international risk premia.

[2] Ilzetzki and Jin (2021) also study the transmission of US monetary policy to other countries, including EMDEs, using high-frequency identification in one of their robustness checks.

economic terms. The impact of the shock on the sovereign CDS and the government bond interest rate reaches approximately 37% of their standard deviation within two weeks, and it amounts to 50% of the standard deviation for the CDS of Pemex. That is, although the CRA announcement refers to the credit performance of the sovereign, its impact is even stronger on the CDS of the oil company. Even less obvious, the effect on variables more closely linked to the private sector is also important. The effect on private bond interest rates is around 38% of their standard deviation within two weeks of the shock. While the effect on the stock market and the exchange rate is somewhat smaller, it remains relevant, accounting for 26% and 23% of their respective standard deviations within the same period. Overall, these findings are consistent with the afore-mentioned statement that sovereign risk is more pervasive in EMDEs.

The debate over whether CRAs influence markets has also permeated the conceptual literature. Millon and Thakor (1985) argue that CRAs provide value by disseminating information when insiders are better informed than outsiders.[3] Other studies highlight that CRAs' ratings are used to determine which bonds qualify as investment grade (White, 2010) and to calculate risk weights for regulatory purposes (Kiff et al, 2012). Boot et al. (2005) note that credit ratings can also serve as coordination mechanisms in markets with multiple equilibria, particularly when a large number of investors rely on them for investment decisions (see also Holden et al., 2018). Thus, the literature presents several reasons why CRAs may influence markets.[4] To the best of our knowledge, this is the first paper to undertake a comprehensive approach capturing empirically the impact of all of these channels.

[3] Kiff et al (2012) and White (2010) questioned the role of CRA as disseminators of private information arguing that they lag behind in signaling default risk.

[4] In a self-fulfilling model of sovereign debt crisis, Holden et al (2018) show that CRAs foster coordination around an equilibrium where investors coordinate in a pro-cyclical manner that increases sovereign default risk.

To test whether CRAs impact markets, we implement our high-frequency IVLP strategy in two steps. First, we acknowledge that CRAs express their views on the sovereign's credit profile not only through statements but also via other communication channels on non-announcement days. Since this communication outside of announcement windows also affect markets, changes in the CDS within these windows are only a noisy measure of the structural CRA shock, raising concerns about potential measurement error and attenuation bias (Gertler and Karadi, 2015 and Stock and Watson, 2018, among others). Thus, we use CDS changes within announcement windows as an instrument. In practice, we regress the daily change in the CDS —referred to in the literature as indicator variable— against a variable that equals the change in Mexico's CDS within announcement windows on announcement days and zero on other dates. In the second step, we regress the predicted value of the first stage on several Mexico's macrofinancial variables for various horizons.

We conduct several statistical tests to ensure that our surprise series—the CDS changes within announcement windows—satisfies the conditions for a valid instrument. First, following Ottonello and Song (2022), we find that the CDS increases when CRAs downgrade Mexico's rating and outlook, or when their statements convey negative sentiment, indicating reduced creditworthiness. This finding confirms that the instrument is correlated with the CRA shock, thus meeting the relevance condition. Second, similar to the approaches of Kanzig (2021) and Ottonello and Song (2022), we test whether the instrument is contemporaneously uncorrelated with shocks unrelated to CRAs. Our results show that the variability of the CDS is significantly higher during announcement windows than in comparable windows without announcements, suggesting that the instrument satisfies the contemporaneous exogeneity condition. Finally, following Ramey (2016), we show that our instrument is not autocorrelated and cannot be forecasted by financial factors, supporting it fulfills the lead-lag exogeneity condition. We also perform several robustness checks, including identification through heteroskedasticity (Rigobon, 2003), varying window sizes (half-hour and two-hour windows), excluding post-market closure announcements, and using an IVVAR approach for estimation. The results remain consistent across all these variations.

This paper relates to the literature emphasizing the correlation between sovereign risk dynamics and public and private asset market dynamics in EMDEs. Within this literature, Hébert and Schreger (2017) explore the impact of sovereign default perceptions on private equity returns by leveraging legal rulings, while Kaas et al. (2020) develop a model describing a mechanism through which this correlation may emerge (for another example, see also Hamann et al., 2023). Also related, in a broader context, Uribe and Yue (2006) model the relationship between country spreads and business cycles in EMDEs. The paper also connects to the IVLP and IVVAR literature on AEs. Significant contributions in this field include Gertler and Karadi (2015), Hanson and Stein (2015), Miranda Agrippino and Ricco (2021), Nakamura and Steinsson (2018), and Swanson (2021), all of which focus on monetary policy in the US.[5] Other significant studies are Ottonello and Song (2022), which use high-frequency changes in the market value of financial intermediaries to identify financial shocks in the US; Känzig (2021), which applies high-frequency market data to detect oil supply news shocks and assess the effects on the US economy; and Balduzzi et al. (2023), which identify political risk shocks during political events in the Eurozone.

Finally, this paper is related to research using high-frequency methods to examine the effects of monetary policy shocks in EMDEs. Using these methods, De Leo et al. (2024) highlight that US monetary policy shocks contribute to the disconnect between policy rates and short-term government bond yields in EMDEs.

[5] Identifying monetary policy shocks using high-frequency methods gained importance following the global financial crisis of 2008, as central banks began to employ policy tools beyond just adjusting interest rates. For a framework on these alternative tools, see Wu and Zhang (2019).

Camara et al. (2024) find that monetary policy shocks lead to more pronounced contractions in EMDEs compared to AEs. Solis (2023) shows that these shocks lead to currency appreciations. Lastly, Pirozhkova et al. (2024) use high-frequency models to show that central bank independence and commitment to inflation targeting in EMDEs can produce significant expansionary effects.

The remainder of the paper is organized as follows. Section 2 outlines the methodology and discusses the empirical challenges, drawing parallels with those in monetary policy studies. Section 3 details the dataset and presents the tests supporting the instrument's validity. Section 4 presents the main results, while Section 5 covers the robustness checks. Finally, Section 6 presents the conclusions.

2. Methodology

In this section, we discuss the empirical challenges associated with estimating the causal effects of CRAs' actions on financial markets. We start from the following model, loosely based on that presented by Gürkaynak and Wright (2013):[6]

(1) $$\Delta Y_t = \alpha(R_t - E_{t-1}R_t) + \delta s_t + \beta z_t + \epsilon_t;$$

(2) $$R_t - E_{t-1}R_t = \alpha_R \Delta Y_t + \beta_R z_t + \epsilon_{R,t};$$

(3) $$E_{t-1}R_t = \sum_{s=1}^{T-1} \gamma_s \, w_{t-s} + R_{t-T},$$

where ΔY_t is a Nx1 vector of changes in a country's variables of interest between *t* and $t-1$; R_t is the rating decision for that country at *t*; s_t is a Sx1 vector of latent variables capturing all CRAs' actions except for their rating decisions; z_t is a Mx1 vector of other determinants of ΔY_t; α, α_R, β, β_R, δ and γ_s are Nx1, 1xN, NxM, 1xM, NxS and 1xW vectors of coefficients; ϵ and ϵ_{R} are vectors of structural shocks to the country's variables and rating, respectively; T is the number of periods that have passed since the last rating decision; $E_{t-1}R_t$ is market expectations at $t-1$

[6] Their model is more general, whereas the one we present here is specifically applied to CRAs.

regarding the rating at t; R_{t-T} is the last rating decision made, at period $t - T$; and w_{t-s} is a Wx1 vector of lagged values of other determinants of $E_{t-1}R_t$.

Equation (1) shows that changes in a country's idiosyncratic variables (ΔY_t), such as changes in the interest rate spread of Mexican government bonds, are influenced by multiple factors. These factors include unexpected shifts in the credit rating for that country ($R_t - E_{t-1}R_t$); other actions undertaken by CRAs (s_t) and other variables unrelated to CRAs (z_t), such as global variables that affect financial markets in EMDEs, like the VIX and oil prices. We focus on the parameters α and δ, which quantify the impact of unexpected shifts in rating and non-rating CRAs' actions on the country's idiosyncratic variables, respectively.

In Equation (2), the unexpected shifts in credit rating are influenced by the changes in the country's idiosyncratic variables (ΔY_t). This dependence introduces reverse causality bias in estimating α. The unexpected shifts in Equation (2) also depend on z_t, the global variables that affect EMDEs. Thus, failing to incorporate all these variables in Equation (1) introduces an additional source of bias in estimating α, known as omitted variable bias. Moreover, even if the unexpected shifts were independent of ΔY_t and z_t, accurately estimating α would necessitate precise measurement of all determinants of rating expectations in Equation (3). However, achieving precise measurement of all these determinants is practically unattainable. This difficulty raises concerns about the emergence of measurement error, which could bias our estimation of α toward 0, a phenomenon known as attenuation bias (Gürkaynak and Wright, 2013). Furthermore, estimation of the other parameter of interest (δ) poses its own challenges because of the latent nature of non-rating CRA actions (s_t).[7]

[7] Although we do not explicitly model the determinants of s_t, other CRAs' actions can also depend on financial market developments and lagged information. Even if these actions were not latent, identification of δ would still be subject to omitted variable and reverse causality bias.

In the remainder of this section, we show that high-frequency data, a high-frequency identification strategy and a IVLP framework enable us to tackle concerns related to reverse causality, omitted variables and measurement error when estimating α and δ.

a) Daily data and timing restrictions

Using daily data helps mitigate concerns about omitted variables and reverse causality. These concerns arise because the unexpected rating shift depends on information on idiosyncratic and global variables (ΔY_t and z_t) released during the announcement. With daily data, this implies that the unexpected shift depends on data released on the same day as the announcement. However, CRAs base their decisions on a significant amount of information accumulated over the entire period since their last decision, not just on the announcement day. If we assume for a moment that the information released the exact day of the announcement is not important at all, that is, if we imposed timing restrictions for a moment, we can rewrite equation (2) and express (1)-(3) as follows —we will further relax this assumption below—:

(4) $\Delta Y_t = \alpha(R_t - E_{t-1}R_t) + \delta s_t + \beta z_t + \epsilon_t;$

(5) $R_t - E_{t-1}R_t = \epsilon_{R,t};$

(6) $E_{t-1}R_t = \sum_{s=1}^{T-1} \gamma_s w_{t-s} + R_{t-T}.$

Unlike in Equations (1)-(3), the subindex t in the system of equations (4)-(6) refers to a specific "day." Thus, this system is less prone to omitted variables and reverse causality concerns, i.e., not subject to these concerns at all under the timing restrictions. However, even with daily data, accurately estimating α requires precise measurement of all determinants of market expectations on credit ratings

($E_{t-1}R_t$) in Equation (6).[8] Gathering all this information is practically unattainable, complicating estimation in this paper compared to event studies that explore the effects of monetary policy and macroeconomic news. These studies often have access to reliable measures of expectations based on market or survey data for their variables of interest (Gürkaynak et al., 2020). Nonetheless, to the best of our knowledge, there are no market or survey expectations available for credit ratings.[9] An additional challenge that the use of daily data alone does not address is the inability to estimate the effects of non-rating CRA actions (δ).

b) High-frequency Identification

In addition to using daily data, we use a high-frequency identification approach. To explain it, we rewrite model (4)-(6) as follows:

(7) $\Delta Y_t = \tilde{\alpha}(R_\tau - E_{\tau-\Delta}R_\tau) + \tilde{\delta}s_\tau + \beta z_t + \epsilon_t;$

(8) $R_\tau - E_{\tau-\Delta}R_\tau = \epsilon_{R,\tau};$

(9) $E_{\tau-\Delta}R_\tau = \tilde{\gamma}w_{\tau-\Delta} + \sum_{s=1}^{T-1}\gamma_s w_{t-s} + R_{t-T};$

(10) $\Delta Y_{1,\tau} = \hat{\alpha}(R_\tau - E_{\tau-\Delta}R_\tau) + \hat{\delta}s_\tau + \beta_1 z_\tau + \epsilon_{1,\tau}.$

Equations (7)-(9) specify not only the day *t* but also the specific time of that day when the announcement is made. Thus, unlike in the previous subsection, the expectations on the credit rating ($E_{\tau-\Delta}R_\tau$) also incorporate information from the day of announcement gathered up until moments before its publication (until τ-Δ; see Equation 9). Hence, this information gathered up until τ-Δ does not influence

[8] Assuming that measurement error satisfies the classical assumptions, i.e., the difference between the measured and the true rating expectation is uncorrelated with either the independent or the dependent variables, there are measurement error and bias towards zero.

[9] One solution is to incorporate lags of w_t as control variables. This approach is akin to measuring market expectations using every variable that influences them. Of course, it is impossible to know and introduce all potential determinants of expectations into a regression.

the unexpected shifts in rating and non-rating actions, and therefore, it does not affect the change in the idiosyncratic variables either (Equation 7).[10]

Equation (10) delineates the change in the first idiosyncratic variable ($\Delta Y_{1,\tau}$) during the announcement. Here, s_τ denotes unexpected shifts in non-rating actions over that period. Just as monetary policy announcements are accompanied by central bank statements, rating announcements are accompanied by statements from CRAs. Since these statements represent the sole non-rating actions concurrent with the announcement, s_τ in equation (10) refers to unexpected shifts in this statement. Using Equation (10), we will link the behavior of $\Delta Y_{1,\tau}$ to what we hereafter call "the structural CRA shock," which is defined as follows:

$$(11) \qquad \epsilon_{CRA,\tau} = (R_\tau - E_{t-\Delta}R_\tau) + s_\tau = \epsilon_{R,\tau} + s_\tau.$$

Equation (11) shows that the structural CRA shock ($\epsilon_{CRA,\tau}$) is the sum of the unexpected shift in rating and non-rating actions during the announcement. Under two considerations, we can use this structural shock to approximate the change in the first idiosyncratic variable defined in Equation (10). First, the variance of z_τ and $\epsilon_{1,\tau}$ in this equation are small compared to those of $R_\tau - E_{t-\Delta}R_\tau$ and s_τ during the announcement. Second, we follow a standard practice in the literature and normalize $\hat{\alpha}$ and $\hat{\delta}$ to 1 —as noted by Stock and Watson (2018), $\epsilon_{CRA,\tau}$ cannot be directly observed and its effect can only be determined up to a scaling. — Using this normalization, we can rewrite equation (10) as follows:

$$(12) \qquad \Delta Y_{1,\tau} = (R_\tau - E_{t-\Delta}R_\tau) + s_\tau = \epsilon_{CRA,\tau}, \qquad \text{for } \tau \in RA,$$

where *RA* is the set of windows within which a CRA rating is announced. Since we can approximate the change in the idiosyncratic variable during the announcement ($\Delta Y_{1,\tau}$) by $\epsilon_{CRA,\tau}$, a natural candidate for $\Delta Y_{1,\tau}$ in our empirical specifications of

[10] Even though we do not explicitly include them in the equation, of course the variables of interest can still respond to other non-rating CRA communication outside of the window.

section 4 is the change in the Mexican sovereign CDS within announcement windows. This variable is likely to be the most affected by credit rating announcements and statements, as both CRAs and CDS contracts refer to the likelihood of a borrower's default.

Using Equation (12), we can rewrite Equation (7) as $\Delta Y_t = A\epsilon_{CRA,\tau} + \beta z_t + \epsilon_t$, where A captures the combined effect of the announcement and CRAs statements.[11] In section 4 we will estimate this equation by using the following specification:

$$\Delta Y_t = a + b\Delta Y_{1,\tau} + u_t, \tag{13}$$

where b is our estimate of A. By not introducing the global variables (z_t) in equation (13), we implicitly state that these variables are not related to the CRA shock during the announcement. Therefore, we do not need to include them in our empirical specification. However, following common practice, we also consider specifications that incorporate these variables to increase efficiency in section 4.[12]

Despite its advantages, this high-frequency approach remains susceptible to measurement error. CRAs also communicate outside of announcement windows, meaning that s_t is not zero even outside them. Hence, $\epsilon_{CRA,\tau}$ serves only a noisy measure of the true structural shock. As noted above, this measurement error raises concerns about attenuation bias.

c) High-frequency IVLP model

To tackle this problem, we follow a recent trend in macroeconometrics by combining the high-frequency approach with a standard LP (Gertler and Karadi,

[11] In this equation, A is a weighted average of coefficients $\tilde{\alpha}$ and $\tilde{\delta}$; specifically, $A = \frac{\tilde{\alpha}(R_\tau - E_{\tau-\Delta}R_\tau) + \tilde{\delta}s_\tau}{\epsilon_{CRA,\tau}}$.

[12] b_i equals $\frac{\alpha_i\sigma_{\epsilon_R}^2 + \delta_i\sigma_S^2}{\sigma_{\epsilon_R}^2 + \sigma_S^2}$, which is a weighted average of the relative (to ΔY_1) response of variable i to the rating surprise statement, with weights given by the variances of the rating surprise and statement shocks. If the effect of the statement is nil, then b recovers the relative effect of the rating surprise, α_i. With equation (8) rewritten as $\Delta Y_{i,t} = A_i\epsilon_{CRA,t} + \beta_i z_t + \epsilon_{i,t}$, in any case b_i is a consistent estimate of A_i.

2015; Balduzzi et al., 2023; Känzig, 2021). Specifically, we use a 2-stage IVLP model where the change in the CDS during a rating announcement window serves as an instrument, rather than as the dependent variable as in Equation (13). Specifically, in the first stage we instrument for what is known in the IVLP literature as indicator variable with the change in the CDS during a rating announcement window; in the second stage, we use the results of the first stage to assess the effect of CRAs on the country's idiosyncratic variables.

The IVLP model also relies on the definition of $\epsilon_{CRA,t}$ in Equation (11) and in Equation (12). Since this shock is unobservable outside announcement windows, we need a scaling similar to that used in the high-frequency approach. In IVLP models, this normalization typically implies that a one-unit increase in $\epsilon_{CRA,t}$ corresponds to a one-unit increase in the indicator variable (Stock and Watson, 2018). Using this normalization, we can express the second stage of the model as follows:[13]

$$(14) \qquad \Delta Y_{t+h} = a_h + b_h \Delta Y_{1,t} + u_{t+h}.^{14}$$

where h is the horizon over which the IVLP is estimated; ΔY_{t+h} refers to changes in the idiosyncratic variables between $t+h$ and $t-1$; and $\Delta Y_{1,t}$ is indicator variable. As our indicator, we choose the daily change in the sovereign Mexican CDS on all days because it meets the two requirements any indicator variable must fulfill: i) it must be strongly affected by the structural CRA shock, including rating and non-rating actions; and ii) it must be measured in "the native units relevant for policy analysis" (Stock and Watson, 2018).

[13] In particular, this assumption allows expressing the indicator variable as the sum of the structural shock of interest and a linear combination of other contemporaneous and past structural shocks, $\{\widetilde{\epsilon_t}, \epsilon_{CRA,t-1}, \widetilde{\epsilon_{t-1}}, \ldots\}$, $Y_{1,t} = \epsilon_{CRA,t} + \{\widetilde{\epsilon_t}, \epsilon_{CRA,t-1}, \widetilde{\epsilon_{t-1}}, \ldots\}$.

[14] $u_{i\ t+h}$ is a linear combination of contemporaneous structural shocks, $\epsilon_{CRA,t}$ excluded, and the leads and lags of all structural shocks, i.e., $u_{i\ t+h} = \{\epsilon_{CRA,t+h}, \widetilde{\epsilon_{t+h}}, \ldots, \widetilde{\epsilon_{,t}}, \epsilon_{CRA,t-1}, \widetilde{\epsilon_{t-1}}, \ldots\}$.

CRA actions notably affects changes in the CDS, making it the most suitable market variable for fulfilling the first requirement. Regarding the second requirement, an alternative could be to use credit ratings, as done in other studies (Binici et al., 2020). Credit ratings are the non-market variable most directly affected by CRAs. However, they fail to capture the effects of non-rating actions, rendering them incompatible with the first requirement. In this sense, our choice is analogous to that of Gertler and Karadi (2015) in the context of monetary policy shocks. They choose the interest rates on government bonds instead of the non-market variable most directly influenced by the Fed, the Fed funds rate, because government bond prices respond to the monetary policy statement and forward guidance.

To instrument for $\Delta Y_{1,t}$ (the daily change in the CDS) we use the variable Z_t, defined as:

$$(15) \qquad Z_t = \Delta Y_{1,\tau} \ \ if\ t \in Rating\ announcement\ days; \quad Z_t = 0 \quad otherwise.$$

For Z_t to be valid, it must fulfill the following requirements: $i)$ $E\left(\epsilon_{CRA,t}\mathrm{Z_t}\right) = B \neq 0$ (relevance); $ii)$ $E(\epsilon_t Z_t) = 0;$ (contemporaneous exogeneity); and $iii)$ $E\left(\epsilon_{t+j}Z_t\right) = E\left(\epsilon_{CRA,t+j}\mathrm{Z_t}\right) = 0;$ ∀i for $j \neq 0$ (lead-lag exogeneity). That is, the instrument must be correlated with the contemporaneous structural CRA shock (the relevance condition), but not with other structural shocks, neither contemporaneous nor lagged (respectively, the contemporaneous and lead-lag exogeneity condition). These requirements are similar to those that make the high-frequency identification valid, meaning that the change in the CDS on announcement days must be closely related to the structural CRA shock $\epsilon_{CRA,t}$ (the relevance condition) and the variance of other shocks, referred to as background noise, must be small (the contemporaneous and lead-lag exogeneity conditions). In

Section (3), we conduct multiple tests to support that the requirements i)-iii) are met.

A key choice refers to the size of the window around announcements. Consistent with previous studies in the high-frequency identification literature, we use a one-hour window (Hoek et al., 2020; Gürkaynak et al., 2005) but perform robustness checks using half-hour and two-hour windows. Smaller intraday windows are more likely to meet the relevance and exogeneity conditions than daily windows. This is because within smaller time frames, the impact of CRAs is more likely to be stronger relative to that of other events.[15]

Using equation (15), we can estimate b_h in Equation (14) as follows:

$$b_h = \frac{E\left(\Delta Y_{t+h}^{\perp} Z_t^{\perp}\right)}{E\left(\Delta Y_{1,t}^{\perp} Z_t^{\perp}\right)}; \tag{16}$$

where $\perp$ indicates that a variable is orthogonal to the controls that may be included in the estimation. Under the requirements mentioned above, $b_{i,h}$ is a consistent estimate of the relative (to $\Delta Y_{1,t}$) impulse response function of variable ΔY_t to the structural shock $\epsilon_{CRA,t}$.

3. Data Sources and Diagnostics of the Instrument

In this section, we provide a comprehensive overview of our dataset construction and perform several diagnostic checks on the instrument to evaluate its validity.

a) Construction of the dataset

Our dataset includes several variables that we use as outcome or control variables, as we explain more in detail below. We rely on two sources. The first source is IHS Markit, from which we obtain information about the daily five-year maturity CDS spreads on Mexico's sovereign debt, as well as on the state-owned oil company (PEMEX) and other emerging markets. The second source is Bloomberg, from

[15] Nakamura and Steinsson (2018) show that intraday windows are less likely to contain background noise in monetary policy studies.

which we gather data on the Mexican Stock Market Index (IPC), the Mexican peso-USD exchange rate, the EMBI+ Mexico Sovereign Spread, the CEMBI Corporate EMBI Mexico Blended Spread, the CBOE implied volatility index (VIX), the Brent crude oil spot price, and intraday information about Mexico's five-year maturity sovereign CDS spread. We use Bloomberg for intraday CDS data because IHS Markit, while providing data for a larger number of days, does not offer this type of information.

To construct the instrument, we identify the dates on which CRAs made announcements regarding Mexico's sovereign 5-year maturity dollar debt. We consider all the rating and outlook decisions of the three major CRAs —Fitch Ratings, Moody's, and Standard & Poor's —from January 1, 2013 to December 31, 2019.[16] During this period, there were 28 rating and outlook decisions: 12 from Fitch Ratings, 5 from Moody's, and 11 from Standard & Poor's. Of these decisions, 14 were rating confirmations (indicating no change in either outlook or rating), 4 were outlook upgrades, 6 were outlook downgrades, 3 were rating upgrades, and 1 was a rating downgrade.[17] We use the publication times from Bloomberg News to pinpoint the exact timing of these announcements within each day.

Next, we calculate the change in the CDS spread from the last available tick before the announcement time to the tick nearest to one hour later. Additionally, we explore the robustness of our results using half-hour and two-hour windows. CDS contracts, being over-the-counter, are generally available at most times. Therefore, we can create our windows even for announcements occurring after the

[16] Excluding the global financial crisis and the Covid-19 pandemic from the estimation period bolsters the credibility of identification by eliminating phases of heightened market volatility. This is particularly pertinent considering that three rating and outlook decisions on Mexico occurred during March and April 2020, amid significant market turmoil. It is important to note that none of the three CRAs issued any watch decision within the timeframe covered by our estimation.

[17] The sample includes 27 dates featuring rating decisions, as there were simultaneous decisions on a single day. On June 5th, 2019, Fitch Ratings downgraded its rating, while Moody's changed its outlook to negative. These two announcements occurred within four minutes of each other, falling within the same intraday window.

market closing time. However, post-market closing, trading volumes diminish significantly, and CDS data often exhibit minimal fluctuations. This implies that the market response to announcements might occur later, such as close to the market opening on the subsequent day. Consequently, we also conduct our empirical analyses exclusive of announcements that occur after the market closing time in our sensitivity section. To ascertain whether an announcement occurs after market closing hours, we reference the opening and closing hours of the New York Stock Exchange (NYSE).

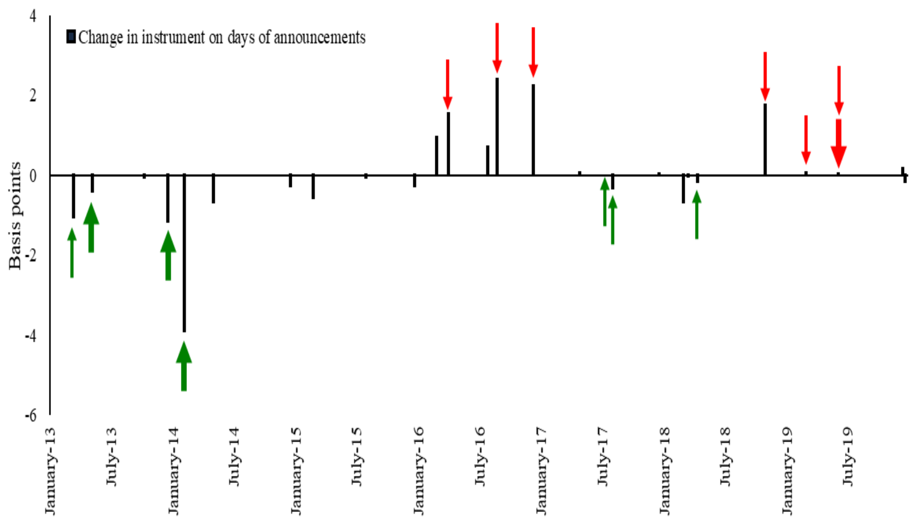
b) Diagnostics of the instrument

Figure 1 shows the changes in the five-year maturity CDS on Mexico's sovereign debt within announcement windows on announcement days, which we use to build our instrument. The arrows represent the direction of rating announcements. Bold and light red arrows indicate rating and outlook downgrades, respectively, while bold and light green arrows indicate rating and outlook upgrades. Events without arrows denote rating and outlook confirmations.

As noted in the introduction, we conduct multiple tests to support the instrument's validity. We begin by examining the correlation between the change in the CDS within announcement windows and the direction of rating decisions. This correlation could be statistically significant or not, depending on how much of the announcement is anticipated by the markets. If the announcements are not fully anticipated and there is a statistically significant correlation between the variables, we would expect it to be positive. This would indicate, for instance, that a rating upgrade reduces the market's perception of default risk. Thus, detecting a positive correlation would enhance the credibility of our shock measure.

Column (a) in Table 1 presents the results of a regression of the change in the CDS within announcement windows against a constant and a variable that indicates changes in the credit rating and outlook. We define this variable so that a rating downgrade (upgrade) is equivalent to 1 (-1), an outlook downgrade (upgrade) is assigned 0.5 (-0.5) and, when there is no rating or outlook change, the variable takes the value of 0. The coefficient on the rating decision is positive and statistically significant at the 1% level, indicating a clear association between the change in the CDS within windows and rating decisions. The results remain consistent regardless of the specific numerical equivalents assigned to the rating changes. However, the R^2 of the regression is 0.5, indicating that market reactions to CRA announcements are influenced also by other factors. These factors could include the sentiment expressed in the statement released at the time of the announcement.

Figure 1. Change in the CDS around rating announcements



Source: Authors' calculations with data from IHS Markit, Fitch Ratings, Moody's, and Standard & Poor's.
Notes: The instrument, plotted as slim blue bars, is the change in the CDS within one-hour announcement windows on announcement days. Bold and light red arrows indicate rating and outlook downgrades, respectively, while bold and light green arrows indicate rating and outlook upgrades. Events without arrows denote rating and outlook confirmations.

Thus, we examine the correlation between the changes in the CDS within announcement windows and this sentiment. To measure the sentiment, we follow Ottonello and Song's approach (2022) and use the Loughran and McDonald (2011) dictionary. This dictionary is advantageous because it categorizes words specifically for economic contexts, classifying them into positive, negative, uncertain, or neutral sentiments. Using these categories, we build three sentiment measures: the percentage of negative words over total words, the percentage of positive words over total words, and the difference between the percentage of negative words and positive words.

Table 1. Relevance of the instrument

	Change in CDS around rating announcements						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rating change	1.79***				1.50***	1.77***	1.43***
	(0.57)				(0.46)	(0.60)	(0.48)
% negative words		0.45**			0.29**		
		(0.19)			(0.13)		
% positive words			-0.32**			-0.03	
			(0.14)			(0.11)	
% negative - % positive words				0.38**			0.21**
				(0.15)			(0.09)
R^2	0.5	0.29	0.07	0.32	0.60	0.5	0.57
Observations	27	27	27	27	27	27	27

Source: Authors' calculations with data from IHS Markit, Fitch Ratings, Moody's, and Standard & Poor's.
Notes: The figure shows the OLS regressions of the change in the CDS within one-hour announcement windows against the rating variable and sentiment expressed in the statements released by CRAs. The rating variable is defined as a variable equal to 1 (-1) in the case of rating downgrades (upgrades), equal to 0.5 (-0.5) in the case of outlook downgrades (upgrades) and 0 in case of rating and outlook confirmations. The percentage of negative and positive words in CRAs' statements is computed as in Ottonello and Song (2022). A constant is included in all regressions. Robust standard deviations of coefficient estimates are reported within brackets. ** - statistically significant at the 5% level. *** - statistically significant at the 1% level.

Columns (2)-(4) in Table 1 present the results. The instrument is statistically significant and positively correlated with the percentage of negative words (column 2) and the difference between the percentage of negative and positive words (column 4) in CRAs' statements. It is also negatively correlated with the percentage of positive words (column 3), indicating that the CDS and markets' perception of default risk diminish when the sentiment of a statement is positive. These results support the idea that market reactions to CRA announcements are partly explained by their response to the sentiment conveyed in statements.

To assess whether this sentiment remains statically significant while controlling for rating decisions, we run three additional regressions. We regress the change in the CDS within windows against: (1) the change in the rating variable and the percentage of negative words; (2) the change in the rating variable and the percentage of positive words; and (3) the change in the rating variable and the difference between the percentages of negative and positive words (Columns 5, 6, and 7, respectively). In these regressions, the coefficient on the rating variable remains statistically significant at the 1% level and positive. The coefficients on the percentage of negative words and on the difference between the percentages of negative and positive words (columns 5 and 7) remain significant at 5% and positive. Only the percentage of positive words in column (6) loses statistical significance. These results indicate that the change in the CDS effectively captures the CRA shock within announcement windows, encompassing both the rating decision and the sentiment conveyed in CRA. Hence, overall, they suggest that the instrumental variable fulfills the relevance condition.

We also examine the correlation between the instrument and the indicator variable. This correlation, calculated in the first stage of any IVLP model, must be sufficiently strong for accurate inference. In the benchmark specification's first stage (i.e., regressing the indicator variable on the instrument), we obtain a coefficient of 0.79 with a robust t-statistic of 4.44, corresponding to an F-value of 19.7—well above the commonly used critical value of 10 in the literature (as noted by Gertler and Karadi, 2015). In Section 4, we will also report the t- and F-statistics for the remaining specifications, where we control for additional variables.

While these results suggest that the instrument satisfies the relevance condition, it is possible that it still contains background noise, thereby not meeting the exogeneity condition. As noted by Nakamura and Steinsson (2018), the use of intraday windows substantially reduces the likelihood of this possibility. Nonetheless, to provide further evidence, we follow Kanzig (2021) and Ottonello and Song (2022) and explore the likelihood of meeting the contemporaneous exogeneity condition by comparing the change in the CDS within announcement windows (the "treatment sample") to the change in the CDS in similar windows without announcements (the "control sample").

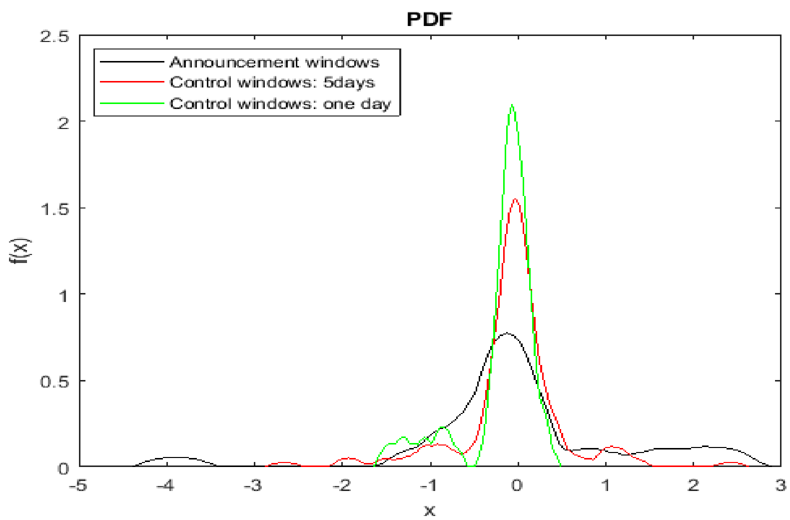
For the control sample, we consider two alternatives. The first one involves the change in the CDS within the same window on the business day before the announcement. The second one includes more observations, consisting of the change in the CDS within the same window over the five days preceding the announcement. We choose control windows proximate to the announcement day to enhance the likelihood that comparable non-CRA shocks affect the CDS. This approach ensures similarity in noise levels between the treatment and control groups. Using control windows distant from the treatment windows increases the risk of employing non-comparable periods. A similar approach is employed by Rigobon and Sack (2004), who use the day before FOMC meetings as control dates.

Figure 2 reports the estimated empirical probability distribution functions of the change in the CDS within announcement windows (the treatment sample); and within the one-day and the five days control samples in black, green and red, respectively. The variance of the treatment sample is 1.42 (standard deviation 1.19) and those of the one-day and five days control samples are 0.17 and 0.35 (standard deviations 0.41 and 0.59), respectively, i.e., the treatment sample has more than 8 and 4 times the variance of the control groups (2.9 and 2 times their standard deviation). A Brown-Forsythe test for the equality of group variance confirms that these differences are statistically significant at the 5% and 1% level, respectively. This evidence suggests that CRA shocks are indeed the major source of variation in the CDS, and thus background noise is substantially less important within announcement windows and the contemporaneous exogeneity condition is met. In

Section 5, we run additional robustness checks using a heteroskedasticity identification approach to more formally prove this point.

Regarding lead-lag exogeneity, we follow the approach of Ramey (2016) and Kanzig (2021), among others. We test for autocorrelation in our instrument and conduct a series of Granger causality tests to assess whether other financial variables can predict it. The results, shown in the appendix, indicate that the instrument is unpredictable based on this information, suggesting that it does not capture the lagged effects of non-CRA shocks.[18]

Figure 2. Empirical PDFs of the change in the CDS



Source: Authors' calculations with data from IHS Markit, Fitch Ratings, Moody's, and Standard & Poor's.
Notes: Empirical PDFs estimated with the Epachnikov kernel. The black line is the PDF of the change in the CDS within one-hour announcement windows. The green line is the PDF of the change in the CDS within the same window on the business day before the announcement. The red line is the PDF of the change in the CDS within the same window over the five business days before the announcement.

4. Results

a) Baseline model

[18] In the additional supplemental appendix we also provide the same tests of this section for two-hour and half-hour windows.

We regress our instrument against the daily change in the CDS in the first stage, and in the second stage, we regress the predicted value of this regression against the change in the country's idiosyncratic variables over various horizons.[19] In our baseline case, we do not include additional controls, as shown in Equation (14), and consider the daily change in Mexico's sovereign CDS over various horizons as the only outcome variable. The scale normalization (see Section 2) is set such that the impact response of this variable for the first period equals 1 basis point. Using this normalization, the left panel of Figure 3 shows the impulse response of Mexico's CDS to a CRA shock. Note that the effect on the CDS in this figure is statistically significant and increases to almost twice the size of the shock on day 2.

We also run additional specifications where we add controls to enhance efficiency. Among the controls, we consider global financial shocks since they are likely important determinants of Mexico's sovereign CDS. These shocks can stem from various factors, such as changes in global investors' risk appetite and market perceptions on oil prices and EMDEs' risks. A lower risk appetite tends to increase risk premiums on Mexico's sovereign debt, while a decline in oil prices can be associated with a downward revision in global growth expectations, leading to increases in Mexico's CDS. Additionally, an increased perception of sovereign risk in an EMDE, possibly due to reasons specific to that country, can spill over to the risk perception of other assets within the same class, affecting Mexico's CDS.

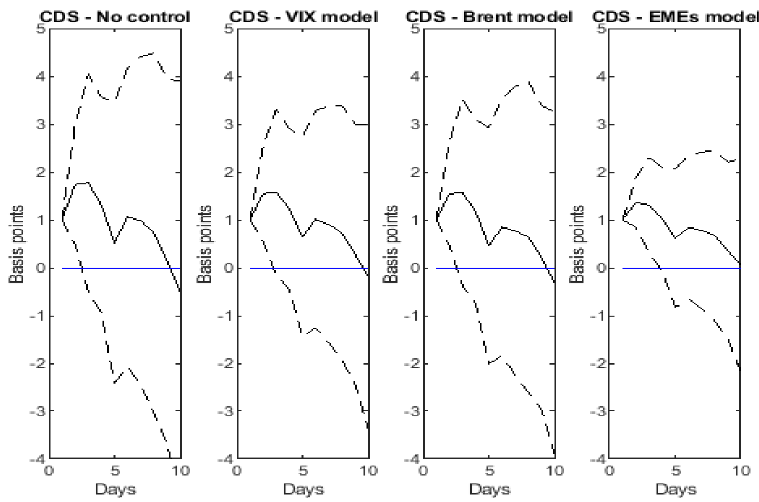
To capture the potential effects of these shocks, we consider three additional specifications.[20] The first specification includes the VIX as an exogeneous control to capture the potential impact of changes in risk appetite, the second specification

[19] Four lags of the daily change in the CDS are incorporated as controls in both the first and second stage regressions. The inclusion of these lags reduces the first-stage robust F statistic to 6.19, below the value reported in the previous section. Nonetheless, the F statistic increases above 10 when control variables or lags of the other dependent variables in the extended model are introduced.
[20] We include contemporaneous and three lags of these variables.

includes the Brent crude oil price, and the third specification includes the average of EMDEs' CDS.[21]

Figure 3 shows the impulse response functions of the CDS for the first, second, and third specifications in the second from the left, third from the left, and right panels, respectively.

Figure 3. Impulse-response of the sovereign CDS



Notes: All panels show the impulse response function from the baseline model with only the sovereign CDS as the endogenous variable. The left panel uses the model with no exogenous controls. The second panel incorporates contemporaneous and three lags of the daily log change in the VIX. The third panel uses the contemporaneous and three lags of the daily log change in Brent prices as controls. The right panel includes the contemporaneous and three lags of the daily change in the average CDS of EMDEs. All models include four lags of the daily CDS change. Solid lines represent impulse responses, and dashed lines represent 90% Newey-West confidence bands robust to autocorrelation and heteroskedasticity.

In all the three cases, the impulse response function is statistically significant and positive. Moreover, the effect of the CRA shock on Mexico's CDS is more than

[21] The robust F-statistics are 11.22, 8.55, and 19.13, respectively. The VIX and particularly the average of EMDEs' CDS notably enhance the instrument's strength. In the average of EMDEs' CDS we include countries that are EMDEs according to the IMF and for which we have CDS data. The countries are reported in the supplemental appendix.

30% above the initial effect after one day in each case. The results (nor reported) are consistent when including all three controls simultaneously.[22]

b) Extended baseline model

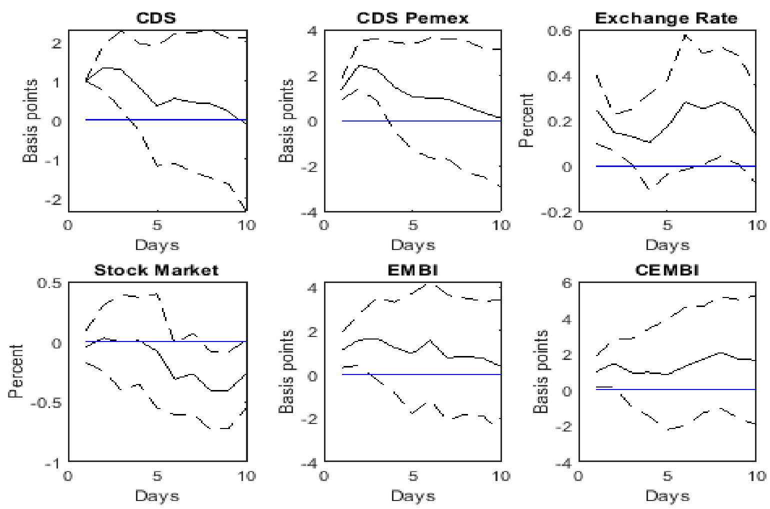
Through their actions, CRAs can affect several variables. While existing literature on sovereign ratings has primarily focused on the sovereign CDS, some studies have also analyzed the impact of CRAs on other macrofinancial variables, including the exchange rate (Ismailescu and Kazemi, 2010). We extend the analysis of the effects of CRA shock to additional macrofinancial variables. This extension provides insights into the impact of sovereign risk perceptions on the private sector, through their influence on borrowing costs, risk premia, and the exchange rate. Moreover, the advantage of the IVLP method used in this paper is that it offers a unified framework to analyze the effects of CRA shocks on several macrofinancial variables simultaneously. Thus, we include the CDS of PEMEX, the EMBI+ and CEMBI spreads, the peso-USD exchange rate, and the stock market index as endogenous variables in our extended IVLP baseline model, in addition to all the exogenous controls considered in the baseline specification.[23]

Figure 4 shows the results. According to the impulse response functions, the impact of the CRA shock on the sovereign CDS is statistically significant, like in the baseline model, and it grows to more than 30% above the initial shock size after one day. Moreover, the CRA shock also has a statistically significant effect on the CDS of PEMEX. A shock that increases Mexico's sovereign CDS by 1 basis point raises the CDS of PEMEX by approximately 1.36 basis points on day 1 and even reaches 2.44 basis points afterward. That is, although the CRA shock pertains to the sovereign's credit performance, it has a stronger impact on the CDS of the oil

[22] We include them in the supplemental appendix.
[23] We include four lags of these endogenous variables and the contemporaneous value and three lags of the exogenous controls. The first stage results show that the coefficient on our instrument is significant and positive (the robust t-statistics is 5.44 and the F statistics is 29.59, larger than 10).

company. Since the sovereign's risk is often used as a benchmark to price the risk of PEMEX, this result shows that the CRA shock also affects the risk premium of the oil company. Similarly, the shock has a statistically significant impact on the EMBI+ spread as well, which increases by 1.12 basis points upon impact and reaches 1.58 basis points on day 2. Overall, these results show that markets consider CRAs' actions in their assessment of the value of public sector bonds.

Figure 4. Impulse-responses in the extended baseline model



Notes: Impulse responses in the extended baseline model with the daily change of the CDS, the CDS of PEMEX, the EMBI+ and CEMBI spreads and the daily change of the log of peso-USD exchange rate and of PCI Mexican stock markets index as endogenous variables. The daily change of the average of the CDS of EMDEs and the daily change of the log of the VIX and of the Brent oil price are included as controls. Four lags of the endogenous variables and three lags of the controls and of the instrument are included. The continuous black line represents the impulse response function after a CRA shock that generates an increase in the Sovereign CDS of 1 basis point. Dashed lines represent the 90% autocorrelation and heteroskedasticity robust Newey-West confidence bands.

Regarding the private sector, the CRA shock also leads to a depreciation of the peso-USD exchange rate. This response is statistically significant and more persistent than that of the sovereign CDS, resulting in a depreciation of approximately 0.28% on day 8. This finding further supports the notion that CRAs' actions can impact not only public sector borrowing costs but also broader macroeconomic outcomes. This conclusion is reinforced by the effects on corporate bonds and the stock market. Figure 6 shows that the CRA shock also significantly influences the CEMBI spread and the stock market. The CEMBI spread response is similar to that of the EMBI+, though slightly smaller, increasing by 1.01 basis points upon impact and reaching 1.46 basis points on day 2. The stock market reaction takes more time than other variables: stock prices do not react immediately but then respond persistently, reaching a reduction of 0.41% on day 9. Thus, CRAs' actions on the sovereign have important effects also on the private sector.

c) Quantification

As explained in Section 2, because the CRA shock is unobservable outside of announcement windows, the high-frequency IVLP model requires us to set a scale for the shock. This normalization means that a one-unit increase in $\epsilon_{CRA,t}$ corresponds to a one-unit increase in the indicator variable, specifically the daily change in the CDS. Consequently, the effects on the CDS on the days following the shock and the impact on other variables can only be quantified in relative terms—relative to the effect on the CDS on the day of the shock. This approach limits our ability to intuitively understand the extent to which CRA actions move the markets.

Nevertheless, by focusing on the shocks that are actually observed -those within announcement windows- we can gain more insight. As noted in section 3, when discussing background noise, the standard deviation of the CDS within these windows (1.19 basis points) is significantly larger—between 2 and 2.9 times—than the standard deviation of the CDS in comparable windows. This result indicates that the impact of CRA shocks on the CDS is quantitatively significant, at least within announcement windows.

Moreover, to quantify the effect of a one standard deviation shock within announcement windows, we can treat our surprise series "as if" it were the true structural shock. Some paper, particularly in the early literature, have followed this practice (see, e.g., Romer and Romer, 2004; Kuttner, 2001).[24]

To do this, we calculate the effect on the CDS on the announcement day (day 1) by multiplying the shock size, 1.19 basis points, by the first-stage coefficient from the extended baseline model (1.36), yielding an effect of 1.62 basis points on the CDS. We then rescale the impulse responses of the sovereign CDS and other variables in Figure 6 by this factor of 1.62.[25] Table 2 presents the maximum of each impulse response in the second column and the day on which the impulse response peaks in the third column. The second column also reports the maximum of each impulse response as a percentage of the standard deviation of the log-change (for the stock market and exchange rate) or the change (for all other variables) over the number of days at which this maximum occurs.

Specifically, the shock's impact on the sovereign and Pemex CDS reaches 2.19 and 3.95 basis points, respectively, on day 2, representing 37% and 50% of the standard deviation of these variables' changes over the corresponding period. Similarly, the government bond interest rate spread increases by 2.56 basis points, equivalent to 37% of its standard deviation. For variables more closely related to the private sector, the shock results in a 2.38 basis point rise in private bond interest rates on day 2 (38% of the standard deviation), a 0.66% decline in the stock market

---

[24] Recent literature has suggested several approaches to address the quantification challenge in IVLPs. Gorodnichenko and Lee (2019), as well as Plagborg-Moller and Wolf (2022), have proposed methods to compute variance decompositions. However, we do not adopt their approach here, as our focus is not on variance decomposition—that is, determining the proportion of variance in our outcome variables attributable to CRA shocks. Instead, we are interested in assessing the significance of the market response to a CRA shock once it has occurred. Variance decomposition reflects both the market response to shocks and the frequency and magnitude of those shocks. Given that observed CRA shocks on announcement days are relatively infrequent within our sample period, they are unlikely to be a major driver of market dynamics overall. Nonetheless, our analysis shows that when these shocks do occur, they have notable effects on the markets.

[25] This is equivalent to running an OLS regression of the outcome variables directly against our surprise series, instead of using it as an instrument, and multiplying the resulting coefficients by the standard deviation of the surprise series.

on day 9 (26% of the standard deviation), and a 0.45% depreciation of the exchange rate on day 8 (23% of the standard deviation). These effects are important.

Table 2. Maximum response to CRA shocks

	Effect at peak	Peak (days)
CDS	2.19 b.p. (37% sd)	2
CDS Pemex	3.95 b.p. (50% sd)	2
Exchange rate	0.4% (23% sd)	8
Stock market	-0.7% (26% sd)	9
EMBI	2.56 b.p. (37% sd)	2
CEMBI	2.38 b.p. (38% sd)	2

Source: Authors' calculations with data from IHS Markit, Fitch Ratings, Moody's, and Standard & Poor's.
Notes: The second column presents the maximum impulse responses to a one standard deviation CRA shock within announcement windows, along with this response as a percentage of the variable's standard deviation (in parentheses). The impulse responses shown in Figure 4 were rescaled as follows: first, the standard deviation of the CDS within announcement windows (1.19 b.p.) was multiplied by the first-stage coefficient of the extended baseline model (1.36) to obtain the effect on the daily change of the CDS on announcement days (resulting in 1.62 b.p.). Then, the impulse response of each variable on the day it reaches its maximum was multiplied by this 1.62 factor. The standard deviation used to calculate the percentage in parentheses was computed using the 8- and 9-day log-change (for the exchange rate and stock market, respectively) and the 2-day change (for all other variables) over the entire sample. The third column reports the day when the impulse response reaches its maximum.

5. Robustness

a) Heteroskedasticity identification

The instrument can become endogenous, introducing bias, if the change in the CDS within announcement windows incorporates background noise. Section 3 shows that this is unlikely in our setup. However, to further support this assertion, we also use the heteroskedasticity model proposed by Rigobon (2003) (see also Kanzig, 2021; Nakamura and Steinsson, 2018; Rigobon and Sack, 2004), which requires less strict assumptions for identifying causal effects than the high-frequency IVLP approach. While the IVLP approach demands the absence of background noise within announcement windows, the heteroskedasticity model requires that the variance of the background noise is the same within announcement windows ("treatment windows") and similar windows without announcements ("control windows"), but the variance of the CRA shock is greater during announcements.[26]

Thus, the heteroskedasticity approach requires defining these treatment and control windows. As our treatment windows, we use the change in the CDS within announcement windows. Similar to section 3.b), for the control windows, we use the change in the CDS within the same window on the business day preceding the announcement and the change in the CDS within the same window over the five days preceding the announcement. In practice, to estimate the heteroskedasticity model, we use the instrumental variable strategy of Rigobon and Sack (2004). [27]

Figures 5 displays the impulse responses from the heteroskedasticity-based models using the window on the business day preceding the announcement (black) and the window over the five days preceding the announcement (red) as controls, respectively.[28] In both cases, all macro-financial variables align in sign with those in the high-frequency IVLP model and are statistically significant.[29]

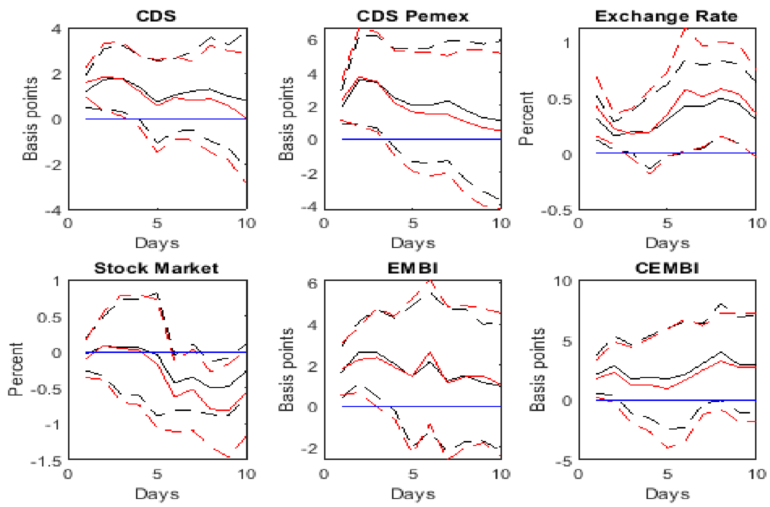
The similarity between the models is also evident in the number of days the impulse responses are statistically significant. In the extended baseline model, the impulse responses of the sovereign and PEMEX CDS are statistically significant for 3 days, the EMBI+ and CEMBI for 2 days, and the exchange rate and stock market for 6 and 3 days, respectively. In the heteroskedasticity-based model using the window on the business day preceding the announcement as a control, most impulse responses remain statistically significant for the same number of days as in the extended baseline model, with some responses being significant for even

---

[26] We report a detailed derivation of the heteroskedasticity estimator in the supplemental appendix.
[27] We include the same lags and controls as in the high-frequency extended baseline IVLP model.
[28] The robust F statistics is 36.09 and 15.23, respectively, in the two heteroskedasticity-identified models. Since the F statistics are above 10, we follow Kanzig (2021) and use standard inference.
[29] Note that, in the heteroskedasticity-identified model, the contemporaneous response of the daily CDS change is not constrained to be equal to one. This is because this method does not account for the possibility of other CRA shocks occurring outside announcement windows. As a result, the impulse responses shown in Figure 5 can be interpreted in absolute terms.

longer periods, such as the exchange rate (7 days vs. 6 days in the extended baseline) and the EMBI (3 days vs. 2 days). In the heteroskedasticity-based model using the window over the five days preceding the announcement as controls, all impulse responses are statistically significant for the same number of days as in the extended baseline model, except for the CEMBI, which is only significant for 1 day (vs. 2 days in the extended baseline).

Figure 5. Impulse responses using heteroskedasticity identification (controls sample: CDS on the previous day and over the 5 previous days)



Notes: The figure shows the impulse responses in the model with the daily change of the CDS, the CDS of PEMEX, the EMBI+ and CEMBI spreads and the daily change of the log of peso-USD exchange rate and of PCI Mexican stock markets index as endogenous variables. The daily change of the average of the CDS of EMDEs, the daily change of the log of the VIX and of the Brent oil price are included as controls. Four lags of the endogenous variables and three lags of controls are included. Black lines: heteroskedasticity identification with the change in the CDS within the same window on the business day preceding the announcement as control sample. Red lines: heteroskedasticity identification with the change in the CDS within the same window over the 5 business days preceding the announcement as control sample. Dashed lines represent the 90% autocorrelation and heteroskedasticity robust Newey-West confidence bands.

b) Excluding announcements occurring after market closing time

CDS contract prices are generally accessible even after the market closes. Yet, during these periods, trading volumes dwindle, potentially leading to inefficient reactions of the CDS to news within small intraday windows. Notably, in our dataset, we note significantly reduced-price volatility in CDS contracts after the market closes. This observation suggests that our surprise series might not fully encapsulate the CRA shock when announcements are made after trading hours. Consequently, in this section, we estimate the high-frequency IVLP model while excluding these post-closing announcements from the instrument series. To ascertain whether an announcement occurs after market closing hours, we reference the opening and closing hours of the NYSE.

Figure 6 shows the impulse response functions of the high-frequency IVLP model using the surprise series with only announcements made during trading hours.[30] The results are similar to those of the extended baseline model, with the impulse responses of all macro-financial variables matching in sign, size, and statistical significance across both models. The only notable difference between the two estimates is observed in the CEMBI, where the response is not statistically significant when announcements made after market closure are excluded.

Specifically, all impulse responses are statistically significant for the same number of days in both models, except for the CEMBI (significant for two days when including all announcements but not significant when excluding after-hours announcements) and the exchange rate (significant for 9 days when considering only trading-hours announcements versus 6 days when considering all announcements).

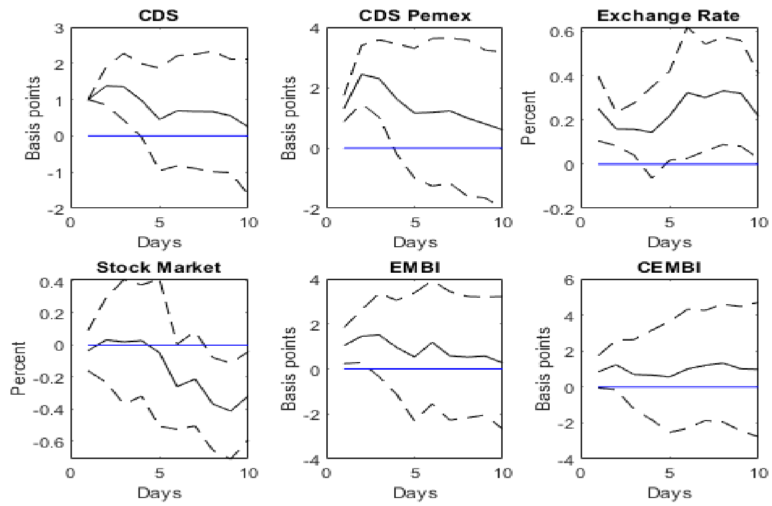
c) Half-hour and two-hour windows

As previously mentioned, a crucial consideration when employing an IVLP is the selection of the announcement window size. A window that is too small might fail to capture the entire market response to the announcement, while one that is too large could introduce background noise and bias the estimates. In section 4, we

[30] The robust t-statistics and F statistics of the first stage regression are 6.42 and 41.22, respectively.

adopted a one-hour window. In this section, we demonstrate the robustness of our results by employing half-hour and two-hour windows.[31]

Figure 6. Impulse responses excluding announcements occurred after market closing time



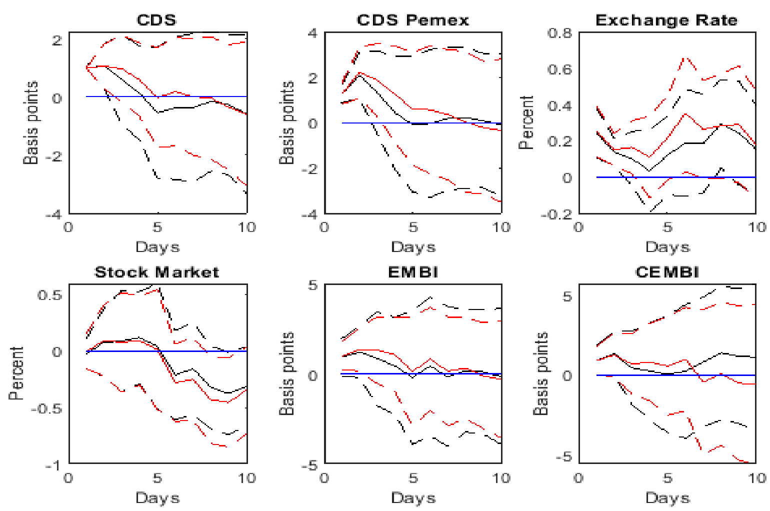
Notes: Impulse responses in the model with the daily change of the CDS, the CDS of PEMEX, the EMBI+ and CEMBI spreads and the daily change of the log of peso-USD exchange rate and of PCI Mexican stock markets index as endogenous variables. The daily change of the average of the CDS of EMDEs, the daily change of the log of the VIX and of the Brent oil price are included as controls. Four lags of the endogenous variables and three lags of controls are included. Black lines: IVLP with the surprise series including only announcements occurring during trading hours. Dashed black lines represent the 90% autocorrelation and heteroskedasticity robust Newey-West confidence bands.

Figures 7 shows the impulse response functions of the model with the half-hour (black) and two-hour (red) windows respectively.[32] The impulse response functions using the half-hour window generally display larger confidence intervals compared to the baseline extended model (which uses one-hour windows), suggesting that the smaller window size, which reduces the shock's magnitude, may worsen the signal-

[31] In the supplemental appendix, we provide diagnostic checks on the surprise series generated with these alternative window sizes. The surprise series, in these cases as well, likely meet the relevance, exogeneity, and lead-lag exogeneity criteria for a reliable instrument.
[32] The robust F statistics is 16 in the model with the half-hour window and 12.4 in the model with the two-hour window.

to-noise trade-off. Despite this, the magnitude of the responses remains similar for most variables, and all responses continue to be statistically significant, except for the EMBI and CEMBI spreads. Nonetheless, possibly due to the worsened signal-to-noise trade-off, the number of days in which the responses are statistically significant also decreases across the variables that remain statistically significant: the sovereign and PEMEX CDS are significant for 2 days instead of 3 as in the extended baseline model with a one-hour window, the exchange rate for 3 days instead of 6, and the stock market for 1 day instead of 3.

Figure 7. Impulse responses using a half-hour and two-hour windows



Notes: The figure shows the impulse responses in the extended baseline model with the surprise series constructed with a half-hour window (black) and two-hour window (red) and with the daily change of the CDS, the CDS of PEMEX, the EMBI+ and CEMBI spreads and the daily change of the log of peso-USD exchange rate and of PCI Mexican stock markets index as endogenous variables. The daily change of the average of the CDS of EMDEs and the daily change of the log of the VIX and of the Brent oil price are included as controls. Four lags of the endogenous variables and three lags of the controls and of the instrument are included. The continuous lines represent the impulse response function after a CRA shock that generates an increase in the Sovereign CDS of 1 basis point. Dashed lines represent the 90% autocorrelation and heteroskedasticity robust Newey-West confidence bands.

For the model using the two-hour window, the results closely mirror those observed with the one-hour window, both in terms of sign and magnitude. Additionally, all impulse responses remain statistically significant. The number of days during which these responses are statistically significant is the same as in the one-hour window model for the PEMEX CDS and EMBI. However, it slightly decreases for the other variables: 2 days instead of 3 for the sovereign CDS and stock market, 1 day instead of 2 for the CEMBI, and 4 days instead of 6 for the exchange rate.

d) IVVAR

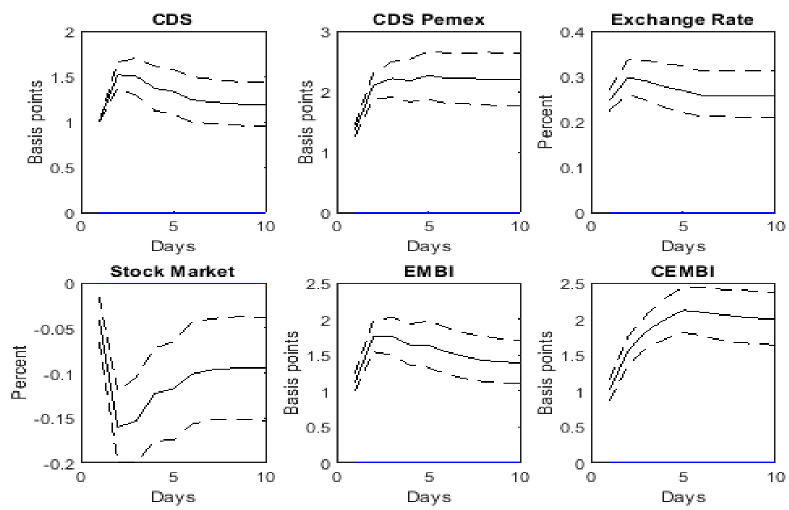
Both IVLPs and IVVARs can be used to combine high-frequency identification with conventional macroeconometric methods. However, these approaches make assumptions that place them at different points along the bias-efficiency trade-off. IVVARs are typically more efficient but more biased, while IVLPs are less biased but less efficient. These distinctions are especially important at longer horizons (Li et al., 2022).[33]

Thus, in this section, we evaluate the impact of using an IVLP by estimating our model using an IVVAR instead.[34] Figure 8 illustrates the impulse responses in the IVVAR. The most notable differences between the IVVAR and the baseline extended model pertain to inference: confidence intervals are much smaller in the IVVAR, consistent with its greater efficiency. Consequently, in the IVVAR, the impulse responses are statistically significant for all variables across all days. However, this efficiency gain may come at a cost in terms of bias. In fact, there are clear differences in the dynamic responses: for most variables, excluding the stock market and Pemex CDS in the first few days after the shock, the responses are slightly more pronounced in the IVVAR. Expectedly, these differences become more pronounced in the longer term, particularly for the sovereign and Pemex CDS, where the response nearly dissipates after ten days in the IVLP model but remains

[33] In the supplemental appendix, we discuss more in detail the bias-efficiency trade-off.
[34] Stock and Watson (2018) describe in detail the empirics of IVVARs. In the supplemental appendix to our paper, we provide a detailed description of the IVVAR estimator.

substantially above zero in the IVVAR. Conversely, in the case of the stock market, the IVVAR suggests a smaller reaction compared to the IVLP in the longer term.

Figure 8. Impulse responses using an IVVAR model



Notes: The figure shows the impulse responses in the IVVAR model with the daily change of the CDS, the CDS of PEMEX, the EMBI+ and CEMBI spreads and the daily change of the log of peso-USD exchange rate and of PCI Mexican stock markets index as endogenous variables. The daily change of the average of the CDS of EMDEs, the daily change of the log of the VIX and of the Brent oil price are included as controls. Four lags of the endogenous variables and three lags of controls are included. Dashed lines represent the 90% confidence bands, computed in the IVVAR model with the wild bootstrap method of Mertens and Ravn (2013).

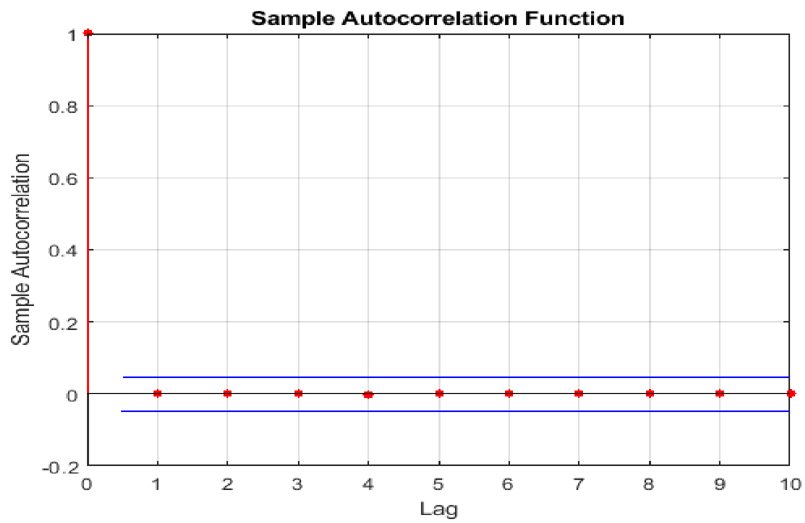
6. Conclusion

The challenges in identifying CRA shocks are similar to those faced in identifying monetary policy shocks. Thus, we use a high-frequency IVLP model to investigate whether CRAs have a significant impact on financial markets. Using this technique, we show that CRAs' actions have statistically significant effects on both public and private asset markets in an EMDE, namely, Mexico’s sovereign CDS spreads, interest rates, private sector funding costs, and the exchange rate.

Appendix

As mentioned in section 3.b, our instrument lacks autocorrelation and is unpredictable with a set of pertinent financial variables. Figure B1 presents the autocorrelation function of our instrument.

Figure B1. Sample Autocorrelation Function



Notes: Autocorrelation function of the instrument (change in the CDS within a one-hour windows).

In table B1, we show a battery of Granger tests: the instrument is not forecastable by past financial series.

Table B1. Granger causality tests of the instruments

Granger causality tests	
Variable	p-value
Instrument	1
VIX	0.36
Brent	0.81
Avg CDS of EMDEs	0.63
CDS of PEMEX	0.66
Peso-US dollar exchange rate	0.5
Mexican stock market	0.3

Notes: The table shows the p-values of Granger causality tests of the instrument (change in the CDS within a one-hour window around CRA announcements). The VIX, the Brent oil price, the exchange rate and the stock market log first differences. The average CDS of EMDEs and the CDS of Pemex were made stationary by taking first differences. The lag order is set to 4 and a constant is included.

References

Balduzzi, Pierluigi, Emanuele Brancati, Marco Brianti, and Fabio Schiantarelli (2023). “Political Risk, Populism and the Economy.” The Economic Journal.

Bank for International Settlements (2008). “Ratings in Structured Finance: What Went Wrong and What Can Be Done to Address Shortcomings?” Committee on the Global Financial System Paper No. 32.

Binici, Mahir, Michael Hutchison, and Evan Weicheng Miao (2020). “Market Price Effects of Agency Sovereign Debt Announcements: Importance of Prior Credit States.” International Review of Economics and Finance 69: 769-787.

Boot, Arnoud W. A., Todd T. Milbourn, and Anjolein Schmeits (2005). “Credit Ratings as Coordination Mechanisms.” Review of Financial Studies 19 (1): 81-118.

Camara, Santiago, Lawrence Christiano, and Husnu Dalgic (2024) "The International Monetary Transmission Mechanism." NBER Macroeconomics Annual 39 (2024).

De Leo, Pierre, Gita Gopinath and Șebnem Kalemli-Özcan, (2022). "Monetary Policy and the Short-Rate Disconnect in Emerging Economies," NBER Working Papers 30458, National Bureau of Economic Research, Inc.

Gertler, Mark, and Peter Karadi (2015). “Monetary Policy Surprises, Credit Costs, and Economic Activity.” American Economic Journal: Macroeconomics 7 (1): 44-76. doi:10.1257/mac.20130329.

Gürkaynak, Refet S., and Jonathan H. Wright (2013). “Identification and Inference Using Event Studies.” The Manchester School 81: 48-65.

Gürkaynak, Refet S., Brian Sack, and Eric T. Swanson (2005). “Do Actions Speak Louder than Words? The Response of Asset Prices to Monetary Policy Actions and Statements.” International Journal of Central Banking, 1: 55–93.

Hanson, Samuel G. and Stein, Jeremy C. (2015)."Monetary policy and long-term real rates," Journal of Financial Economics, Elsevier, vol. 115(3), pages 429-448.

Hébert, Benjamin, and Jesse Schreger (2017). “The Costs of Sovereign Default: Evidence from Argentina.” American Economic Review, American Economic Association, vol. 107(10), pages 3119-3145, October.

Hoek, Jasper, Steve Kamin, and Emre Yoldas (2020). “When is Bad News Good News? U.S. Monetary Policy, Macroeconomic News, and Financial Conditions in Emerging Markets.” International Finance Discussion Papers 1269.

Holden, Steinar, Gisle James Natvik, and Adrien Vigier (2018). “Credit Rating and Debt Crises.” International Economic Review 59 (2): 973-987.

Ismailescu, Iuliana, and Hossein Kazemi (2010). “The Reaction of Emerging Market Credit Default Swap Spreads to Sovereign Credit Rating Changes.” Journal Of Banking and Finance 34 (12): 2861-2873.

Ilzetzki, Ethan and Keyu, Jin (2021). "The puzzling change in the international transmission of U.S. macroeconomic policy shocks," Journal of International Economics, Elsevier, vol. 130(C).

Kaas, Leo, Jan Mellert, and Almuth Scholl (2020). “Sovereign and Private Default Risks over the Business Cycle.” Journal of International Economics, Elsevier, vol. 123(C).

Känzig, Diego R. (2021). “The Macroeconomic Effects of Oil Supply News: Evidence from OPEC Announcements.” American Economic Review 111 (4): 1092-1125.

Kiff, John, Sylwia Nowak, and Liliana B. Schumacher (2012). “Are Rating Agencies Powerful? An Investigation into the Impact and Accuracy of Sovereign Ratings.” IMF Working Papers 2012/023. International Monetary Fund.

Kuttner, Kenneth N., (2001). "Monetary policy surprises and interest rates: Evidence from the Fed funds futures market," Journal of Monetary Economics, Elsevier, vol. 47(3), pages 523-544, June.

Li, D., Plagborg-Møller, M., & Wolf, C. K. (2024).” Local projections vs. vars: Lessons from thousands of dgps”. Journal of Econometrics, 105722.

Mertens, Karel, and Morten O. Ravn (2013). “The Dynamic Effects of Personal and Corporate Income Tax Changes In The United States.” American Economic Review 103 (4): 1212-1247.

Millon, Marcia H., and Anjan V. Thakor (1985). “Moral Hazard and Information Sharing: A Model of Financial Information Gathering Agencies.” The Journal of Finance 40 (5): 1403-1422.

Miranda Agrippino, Silvia -and Giovanni Ricco (2021)."The Transmission of Monetary Policy Shocks," American Economic Journal: Macroeconomics, American Economic Association, vol. 13(3), pages 74-107, July.

Nakamura, Emi, and Jón Steinsson (2018). “High-Frequency Identification of Monetary Non-Neutrality: The Information Effect.” The Quarterly Journal of Economics 133 (3): 1283-1330.

Ottonello, P and Wenting Song (2022). “Financial Intermediaries and the Macroeconomy: Evidence from a High-Frequency Identification.” NBER Working Papers 29638, National Bureau of Economic Research, Inc.

Pirozhkova, Ekaterina, Giovanni Ricco, and Nicola Viegi (2024) "Trouble Every Day: Monetary Policy in an Open Emerging Economy: Working Paper 891." ERSA Working Paper Series (2024).

Ramey, Valerie A. (2016). “Macroeconomic Shocks and Their Propagation.” Handbook of Macroeconomics, in: J. B. Taylor & Harald Uhlig (ed.), Handbook of Macroeconomics, edition 1, volume 2, chapter 0, pages 71-162, Elsevier.

Rigobon, Roberto (2003). “Identification Through Heteroskedasticity.” The Review of Economics and Statistics 85 (4): 777-792. doi:10.1162/003465303772815727.

Rigobon, Roberto, and Brian Sack (2004). “The Impact of Monetary Policy on Asset Prices.” Journal of Monetary Economics 51 (8): 1553-1575. doi:10.1016/j.jmoneco.2004.02.004.

Rogers, John H., Chiara Scotti and Jonathan H. Wright, 2018. "Unconventional Monetary Policy and International Risk Premia," Journal of Money, Credit and Banking, Blackwell Publishing, vol. 50(8), pages 1827-1850, December.

Romer, Christina D., and David H. Romer (2004). “A New Measure of Monetary Shocks: Derivation and Implications.” American Economic Review, 94 (4): 1055-1084.

Solis, Pavel (2023). “Does the Exchange Rate Respond to Monetary Policy in Mexico? Solving an Exchange Rate Puzzle in Emerging Markets.” Journal of Money, Credit and Banking.

Stock, James H., and Mark W. Watson (2018). “Identification and Estimation of Dynamic Causal Effects In Macroeconomics Using External Instruments.” The Economic Journal 128 (610): 917-948. doi:10.1111/ecoj.12593.

Swanson, Eric T. (2021). “Measuring the Effects of Federal Reserve Forward Guidance and Asset Purchases on Financial Markets.” Journal of Monetary Economics, Elsevier, vol. 118(C), pages 32-53.

Uribe, Martin and Yue, Vivian Z., (2006). "Country spreads and emerging countries: Who drives whom?," Journal of International Economics, Elsevier, vol. 69(1), pages 6-36, June.

White, Lawrence J. (2010). “Markets: The Credit Rating Agencies.” Journal of Economic Perspectives, 24 (2): 211-26.

Wu, Jing Cynthia and Zhang, Ji, (2019). "A shadow rate New Keynesian model," Journal of Economic Dynamics and Control, Elsevier, vol. 107(C), pages 1-1.