A Data

A.1 Data Sources

Table A.1 provides the list of data sources, along with relevant information on the variables, frequency, and the sample period.

Table A.1: Data Sources

Source	Variables	Frequency	Sample Period
S&P Capital IQ	CDS spread	Daily	2005M7–2022M12
International Monetary Fund	Announcement dates	Daily	2005M7–2022M12
Ámbito Financiero	EMBI spread	Daily	2002M1–2022M12
	Blue Dollar rate	Daily	2002M1–2022M12
	Blue Chip Swap rate	Daily	2002M1–2022M12
	Official exchange rate	Daily	2002M4–2022M12
BCRA	Interest rates	Daily	2002M1–2022M12
	International reserves	Daily	2002M1–2022M12
	IPMP	Daily	2002M1–2022M12
	Professional forecasts	Monthly	2016M6–2022M12
	Consolidated bank balance sheet	Monthly	2002M1–2022M12
	Import/export index by type	Monthly	2002M1–2022M12
INDEC	GDP	Monthly	2002M1–2022M12
	CPI	Monthly	2002M1–2006M12
			2017M1–2022M12
	GDP composition	Quarterly	2005Q3–2022Q4
	Sectoral GDP	Quarterly	2005Q3–2022Q4
	FDI net inflow	Quarterly	2005Q3–2022Q4
	Terms of trade	Quarterly	2005Q3–2022Q4
Graciela Bevacqua	CPI	Monthly	2007M1–2016M12
BIS	Policy Rate (ARG)	Monthly	2002M1–2022M12
CBOE	VIX	Daily	2002M1–2022M12
Wall Street Journal	MERVAL index	Daily	2002M1–2022M12
Bloomberg	ICE BofA HY EM Corporate Plus Index (EARH)	Monthly	2002M1–2022M12
MSCI	MSCI Argentina index	Monthly	2004M8–2022M12
ISDA	Credit event dates	Daily	2005M7–2022M12
Gürkaynak et al. (2007)	Risk free rate	Daily	2005M7–2022M12

Notes: This table provides the list of data sources used for this paper, along with the relevant information for each variable. When indicating the sample period for variables available at the daily frequency, the year-months correspond to periods for which the daily dataset is available for the entire month.

A.2 Announcement Dates

Table A.2 lists all IMF announcements used in the paper, along with a brief description of the announcement. Note that this does not encompass every IMF announcement in the sample period, as I only use IMF announcements that are specific to Argentina. I also exclude any announcements related to forecasts of the Argentine economy, including the World Economic Outlook or the Regional Economic Outlook. This minimizes concerns for any information effects of the IMF announcements revealing information about the state of the economy or forecasts of the economy. This list includes a total of 71 announcements, 4 of which occur during periods of default when there is no CDS spread available.[35]

During the sample period, there were five lending arrangements between Argentina and the IMF: a Stand-By Arrangement (SBA) from March 2000 to January 2003; an SBA from January 2003 to August 2003; an SBA from September 2003 to January 2006; an SBA from June 2018 to July 2020; and an Extended Fund Facility from March 2022. In addition, some announcements from 2010 to 2016 concern the relationship between Argentina and the IMF in response to Argentina misreporting its CPI. The IMF issued a declaration of censure in February 2013, which served as an official threat towards sanctions and potential expulsion. IMF's disciplinary actions influenced sovereign spreads, as it affected expectations regarding Argentina's ability to access credit from the IMF.

Table A.2: List of Announcements

Month	Announcement date	Description
2007M12	2007-12-11	Statement by Managing Director
2010M11	2010-11-23	IMF statement
2010M12	2010-12-16	IMF statement (technical mission)
2011M3	2011-03-24	IMF statement (technical mission)
2011M4	2011-04-11	IMF statement (technical mission)
2011M7	2011-07-13	IMF Executive Board statement
2012M2	2012-02-01	IMF Executive Board statement
2012M9	2012-09-18	IMF Executive Board statement
2012M12	2012-12-17	IMF statement
2013M1	2013-01-29	IMF Executive Board informal briefing
2013M2	2013-02-01	IMF Executive Board statement
2013M12	2013-12-09	IMF Executive Board statement
2014M3	2014-03-14	IMF Executive Board informal briefing
2014M6	2014-06-06	IMF Executive Board statement
2014M12	2014-12-15	IMF Executive Board statement*
2015M5	2015-05-08	IMF Executive Board informal briefing*

Continued on next page

[35]There are two periods of default during the sample period: August 1, 2014 to May 24, 2016, and May 26, 2020 to September 16, 2020. The timings correspond to declarations of credit events by ISDA.

Table A.2 – Continued from previous page

Month	Announcement date	Description
2015M6	2015-06-03	IMF statement (technical mission)*
2016M7	2016-07-01	IMF statement (technical mission)
2016M8	2016-08-31	IMF Executive Board statement
2016M11	2016-11-09	IMF statement (removal of censure)
2017M4	2017-04-07	Statement by First Deputy Managing Director
2018M5	2018-05-08	Statement by Managing Director
2018M5	2018-05-10	Statement by Managing Director
2018M5	2018-05-14	Statement by Managing Director
2018M5	2018-05-18	IMF statement
2018M6	2018-06-04	IMF statement
2018M6	2018-06-07	Staff-level agreement
2018M6	2018-06-09	Statement by Managing Director
2018M6	2018-06-13	Statement by Managing Director
2018M6	2018-06-20	Board approval
2018M7	2018-07-21	Statement by Managing Director
2018M8	2018-08-29	Statement by Managing Director
2018M9	2018-09-04	Statement by Managing Director
2018M9	2018-09-26	Staff-level agreement°
2018M10	2018-10-26	Board approval°
2018M11	2018-11-26	IMF statement (mission)°
2019M1	2019-01-24	Statement by Managing Director°
2019M3	2019-03-18	IMF statement (mission)°
2019M4	2019-04-05	Board approval°
2019M4	2019-04-29	IMF statement°
2019M6	2019-06-08	Statement by Managing Director°
2019M6	2019-06-28	Statement by Managing Director°
2019M7	2019-07-05	Statement by Acting Managing Director°
2019M7	2019-07-12	Board approval°
2019M8	2019-08-28	IMF statement
2019M9	2019-09-24	Statement by Acting Managing Director
2019M11	2019-11-19	Statement by Managing Director
2020M1	2020-01-28	IMF statement
2020M2	2020-02-04	Statement by Managing Director
2020M2	2020-02-19	IMF statement
2020M2	2020-02-22	Statement by Managing Director
2020M3	2020-03-20	Statement by Managing Director
2020M6	2020-06-01	IMF statement*
2020M10	2020-10-12	IMF statement
2020M11	2020-11-20	IMF statement
2021M3	2021-03-25	IMF statement (mission)
2021M5	2021-05-14	Statement by Managing Director
2021M7	2021-07-13	IMF statement (mission)

Continued on next page

Table A.2 – Continued from previous page

Month	Announcement date	Description
2021M12	2021-12-10	IMF statement
2021M12	2021-12-22	IMF Executive Board statement
2022M1	2022-01-28	IMF statement
2022M3	2022-03-03	Staff-level agreement
2022M3	2022-03-19	IMF statement
2022M3	2022-03-25	Board approval
2022M6	2022-06-08	Staff-level agreement°
2022M6	2022-06-24	Board approval°
2022M9	2022-09-12	Statement by Managing Director°
2022M9	2022-09-19	Staff-level agreement°
2022M10	2022-10-07	Board approval°
2022M12	2022-12-03	Staff-level agreement°
2022M12	2022-12-22	Board approval°

Notes: * indicates an announcement that occurred during periods of default;
° indicates an announcement that occurred during periods of quarterly reviews.

A.3 Professional Forecast Survey

In this section, I provide an overview of the Market Expectations Survey (Relevamiento de Expectativas de Mercado) conducted monthly by the BCRA since June 2016.

The Market Expectations Survey is a monthly survey asking participants their forecasts of key macroeconomic variables. The participants consist of banks, consulting firms, universities, and investment analysts. More than 60 institutions were invited to participate by the BCRA, and participation is voluntary. As of April 2024, there were 47 survey participants. The survey is conducted during the last three business days of each month, with each participant submitting their forecasts to the BCRA via email.

Each participant is asked to provide their forecast on eight key variables: CPI, interest rates, nominal exchange rates, level of exports and imports, unemployment rate, GDP, and the primary fiscal deficit. The survey collects forecasts on the primary deficit and the GDP growth rate for the following calendar year relative to the year of survey. I use these two forecasts to examine the correlation between the market surprises and changes in expectations.

For each variable and forecast horizon, the BCRA publishes the average, median, standard deviation, maximum and minimum, quartiles, and the number of respondents. The results from the survey are usually published during the first week of the next calendar month (one week after the survey).

A.4 Surprise by Type of Announcement

Figure A.1 shows the market surprises in CDS spreads across tenors in response to each of the three types of announcements. I scale the market surprises such that the average absolute value surprise across tenors within each type of announcement is set to 1. The credit access events are characterized by large responses in the CDS spreads of the shorter tenors.

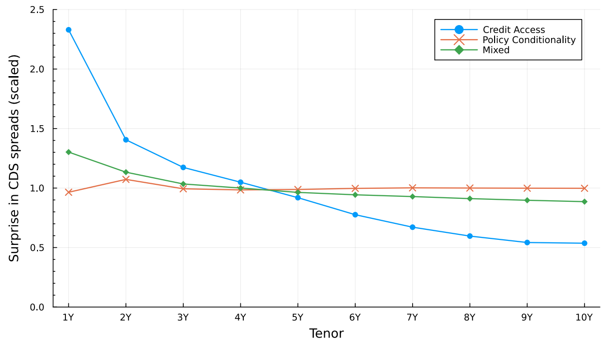


Figure A.1: Surprise in CDS Spreads by Announcement Type

Notes: This figure shows the absolute value of the changes in CDS spreads around IMF announcements for each type of announcement. The magnitudes are scaled such that the average change in CDS spreads across tenors is equal to 1 for each type of announcement.

A.5 Forecast Revisions and Surprises

	Real GDP Growth	Real GDP Growth	Primary Deficit	Primary Deficit
	(1)	(2)	(3)	(4)
CDS 1Y Surprise	−0.013	−0.010	0.286	0.008
	(0.012)	(0.009)	(0.715)	(1.036)
p-value	0.279	0.278	0.701	0.994
Observations	20	29	9	29

Table A.3: Forecast Revisions and Market Surprises

Notes: This table reports the results for the OLS estimation corresponding to Equations 36 and 37 in Appendix B.5. The dependent variable is the change in professional forecast survey responses regarding the expectation of the relevant economic variable for the next calendar year (maximum horizon over which forecasts are available). I measure the forecast revisions by computing the changes in the mean forecasts between the closest monthly surveys before and after the announcement. The forecast revision for the real GDP growth rate is in percentage points; the forecast revision for the primary deficit is in percentages; and the 1-year CDS spread surprise is in percentages. The total sample size is limited to 29 months, as the survey dataset is only available from June 2016. Columns 1 and 3 have sample sizes of 20 and 9, as they are mutually exclusive subsamples based on whether the announcements are part of quarterly reviews or not.

A.6 Granger Causality Tests

In order for the sovereign liquidity shocks to be a valid shock, it cannot be predictable. I perform a number of Granger causality test to examine whether the surprise series can be forecasted using past economic and financial variables. Table A.4 shows the results, suggesting that the series cannot be forecasted by past economic variables.

Variable	p-value
EMBI spread	0.11
GDP	0.54
CPI	0.56
Policy rate	0.86
Blue Chip Swap rate	0.62
Blue Dollar rate	0.67
Net Exports	0.32
IPMP (commodity price index)	0.65
MERVAL (stock market index)	0.80
BCRA International Reserves	0.56
Global Geopolitical Risk	0.36

Table A.4: Granger causality tests

Notes: This table shows the p-values of the Granger causality tests of the monthly surprise series using a number of variables.

A.7 Autocorrelation of Surprise Series

Figure A.2 shows the autocorrelation function of the monthly surprise series for various lag lengths.

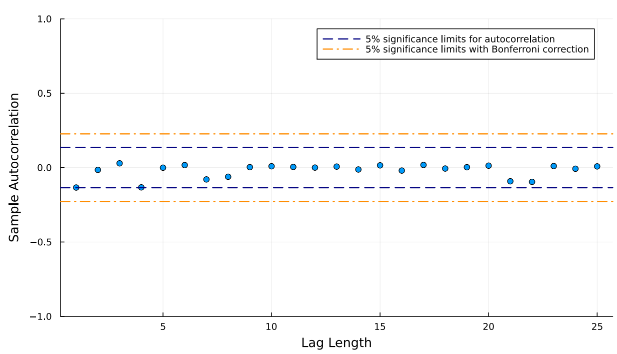


Figure A.2: Autocorrelation Plot

Notes: This figure shows the autocorrelation function of the constructed monthly surprise series z_t^ℓ. Each point shows the sample autocorrelation (vertical axis) for the corresponding number of lags (horizontal axis). The dashed line represents the 5% significance threshold for autocorrelation; the dash-dotted line represents the 5% significance threshold for autocorrelation with a Bonferroni correction.

A.8 Correlation with Other Shocks

Table A.5 shows the correlation between the monthly shock series and other shocks from the literature.

Table A.5: Correlation with other shocks

Shock	Source	ρ	p-value	Sample Period
Monetary Policy				
US monetary policy	Bauer and Swanson (2023b)	-0.10	0.15	2002M7–2019M1
	Jarociński and Karadi (2020)	-0.15	0.14	2002M7–2022M12
US central bank info	Jarociński and Karadi (2020)	-0.10	0.16	2002M7–2022M12
EU monetary policy	Jarociński and Karadi (2020)	0.18	0.09	2002M7–2022M12
EU central bank info	Jarociński and Karadi (2020)	0.00	0.92	2002M7–2022M12
Uncertainty				
Global policy uncertainty	Baker et al. (2016)	0.02	0.79	2002M7–2022M12
VIX residual	Bloom (2009)	0.16	0.05	2002M7–2011M9
Gold prices	Piffer and Podstawski (2018)	0.01	0.90	2002M7–2022M12
Oil				
Oil supply news	Känzig (2021)	-0.05	0.55	2002M7–2022M12
Oil demand	Baumeister and Hamilton (2019)	-0.15	0.09	2002M7–2022M12
Oil demand (consumption)	Baumeister and Hamilton (2019)	-0.15	0.19	2002M7–2022M12
Oil demand (inventory)	Baumeister and Hamilton (2019)	0.07	0.11	2002M7–2022M12
Oil supply	Baumeister and Hamilton (2019)	0.23	0.04	2002M7–2022M12
Food				
Food commodity price	Peersman (2022)	0.14	0.39	2002Q3–2013Q4
Productivity				
Rainfall	Constructed	-0.05	0.17	2002M7–2022M12

Notes: This table shows the correlation between the monthly surprise series and other identified shocks. The ρ reports the correlation coefficient, along with the corresponding p-values. All shocks other than the rainfall shocks use existing shocks from the literature. I construct rainfall shocks as a measure of agricultural productivity shocks, following the methodology from Jayachandran (2006). I use Argentine rainfall data from 1981 to 2024 provided by the World Food Programme (WFP) and UC Santa Barbara's Climate Hazards Center.

B Methodology

B.1 Interpretation of CDS Spread Changes

This section provides the asset pricing equations relevant for the interpretation that the high-frequency changes in the CDS spreads correspond to revisions in default expectations.

Standard asset pricing implies that

$$\begin{aligned} P_{t,d} &= \mathbb{E}_{t,d}[m_{t+h}\delta_{t+h}] && (11)\\ &= \mathbb{E}_{t,d}[m_{t+h}]\mathbb{E}_{t,d}[\delta_{t+h}] + \text{Cov}_{t,d}[m_{t+h}, \delta_{t+h}] && (12)\\ &= \mathbb{E}_{t,d}[m_{t+h}]\mathbb{E}_{t,d}[\delta_{t+h}] - \mathbb{E}_{t,d}[R^e_{t+h}] && (13)\\ &= \frac{1}{R^f_{t,d}}\mathbb{E}_{t,d}[\delta_{t+h}] - \mathbb{E}_{t,d}[R^e_{t+h}], && (14) \end{aligned}$$

where $P_{t,d}$ is the CDS spread in month t on day d; m_{t+h} is the stochastic discount factor at month $t+h$; δ_{t+h} is the payoff of the CDS contract at month $t+h$; $\mathbb{E}_{t,d}[R^e_{t+h}]$ is the risk premium; and R^f_{t+h} is the risk-free rate. Note here that I use two time indices, month and day, to distinguish between the horizon of the asset payoff (in months) and the date of measurement of the high-frequency responses (in days). Equation 11 comes from the standard asset pricing equation of expected discounted payoffs; Equation 12 follows from the definition of covariance; Equation 13 follows from the definition of risk premium; and Equation 14 follows from the definition of the risk-free rate.[36]

Assuming that neither the risk-free rate nor the risk premium do not change within the specified window around the announcement, the changes in CDS spreads can be interpreted to be proportional to changes in the sovereign default probability:

$$\begin{aligned} Surprise_{t,d} &= P_{t,d+1} - P_{t,d-1} \\ &= \frac{1}{R_t^f}(\mathbb{E}_{t,d+1}[\delta_{t+h}] - \mathbb{E}_{t,d-1}[\delta_{t+h}]) \\ &\propto \pi_{t,d+1}^h - \pi_{t,d-1}^h, \end{aligned} \tag{15}$$

where $\pi_{t,d}^h$ is the cumulative h-month default probability at month t and day d. The last line follows from the fact that the expected payoff $\mathbb{E}_{t,d}[\delta_{t+h}]$ is proportional to the probability of default, given that the payoff is positive in the case of default and zero otherwise.

B.2 Surprise Series Decomposition: PCA and Rotation

I decompose the surprise series by implementing principal component analysis and a rotation of the extracted factors, following the methodology from Gürkaynak et al. (2005).

Using the surprises of all tenors of credit default swaps on announcement dates, denoted by matrix X, I first estimate F, composed of two components $\mathbf{f_1}$ and $\mathbf{f_2}$, using principal components analysis. Note here that X is a matrix with the number of rows corresponding to the number of announcements and the number of columns corresponding to the number of tenors. $\mathbf{f_1}$ and $\mathbf{f_2}$ are both vectors with the dimension equal to the number of announcements, and correspond to the first and second columns of F respectively.

Once I extract the components in F, I rotate F such that the following holds: the first component corresponds to the changes in the CDS spreads of the shortest tenor; and the second component corresponds to the changes in CDS spreads of all other tenors that are not driven by the changes in the shortest-tenor CDS. I implement this by defining matrix Z as

$$Z = FU, \text{ where } U = \begin{pmatrix} \alpha_1 & \beta_1 \\ \alpha_2 & \beta_2 \end{pmatrix}, \tag{16}$$

[36] See Cochrane (2007) for derivation of the relationship between the risk premium and the covariance between the asset and the discount factor.

and U has the following four restrictions:

$$\alpha_1^2 + \alpha_2^2 = 1 \quad \text{Unit length} \tag{17}$$

$$\beta_1^2 + \beta_2^2 = 1 \quad \text{Unit length} \tag{18}$$

$$\alpha_1\beta_1 + \alpha_2\beta_2 = 0 \quad \text{Orthogonality of } \mathbf{z_1} \text{ and } \mathbf{z_2} \tag{19}$$

$$\gamma_2\alpha_1 - \gamma_1\alpha_2 = 0 \quad Z_2 \text{ does not influence shortest tenor surprise} \tag{20}$$

where γ_1 and γ_2 denote the loadings of the shortest tenor surprise on $\mathbf{f_1}$ and $\mathbf{f_2}$ respectively. This system of equations allows me to solve for U, and consequently $\mathbf{z_1}$ and $\mathbf{z_2}$ that make up the columns of Z. I use this decomposed vector $\mathbf{z_1}$ as the external instrument in the proxy VAR by aggregating to the monthly level.

B.3 Surprise Series Decomposition: Factor Analysis

This section outlines the methodology of directly estimating a latent factor model to decompose the surprise series. As with the methodology outlined in Appendix B.2, this methodology involves the key assumption that the factor representing policy conditionality do not influence the shortest-tenor CDS spreads.

I first assume that the surprises in CDS spreads around announcements can be characterized by the following two-factor latent model, with each t corresponding to an announcement:

$$\Delta\mathbf{s}_t = \Lambda\mathbf{f}_t + \boldsymbol{\xi}_t, \tag{21}$$

where

$$\Delta\mathbf{s}_t \equiv (\Delta s_{1,t}, \Delta s_{2,t}, \ldots, \Delta s_{10,t})^\top, \tag{22}$$

$$\Lambda \equiv \begin{pmatrix} \lambda_{1,1} & \lambda_{1,2} \\ \vdots & \vdots \\ \lambda_{10,1} & \lambda_{10,2} \end{pmatrix}, \tag{23}$$

$$\mathbf{f}_t \equiv (f_{1,t}, f_{2,t})^\top, \tag{24}$$

$$\boldsymbol{\xi}_t \equiv (\xi_{1,t}, \xi_{2,t}, \ldots, \xi_{10,t})^\top, \tag{25}$$

$$\mathbf{f}_t \sim \mathcal{N}(0, I_2), \tag{26}$$

$$\boldsymbol{\xi}_t \sim \mathcal{N}(0, \Psi). \tag{27}$$

The surprises in CDS spreads are represented by $\Delta\mathbf{s_t}$, which is a 10-dimensional vector with each element corresponding to the changes in CDS spreads for a particular tenor; Λ is a 10×2 matrix representing the loadings corresponding to combinations between each CDS tenor and the two latent factors; $\mathbf{f}_t$ is a 2-dimensional vector of the two latent factors; and $\boldsymbol{\xi}_t$ is a 10-dimensional error term. I impose distributional assumptions on $\mathbf{f}_t$ and $\boldsymbol{\xi}_t$ that are commonly used in factor analysis. Note that the distributional assumption on $\mathbf{f}_t$ implies that both factors have unit variance and the two factors are orthogonal. I also assume that Ψ is a diagonal matrix, implying that the errors are idiosyncratic for each tenor.

I make one additional constraint that the second factor has a loading of zero on the shortest tenor CDS spread (one-year CDS):

$$\lambda_{1,2} = 0. \tag{28}$$

This constraint is analogous to the assumption from Equation 20 when decomposing the surprises using principal component analysis and a rotation of the factors. Using this assumption, I interpret the first factor to correspond to surprises in Argentina's access to credit and the second factor to correspond to surprises in policy conditions imposed by the IMF.

Given the assumptions discussed above, I estimate the loadings Λ and the variance of the error term Ψ using maximum likelihood estimation. The negative log-likelihood is given by:

$$-\ln L(\Lambda, \Psi) = \frac{T}{2}\left[\ln(\det(\Sigma)) + \mathrm{tr}(\Sigma^{-1}S)\right], \tag{29}$$

where $\Sigma = \Lambda\Lambda^\top + \Psi$ is the implied covariance of $\Delta\mathbf{s}_t$, and S is the sample covariance of the surprises.

After estimating $\hat{\Lambda}$ and $\hat{\Psi}$ using MLE, I compute the estimated factor realizations $\hat{\mathbf{f}}_t$ using OLS:

$$\hat{\mathbf{f}}_t = (\hat{\Lambda}^\top\hat{\Psi}^{-1}\hat{\Lambda})^{-1}\hat{\Lambda}^\top\hat{\Psi}^{-1}\Delta\mathbf{s}_t. \tag{30}$$

I then use the decomposed vector composed of $\hat{f}_{1,t}$ for all announcements t as the external instrument in the proxy VAR by aggregating to the monthly level. I present the results in Figure C.2i of Appendix C.5.

B.4 Surprise Series Decomposition: Narrative Zero Restrictions

This section outlines the methodology of using narrative zero-restrictions and a latent factor model to decompose the surprise series. In contrast to the methodologies discussed in Appendices B.2 and B.3, this methodology does not impose any assumptions on the loadings of factors (i.e., I do not assume that the factor corresponding to policy conditionality has zero impact the shortest tenor CDS spread). Rather, this methodology involves a narrative approach that imposes restrictions on the factors. Using the textual content of each announcement, I classify whether each announcement involved a surprise to credit-access, a surprise to policy conditions, or a mixture of both. I then impose constraints that the shock that is absent implies a value of zero for the corresponding factor.

Consistent with the methodology discussed in B.3, I first assume that the surprises in CDS spreads around announcements can be characterized by a two-factor latent model, as characterized by Equations 21 to 27 in the previous section. I label the first factor, $f_{1,t}$, to be the "credit-access" factor, and the second factor, $f_{2,t}$, to be the "policy-conditionality" factor.

For each announcement t, I use the textual content of the press releases and any other relevant documents corresponding to the IMF announcement to systematically classify which factor(s) were present. I classify the announcements using the following set of rules:

1. Announcement t is a **pure credit-access** event if the announcement (a) includes new information on the future expected path of Argentina's access to credit from the IMF; and (b) either explicitly mentions that the announcement does not pertain to policy conditionality or the announcement does not mention anything remotely related to policy conditionality.

2. Announcement t is a **pure policy-conditionality** event if the announcement (a) includes new information on the policy conditions that the IMF imposes; and (b) does not include any new information on the future expected path of Argentina's access to credit from the IMF. This requires that the announcement provides the exact size of the lending program that is identical to the information from a previous announcement that has occurred less than a month earlier.

3. Otherwise, announcement t is a **mixed** event, where both factors may be present.

Following these rules, I classify the all of the announcements into the three categories. Out of the 67 total announcements, 19 announcements are pure credit-access events, 7 announcements are pure policy-conditionality events, and 41 announcements are mixed events. I provide some examples of each category below:

- **Pure credit-access events example**: Extension of repayment schedule

> *"The Executive Board of the International Monetary Fund (IMF) today approved a one-year* ***extension of Argentina's repayment expectations*** *... The decision to approve an extension of repayment expectations is based on these technical considerations, and is* ***not based on an assessment of the authorities' economic program****."*

- **Pure policy-conditionality events example**: Board approval of a lending program that outlines details on policy conditionality without any changes in lending program size from the staff approval few weeks prior:

> *"The Executive Board of the International Monetary Fund (IMF) today approved a three-year* ***Stand-By Arrangement (SBA) for Argentina amounting to US\$50 billion*** *... Anchoring this effort is a* ***fiscal adjustment that ensures that the federal government reaches primary balance by 2020****"*

  An announcement 13 days earlier already mentioned the identical lending program size of exactly \$50 billion, with the only new information being a detailed explanation of the policy targets, a snippet of which I include in the selected quotation above.

- **Mixed events example**: Announcement that could involve both factors:

> *"IMF staff are* ***continuing discussions with the Argentine authorities toward a Fund-supported program****. Our shared goal is to reach a rapid conclusion of these discussions. An IMF Board meeting on Argentina is scheduled for Friday, May 18. This will be an informal meeting, as part of our usual process of briefing the Board on negotiations for high access IMF programs."*

Using the narrative classification of each announcement, I impose zero restrictions on the factors. I denote the set of pure credit-access events as $\mathcal{T}_{credit}$ and the set of pure policy-conditionality events as $\mathcal{T}_{policy}$. I impose that $f_{2,t} = 0$ for $t \in \mathcal{T}_{credit}$ and $f_{1,t} = 0$ for $t \in \mathcal{T}_{policy}$. In other words, the factor corresponding to policy conditionality has a value of zero for all pure credit-access events and the factor corresponding to credit access has a value of zero for all pure policy-conditionality events. This is the key identification assumption for the decomposition: that a subset of events does not contain one of the factors, and thus the absent factor has a value of zero.

I then jointly estimate the loadings Λ and the factors $\mathbf{f}_t$ by solving the following minimization problem:

$$\begin{aligned} \min_{\Lambda,\mathbf{f}_t} \sum_{t=1}^{T} \sum_{i=1}^{10} (\Delta s_{i,t} - &\lambda_{i,1} f_{1,t} - \lambda_{i,2} f_{2,t})^2 \\ \text{s.t. } f_{2,t} &= 0 \text{ if } t \in \mathcal{T}_{credit} \\ f_{1,t} &= 0 \text{ if } t \in \mathcal{T}_{policy}. \end{aligned} \tag{31}$$

I then use the decomposed vector composed of $\hat{f}_{1,t}$ for all announcements t as the external instrument in the proxy VAR by aggregating to the monthly level. I present the results in Figure C.2j of Appendix C.5.

B.5 Model of Information Effects

This section introduces a model that formalizes the interpretation of sovereign liquidity shocks and the potential information effects discussed in Section 2.1.4. The set up of the model is based on Sastry (2024), which formalizes disagreements about monetary policy between the Fed and the market.

The model generates testable predictions regarding the relationship between forecast revisions and the market surprises, which I use to test for the potential presence of information effects.

In Section B.5.1 I introduce a baseline model to precisely illustrate the interpretation of sovereign liquidity shocks. Then, in Section B.5.2, I characterize a model with private signals to examine the implication of information effects on the market surprises and forecast revisions. Finally, in Section B.5.3, I discuss the interpretation of the model to bridge the model predictions with the empirical tests that I conduct to address concerns for the presence of information effects.

B.5.1 Baseline model without private signals

Set-up. The model consists of two agents, the official lender (IMF), denoted by I, and a representative investor (Market), denoted by M. There are three periods, $t \in \{0, 1, 2\}$, and one exogenous fundamental that is stochastic:

$$\theta \sim \mathcal{N}(0, \tau_\theta^{-1}).$$

The exogenous fundamental θ can either be interpreted as the state of aggregate demand or a country's policy performance with respect to abiding by the policy conditionality. I discuss the interpretation of θ more in detail in Section B.5.3. To maintain analytical tractability, I only focus on one fundamental rather than introducing multiple fundamentals that each have their own set of signals.

At $t = 0$, both the IMF and the market observe one public signal about fundamental θ:

$$Z_\theta = \theta + \varepsilon_Z,$$

where $\varepsilon_Z \sim \mathcal{N}(0, \tau_Z^{-1})$ is an independent noise term.

The IMF decides on policy action s, which depends on its expectation about the fundamental θ with some exogenous error:

$$s = \mathbb{E}_{I,0}[\theta] + \varepsilon_I,$$

where $\varepsilon_I \sim \mathcal{N}(0, \tau_I^{-1})$ is an independent noise term. The policy action s can be interpreted as the sovereign spread of the borrowing country. The IMF chooses the funding schedule that maps to s, which in turn impacts the economy. The ε_I term is the exogenous shock to IMF policy, which I interpret as a measure of sovereign liquidity shocks.

The market predicts policy action s based on the public signal.

$$P = \mathbb{E}_{M,0}[s].$$

This prediction P can be interpreted as the price of an asset that pays off in proportion to s at $t = 1$.

At $t = 1$, the IMF announces policy action s to the market. This induces a market surprise, defined as:

$$\Delta \equiv s - P.$$

At $t = 2$, output is realized as:

$$Y = \beta_\theta \theta - \beta_s s,$$

where β_θ and β_s map the fundamental θ and sovereign spread s to output Y.

Beliefs. At $t = 0$, the IMF uses Bayes' rule to form its beliefs about the fundamental θ:

$$\mathbb{E}_{I,0}[\theta] = \delta_Z Z,$$

where $\delta_Z \equiv \frac{\tau_Z}{\tau_Z + \tau_\theta}$ is the precision weight from Gaussian signal extraction. Therefore, the IMF will set its policy s to be the following:

$$s = \delta_Z Z + \varepsilon_I$$

The market also uses Bayes' rule to predict fundamental θ, policy action s, and output

Y:

$$
\begin{aligned}
&\mathbb{E}_{M,0}[\theta] = \delta_Z Z \\
&P = \mathbb{E}_{M,0}[s] = \mathbb{E}_{M,0}[\mathbb{E}_{I,0}[\theta] + \varepsilon_I] = \delta_Z Z \\
&\mathbb{E}_{M,0}[Y] = \beta_\theta \mathbb{E}_{M,0}[\theta] - \beta_s \mathbb{E}_{M,0}[s] = (\beta_\theta - \beta_s)\delta_Z Z.
\end{aligned}
$$

Market surprise and forecast revisions. Once the IMF makes its announcement at $t = 1$, the policy action s is revealed to the market, resulting in the following market surprise:

$$\Delta \equiv s - P = \delta_Z Z + \varepsilon_I - \delta_Z Z = \varepsilon_I.$$

This represents the market surprises I use as an instrument in the baseline methodology of the paper, which I interpret to be an imperfect measure of sovereign liquidity shocks.

The market's forecasts of the fundamental θ and output Y after observing s are the following:

$$
\begin{aligned}
&\mathbb{E}_{M,1}[\theta] = \delta_Z Z \\
&\mathbb{E}_{M,1}[Y] = \beta_\theta \mathbb{E}_{M,1}[\theta] - \beta_s s = \beta_\theta \delta_Z Z - \beta_s(\delta_Z Z + \varepsilon_I).
\end{aligned}
$$

The forecast revisions can be expressed as:

$$
\begin{aligned}
\mathbb{E}_{M,1}[\theta] - \mathbb{E}_{M,0}[\theta] &= 0 \\
\mathbb{E}_{M,1}[Y] - \mathbb{E}_{M,0}[Y] &= -\beta_s \varepsilon_I.
\end{aligned}
$$

Note that the market forecast for θ remains the same between $t = 0$ and $t = 1$ in this setting, since there is no new information about θ in the announcement. On the other hand, the market will update its forecast of Y after observing s.

The covariance between each forecast revision and the market surprise Δ are the following:

$$\text{Cov}\big[\mathbb{E}_{M,1}[\theta] - \mathbb{E}_{M,0}[\theta], \Delta\big] = 0 \tag{32}$$

$$\text{Cov}\big[\mathbb{E}_{M,1}[Y] - \mathbb{E}_{M,0}[Y], \Delta\big] = -\beta_s \text{Var}[\Delta] \tag{33}$$

In this baseline model with a shock to the policy rule and no private signal, the coefficient when regressing the forecast revision for θ on the market surprises is 0, since the policy announcement does not provide any new information about θ. When regressing the output forecast revisions on the market surprises, the coefficient is $-\beta_s$, which captures the expected effect of the increase in sovereign spreads on output.

B.5.2 Model with private signals

Set-up. The model with private signals is identical to the set up described in Section B.5.1, but with two exceptions: the IMF observes a private signal about fundamental θ and there is no policy shock ε_I. The omission of the policy shock provides a simple interpretation of the implication of the information effects.

At $t = 0$, the IMF observes one private signal in addition to the public signal:

$$X = \theta + \varepsilon_X,$$

where $\varepsilon_X \sim \mathcal{N}(0, \tau_X^{-1})$ is an independent noise term.

The IMF decides on policy action s, which no longer involves any error:

$$s = \mathbb{E}_{I,0}[\theta].$$

This set up allows us to generate model predictions in the setting where the market surprises are entirely driven by the information effect.

Beliefs. At $t = 0$, the IMF uses Bayes' rule to form its beliefs and set its policy:

$$s = \mathbb{E}_{I,0}[\theta] = \delta_X^I X + \delta_Z^I Z,$$

where $\delta_X^I \equiv \frac{\tau_X}{\tau_X+\tau_Z+\tau_\theta}$ and $\delta_Z^I \equiv \frac{\tau_Z}{\tau_X+\tau_Z+\tau_\theta}$ are the precision weights from Gaussian signal extraction.

The market also uses Bayes' rule to predict fundamental θ, policy action s, and output Y:

$$\begin{aligned}
&\mathbb{E}_{M,0}[\theta] = \delta_Z^M Z \\
&P = \mathbb{E}_{M,0}[s] = \mathbb{E}_{M,0}\big[\mathbb{E}_{I,0}[\theta]\big] = \mathbb{E}_{M,0}[\delta_X^I X + \delta_Z^I Z] = \delta_X^I \delta_Z^M Z + \delta_Z^I Z \\
&\mathbb{E}_{M,0}[Y] = \beta_\theta \mathbb{E}_{M,0}[\theta] - \beta_s \mathbb{E}_{M,0}[s] = \beta_\theta \mathbb{E}_{M,0}[\theta] - \beta_s P
\end{aligned}$$

where $\delta_Z^M \equiv \frac{\tau_Z}{\tau_Z+\tau_\theta}$ is the precision weight from Gaussian signal extraction.

Market surprise and forecast revisions. The policy action s is revealed to the market at $t = 1$ results in the following market surprise:

$$\Delta \equiv s - P = \delta_X^I X + \delta_Z^I Z - (\delta_X^I \delta_Z^M Z + \delta_Z^I Z) = \delta_X^I (X - \delta_Z^M Z).$$

The sign and magnitude of the market surprise depends on the difference between the realization of the private signal X and the market expectation of θ at $t = 0$. For example, if the realization of the private signal X is high, the IMF would provide a lending schedule that is associated with a higher sovereign spread s, which would induce a market surprise that is positive in value. I discuss the interpretation of the market surprise in detail in Section B.5.3.

When the market observes s, it is equivalent to observing the signal:

$$\tilde{s} \equiv s - \delta_Z^I Z = \delta_X^I X = \delta_X^I \theta + \delta_X^I \varepsilon_X = \delta_X^I \theta + \eta,$$

where $\eta \sim \mathcal{N}(0, {\delta_X^I}^2 \tau_X^{-1})$.

Standard Gaussian updating therefore implies that

$$\begin{aligned}\mathbb{E}_{M,1}[\theta] &= \mathbb{E}_{M,0}[\theta] + \frac{\delta_X^I (\tau_\theta + \tau_Z)^{-1}}{{\delta_X^I}^2((\tau_\theta + \tau_Z)^{-1} + \tau_X^{-1})}(\tilde{s} - \delta_X^I \delta_Z^M Z) \\ &= \mathbb{E}_{M,0}[\theta] + (\tilde{s} - \delta_X^I \delta_Z^M Z) \\ &= \mathbb{E}_{M,0}[\theta] + \delta_X^I (X - \delta_Z^M Z) \\ &= \mathbb{E}_{M,0}[\theta] + \Delta\end{aligned}$$

The market forecast of output Y after observing s is the following:

$$\mathbb{E}_{M,1}[Y] = \beta_\theta \mathbb{E}_{M,1}[\theta] - \beta_s s = \beta_\theta (\mathbb{E}_{M,0}[\theta] + \Delta) - \beta_s s$$

Therefore, the forecast revisions can be expressed as:

$$\begin{aligned}\mathbb{E}_{M,1}[\theta] - \mathbb{E}_{M,0}[\theta] &= \Delta \\ \mathbb{E}_{M,1}[Y] - \mathbb{E}_{M,0}[Y] &= (\beta_\theta - \beta_s)\Delta\end{aligned}$$

The covariance between each forecast revision and the market surprise Δ are the following:

$$\text{Cov}\big[\mathbb{E}_{M,1}[\theta] - \mathbb{E}_{M,0}[\theta], \Delta\big] = \text{Var}[\Delta] \tag{34}$$

$$\text{Cov}\big[\mathbb{E}_{M,1}[Y] - \mathbb{E}_{M,0}[Y], \Delta\big] = (\beta_\theta - \beta_s)\text{Var}[\Delta] \tag{35}$$

In the presence of private signals, the market surprises reflect news about the private signal at $t = 1$. When regressing the forecast revision for θ on the market surprises, the coefficient is 1, meaning that the market adjusts its forecast of θ one-to-one with respect to the market surprise. When regressing the output forecast revisions on the market surprises, the coefficient is $\beta_\theta - \beta_s$. This no longer captures the effect of the increase in sovereign spreads on output, but rather the combination of the effect of higher θ and higher s on output.

B.5.3 Interpretation and implications for empirical tests

The models discussed above generate testable predictions about the relationship between forecast revisions and the market surprises, as expressed in Equations 32–35. In the baseline model, the market surprises reflect idiosyncratic policy shocks and do not provide any new information about the fundamental θ. In contrast, in the model with private signals, the market surprises reflect an information effect. The announcement reveals news about the private signal for θ, and thus the market updates its forecast of θ when observing s. I present the model-implied coefficients corresponding to regressions of forecast revisions on the market surprises in Table B.1.

Regression	**Baseline**	**Information Effect**
Forecast revision of θ on market surprise Δ	0	1
Forecast revision of Y on market surprise Δ	$-\beta_s$	$\beta_\theta - \beta_s$

Table B.1: Model Prediction of Regression Coefficients

Notes: This table reports the regression coefficients implied by the model introduced in Sections B.5.1 and B.5.2.

I conduct a series of empirical tests for the potential presence of information effects based on the model predictions above. As a measure of forecast revisions, I use changes in forecasts from monthly professional forecast surveys between periods after and before each announcement. For market surprises, I use the decomposed monthly surprise series. This is analogous to the empirical tests used to estimate information effects in the monetary policy shock literature (Nakamura and Steinsson, 2018).

The key difference with respect to information effects between the monetary policy shock literature and this paper is that there are two potential types of information effects. The two types of information effects correspond to two different interpretations of θ. Under the interpretation that θ represents the state of aggregate demand, *higher* values of θ would be associated with *stronger* aggregate demand. Given that the IMF's mandate is to promote macroeconomic stability, when the IMF observes a high value of X (i.e., signal indicating strong aggregate demand), it would provide a smaller lending program than otherwise expected, which would increase the sovereign spread s. The market would interpret the announcement as news of an optimistic private signal about aggregate demand, and adjust its forecasts of θ and Y accordingly. Under the interpretation that θ represents the borrowing country's performance with respect to policy conditionality, *higher* values of θ would be associated with *worse* performance in abiding by the conditions. Since the IMF imposes policy conditionality to promote fiscal sustainability, the IMF may reward or penalize the borrowing country based on its performance. Similarly to the first interpretation, when the

IMF observes a high value of X (i.e., signal indicating poor policy performance), it would provide a smaller lending program than otherwise expected (to penalize the country), which would increase the sovereign spread s. The market would interpret the announcement as news about the private signal indicating poor policy performance, and adjust its forecasts accordingly.

The two interpretations involve different sets of assumptions regarding β_θ and β_s, which map the fundamental and the policy action to output $Y = \beta_\theta \theta - \beta_s s$. I list the set of assumptions in Table B.2. Under the aggregate demand interpretation of θ, higher aggregate demand results in higher output, implying that $\beta_\theta > 0$; higher sovereign spreads result in lower output, implying that $\beta_s > 0$; and higher aggregate demand correlates with higher output despite the IMF's reaction, implying that $\beta_\theta > \beta_s$. Under the policy performance interpretation of θ, higher sovereign spreads would still result in lower output, implying that $\beta_s > 0$. However, it's unclear whether better policy performance will result in higher or lower output, especially in the short term. For example, abiding by the policy condition to reduce primary government deficit to a target level may involve decreasing government spending, which would mechanically contribute to lower GDP, but may improve output through improved fiscal sustainability. Consequently, it's unclear whether β_θ is positive or negative, and also unclear whether β_θ is greater or less than β_s.

Interpretation of θ	**Assumptions**
Aggregate demand	$\beta_\theta > 0$, $\beta_s > 0$, and $\beta_\theta > \beta_s$
Policy performance	$\beta_\theta \lesseqqgtr 0$, $\beta_s > 0$, and $\beta_\theta \lesseqqgtr \beta_s$

Table B.2: Assumptions by Interpretation of Fundamental θ

Notes: This table lists the assumptions on β_θ and β_s associated with each of the two interpretations of the fundamental θ.

Given the potential presence of these two types of information effects, regressing the forecast revision on the market surprises for all announcements would not be effective in identifying whether or not information effects are present. In particular, when good performance with respect to policy conditionality decreases output forecasts, the two types of information effects may cancel out the effects on forecast revisions. To address this issue, I isolate the sample of announcements and conduct separate tests for each type of information effect.

To test for the presence of the information effect about aggregate demand, I isolate the sample to announcements that are extremely unlikely to involve any information effects about policy performance. To do so, I exclude any announcements from quarterly reviews of lending arrangements, as the quarterly reviews are the only announcements that could reasonably contain information about performance with respect to policy conditionality. For other announcements, such as announcements preceding the origination of lending programs, there is no set of policy conditions in the first place. Using this limited sample of announcements that could only suffer from information effects about aggregate demand, I estimate the following regression:

$$\mathbb{E}_{M,t+1}[Y_{t+h}] - \mathbb{E}_{M,t}[Y_{t+h}] = \beta_0 + \beta^{\Delta}\Delta_t + \varepsilon_t, \tag{36}$$

where $\mathbb{E}_{M,t+1}[Y_{t+h}] - \mathbb{E}_{M,t}[Y_{t+h}]$ is the one-year-ahead GDP forecast revision from the professional forecast survey in the month before and after month t, and Δ_t is the decomposed monthly surprise in month t. I provide details of the survey in Appendix A.3. A positive estimate of β^{Δ} would provide evidence for the presence of the information effect about aggregate demand. I present the results in Appendix A.5. I find no evidence for the presence of the information effect about aggregate demand.

To test for the presence of the information effect about policy performance, I use the sample of announcements that could potentially suffer from information effects about policy performance, which consists of announcements from quarterly reviews. Using this sample, I estimate the following regression:

$$\mathbb{E}_{M,t+1}[\theta_{t+h}] - \mathbb{E}_{M,t}[\theta_{t+h}] = \gamma_0 + \gamma^{\Delta}\Delta_t + \eta_t, \tag{37}$$

where $\mathbb{E}_{M,t+1}[\theta_{t+h}] - \mathbb{E}_{M,t}[\theta_{t+h}]$ is the one-year-ahead primary deficit forecast revision from the professional forecast survey in the month before and after month t, and Δ_t is the decomposed monthly surprise in month t. Given that I find no evidence for the presence of the information effect about aggregate demand when estimating the regression in Equation 36, I can test for the presence of the information effect about policy performance directly without concerns of any offsetting effects.

I estimate the regression in Equation 37 with primary deficit forecasts rather than Equation 36 with GDP forecasts, as GDP forecast revisions would not be helpful to test for the presence or absence of information effects regarding policy performance. This is due to the fact that it's unclear if better performance with respect to policy conditionality would lead to positive or negative GDP forecast revisions.

I use primary deficit as the variable corresponding to θ from the model since it is the most frequently used metric for policy conditionality set by the IMF. In this case, the conditionality almost always involves reducing the primary deficit to achieve fiscal sustainability. Therefore, in the presence of the information effect about policy performance, the coefficient γ^{Δ} would be positive. An announcement with a positive market surprise Δ (i.e., increasing the sovereign spread as a punishment for unsatisfactory performance) would result in positive forecast revisions (i.e., markets updating forecasts to reflect the unsatisfactory performance). In the absence of information effects, the coefficient γ^{Δ} would be 0, since the market surprises would not contain any news about θ. I present the results in Appendix A.5. I find no evidence for the presence of the information effect about policy performance.

B.6 External Instruments Methodology

In this section, I explain the external instruments approach to derive the structural impact vector for the case with one instrument and one shock.

Recall the reduced-form VAR from Section 2:

$$\mathbf{y}_t = \boldsymbol{\alpha} + \mathbf{B}_1\mathbf{y}_{t-1} + \ldots + \mathbf{B}_p\mathbf{y}_{t-p} + \mathbf{u}_t, \tag{38}$$

where $\mathbf{y}_t$ is an $n \times 1$ vector of endogenous variables, $\boldsymbol{\alpha}$ is an $n \times 1$ vector of constants, and $\mathbf{B}_1, \ldots, \mathbf{B}_p$ are $n \times n$ coefficient matrices (with p denoting the lag length), and $\mathbf{u}_t$ is the $n \times 1$ vector of reduced-form innovations with covariance matrix $\boldsymbol{\Sigma}$.

I make the following assumptions regarding the relationship between the reduced-form innovations, structural shocks, and the instrument:

$$\mathbf{u}_t = \mathbf{S}\boldsymbol{\varepsilon}_t, \tag{39}$$

$$\mathbb{E}[z_t\varepsilon_{1,t}] = \alpha \neq 0, \tag{40}$$

$$\mathbb{E}[z_t\boldsymbol{\varepsilon}_{2:n,t}] = \mathbf{0}, \tag{41}$$

corresponding to the invertibility assumption, relevance assumption, and exogeneity assumption, as discussed in the paper. Under these assumptions, $\mathbf{s}_1$ is identified up to sign and scale:

$$\begin{aligned}
\mathbb{E}[z_t\mathbf{u}_t] &= \mathbb{E}[z_t\mathbf{S}\boldsymbol{\varepsilon}_t] \\
&= \mathbf{S}\mathbb{E}[z_t\boldsymbol{\varepsilon}_t] \\
&= \begin{pmatrix} \mathbf{s}_1 & \mathbf{S}_{2:n} \end{pmatrix} \begin{pmatrix} \mathbb{E}[z_t\varepsilon_{1,t}] \\ \mathbb{E}[z_t\boldsymbol{\varepsilon}_{2:n,t}] \end{pmatrix} \\
&= \begin{pmatrix} \mathbf{s}_1 & \mathbf{S}_{2:n} \end{pmatrix} \begin{pmatrix} \alpha \\ \mathbf{0} \end{pmatrix} \\
&= \mathbf{s}_1\alpha
\end{aligned} \tag{42}$$

The above relationship can be partitioned into the following:

$$\mathbb{E}[z_t \mathbf{u}_t] = \begin{pmatrix} \mathbb{E}[z_t u_{1,t}] \\ \mathbb{E}[z_t \mathbf{u}_{2:n,t}] \end{pmatrix} = \begin{pmatrix} s_{1,1}\alpha \\ \mathbf{s}_{2:n,1}\alpha \end{pmatrix}. \tag{43}$$

Then, the vectors can be rescaled to obtain:

$$\begin{pmatrix} 1 \\ \mathbb{E}[z_t \mathbf{u}_{2:n,t}]/\mathbb{E}[z_t u_{1,t}] \end{pmatrix} = \begin{pmatrix} 1 \\ \mathbf{s}_{2:n,1}/s_{1,1} \end{pmatrix} = \begin{pmatrix} 1 \\ \tilde{\mathbf{s}}_{2:n,1} \end{pmatrix}, \tag{44}$$

where $\tilde{\mathbf{s}}_{2:n,1} \equiv \mathbf{s}_{2:n,1}/s_{1,1}$. Note that this requires $\mathbb{E}[z_t u_{1,t}] \neq 0$, which holds iff $\alpha \neq 0$ and $s_{1,1} \neq 0$.

Once $\mathbf{s_1}$ is identified up to scale, the scale of $\mathbf{s_1}$ can be normalized subject to

$$\boldsymbol{\Sigma} = \mathbf{S}\boldsymbol{\Omega}\mathbf{S}'. \tag{45}$$

In this paper, I set $s_{1,1} = x$ $\boldsymbol{\Omega} = \mathrm{diag}(\sigma^2_{\varepsilon_1}, \ldots, \sigma^2_{\varepsilon_n})$, resulting in the following structural impact vector:

$$\mathbf{s}_1 = \begin{pmatrix} x \\ \tilde{\mathbf{s}}_{2:n,1} x \end{pmatrix}. \tag{46}$$

This scales the structural impact vector $\mathbf{s}_1$ such that a unit positive value of $\varepsilon_{1,t}$ has a positive effect of magnitude x on $y_{1,t}$.

To obtain the sample analogue of $\mathbf{s}_1$, denoted as $\hat{\mathbf{s}}_1$, one can run the following regression

$$\mathbf{y}_t = \tilde{\boldsymbol{\alpha}} + \tilde{\mathbf{B}}(\mathbf{L})\mathbf{y}_{t-1} + \mathbf{s}_1 y_{1,t} + \tilde{\mathbf{u}}_t, \tag{47}$$

via equation-by-equation two-stage least squares using z_t as the instrument for $y_{1,t}$. The lag polynomial $\tilde{\mathbf{B}}(\mathbf{L})$ has the same number of lags as the reduced-form VAR. The point estimates of this regression are equivalent to running the regression:

$$\hat{\mathbf{u}}_t = \boldsymbol{\gamma} + \mathbf{s}_1 \hat{u}_{1,t} + \boldsymbol{\eta}_t, \tag{48}$$

using z_t as the instrument for $\hat{u}_{1,t}$. However, the specification from Equation 47 yields the correct large-sample, strong-instrument standard errors (Stock and Watson, 2018). Using the estimated structural impact vector, one can impose the desired normalization to obtain a normalized estimate of the structural impact vector $\hat{\mathbf{s}}_1$.

Using the structural impact vector $\hat{\mathbf{s}}_1$ and the coefficient matrices $\hat{\mathbf{B}}_1, \ldots, \hat{\mathbf{B}}_p$ from the reduced-form VAR estimates, one can estimate impulse response functions, the structural shock series, and other estimates of interest.

C Results

C.1 High-Frequency Responses: Event Study Approach

Table C.1 provides the estimates for the same set of regressions as the estimates in Table 2, except with either a restricted sample or a different explanatory variable. The first row shows the estimates with the sample restricted to the announcements used for the baseline analysis. The discrepancy between the two samples is due to the fact that multiple announcements occurred during periods of default for which the Argentine EMBI spread exists, while the CDS spreads do not. The second row provides the estimates for the high-frequency responses using the event study approach with the five-year cumulative risk-neutral probability of default as the explanatory variable.

	Equity Index	Equity Index (USD, Blue Dollar)	Equity Index (USD, Blue Chip)	Equity Index (USD, Official)	Commodity Index	Blue Dollar Exch. Rate	Blue Chip Swap Exch. Rate	Official Exch. Rate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ARG EMBI Spread	-0.828	-1.905^{**}	-1.731^{**}	-1.624^{*}	0.314^{*}	1.077^{*}	0.902^{*}	0.796^{*}
	(0.565)	(0.953)	(0.836)	(0.828)	(0.164)	(0.562)	(0.528)	(0.469)
Observations	67	67	67	67	67	67	67	67
	Equity Index	Equity Index (USD, Blue Dollar)	Equity Index (USD, Blue Chip)	Equity Index (USD, Official)	Commodity Index	Blue Dollar Exch. Rate	Blue Chip Swap Exch. Rate	Official Exch. Rate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
5Y Default Prob.	-0.491	-1.744^{***}	-0.889^{***}	-1.812^{***}	-0.148^{*}	1.253^{**}	0.398	1.320^{**}
	(0.376)	(0.307)	(0.284)	(0.333)	(0.084)	(0.515)	(0.300)	(0.580)
Observations	67	67	67	67	67	67	67	67

Table C.1: High-Frequency Responses

Notes: This table reports the results for the OLS estimation corresponding to Equation 10. All outcome variables are changes in logs multiplied by 100, and the Argentine EMBI spread is in percents. This set of regressions is restricted to the sample of announcements that occur outside of credit event periods. All regressions use heteroskedasticity-robust standard errors. *p<0.1; **p<0.05; ***p<0.01.

C.2 High-Frequency Responses: Heteroskedasticity-Based Identification

Table C.2 provides the estimates using the heteroskedasticity-based identification strategy from Rigobon and Sack (2004). The first row corresponds to the comparison of the estimates with results from Hébert and Schreger (2017) in Figure 4. The second row provides the estimates using the Argentine EMBI spread as the explanatory variable, and the third row provides the estimates that exclude observations during periods of default.

	Equity Index	Equity Index (USD, Blue Dollar)	Equity Index (USD, Blue Chip)	Equity Index (USD, Official)	Commodity Index	Blue Dollar Exch. Rate	Blue Chip Swap Exch. Rate	Official Exch. Rate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
5Y Default Prob.	-0.591^{***}	-0.749^{***}	-0.719^{***}	-0.727^{***}	-0.142^{***}	0.158^{***}	0.128^{***}	0.135^{***}
	(0.072)	(0.109)	(0.112)	(0.114)	(0.019)	(0.046)	(0.047)	(0.053)
Events	67	67	67	67	67	67	67	67
Observations	3,597	3,597	3,597	3,597	3,597	3,597	3,597	3,597

	Equity Index	Equity Index (USD, Blue Dollar)	Equity Index (USD, Blue Chip)	Equity Index (USD, Official)	Commodity Index	Blue Dollar Exch. Rate	Blue Chip Swap Exch. Rate	Official Exch. Rate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ARG EMBI Spread	-2.040^{***}	-2.568^{***}	-2.528^{***}	-2.400^{***}	-0.462^{***}	0.528^{***}	0.488^{***}	0.361^{**}
	(0.293)	(0.405)	(0.434)	(0.404)	(0.062)	(0.152)	(0.176)	(0.158)
							7	
Events	71	71	71	71	71	71	71	71
Observations	4,245	4,245	4,245	4,245	4,245	4,245	4,245	4,245

	Equity Index	Equity Index (USD, Blue Dollar)	Equity Index (USD, Blue Chip)	Equity Index (USD, Official)	Commodity Index	Blue Dollar Exch. Rate	Blue Chip Swap Exch. Rate	Official Exch. Rate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ARG EMBI Spread	-2.337^{***}	-2.967^{***}	-2.957^{***}	-2.841^{***}	-0.561^{***}	0.631^{***}	0.621^{***}	0.504^{***}
	(0.246)	(0.361)	(0.372)	(0.374)	(0.060)	(0.169)	(0.181)	(0.178)
Events	67	67	67	67	67	67	67	67
Observations	3,597	3,597	3,597	3,597	3,597	3,597	3,597	3,597

Table C.2: High-Frequency Responses using Heteroskedasticity-Based Identification

Notes: This table reports the results for the high-frequency response estimates using the heteroskedasticity-based identification strategy. All outcome variables are changes in logs multiplied by 100, and the five-year cumulative risk-neutral probability of default is in percents. All regressions use heteroskedasticity-robust standard errors. *p<0.1; **p<0.05; ***p<0.01.

C.3 Heteroskedasticity-robust F-statistics

Table C.3 reports the heteroskedasticity-robust F-statistics to assess the relevance of the instrument. The baseline results reported in the main text of the paper corresponds to the baseline specification with the full sample. The 8-variable VAR specification corresponds to the specification in Appendix C.4, which includes Argentine commodity prices and the Argentine central bank's international reserves as two additional variables in the VAR. The specification with the Blue Dollar exchange rate corresponds to the specification in Figure C.2a of Appendix C.5, which uses an alternative exchange rate measure called the Blue Dollar exchange rate instead of the Blue Chip Swap rate. The specification with 9 and 12 lags correspond to the specifications in Figures C.2b and C.2c of Appendix C.5, which extend the lag lengths in a specification that is otherwise identical to the baseline specification.

Equation 6: $y_{1,t}$ on z_t^ℓ and lags of $\mathbf{y}_t$	
Specification	Robust F-statistic
Baseline	28.4
8-Variable VAR	34.5
Blue Dollar exchange rate	26.6
9 lags	21.5
12 lags	26.5
Equation 7: $\hat{u}_{1,t}$ on z_t^ℓ	
Specification	Robust F-statistic
Baseline	21.4
8-Variable VAR	22.9
Blue Dollar exchange rate	20.1
9 lags	18.6
12 lags	27.6

Table C.3: F-statistics

Notes: This table reports the outcomes of the first-stage heteroskedasticity-robust F-statistics for the null hypothesis that the instrument has no explanatory power. Equation 6 corresponds to the first-stage regression that regresses the EMBI spread $y_{1,t}$ on the instrument z_t^ℓ and the lags of all of the outcome variables in the VAR. Equation 7 corresponds to the first-stage regression that regresses the EMBI spread residual $\hat{u}_{1,t}$ on the instrument z_t^ℓ. Under identical samples, the two methodologies result in identical point estimates for the structural impact vector $\mathbf{s_1}$, but yield different first-stage standard errors.

C.4 Alternative Specification

I examine whether the main results are robust to alternative VAR specifications. I estimate the impulse responses using the external instruments approach with an alternative VAR specification that includes two additional variables: the Argentine commodity price index (IPMP) and the Argentine central bank's international reserves (in USD). Figure C.1 shows the estimated impulse responses.

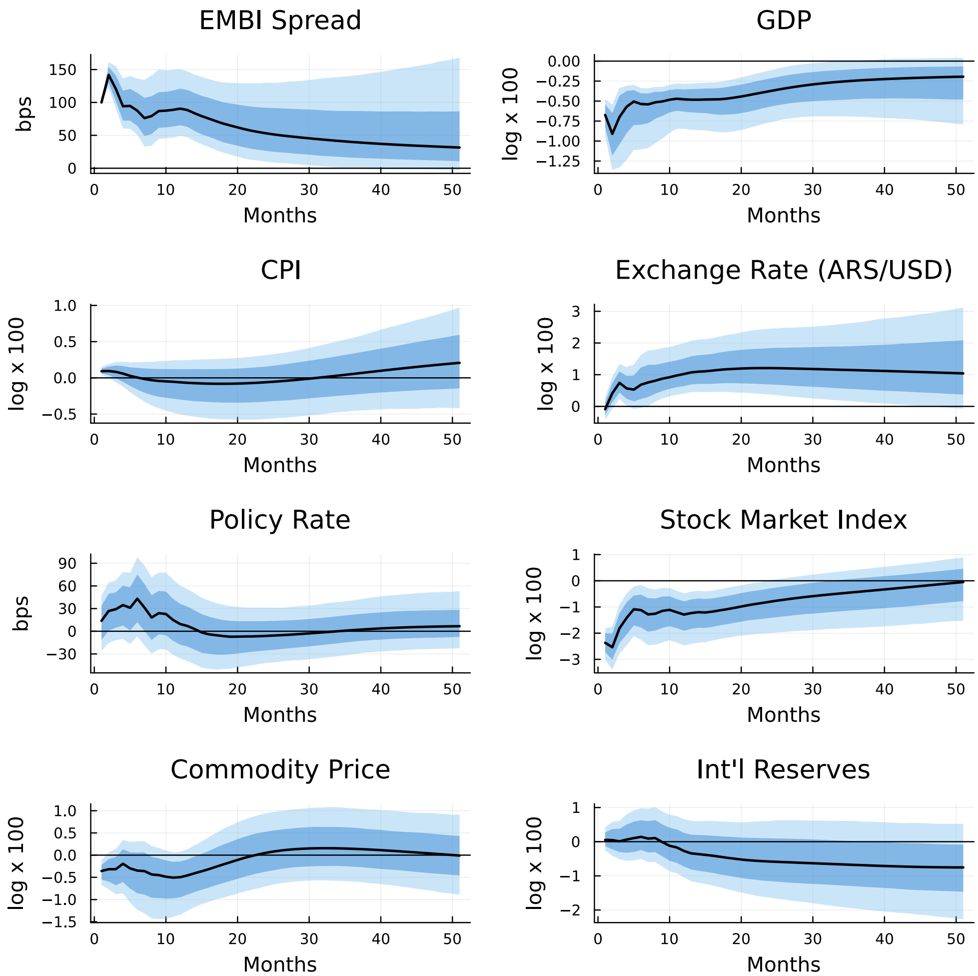


Figure C.1: Impulse Responses using an Alternative Set of Variables

Notes: This figure shows the impulse responses to a sovereign liquidity shock estimated using the external instruments approach. The shock is scaled such that it corresponds to a 100-basis-point increase in the Argentine EMBI spread on impact. The solid lines represent the point estimates; the dark and light shaded areas correspond to the 68 and 90 percent confidence intervals respectively.

C.5 VAR Robustness Checks

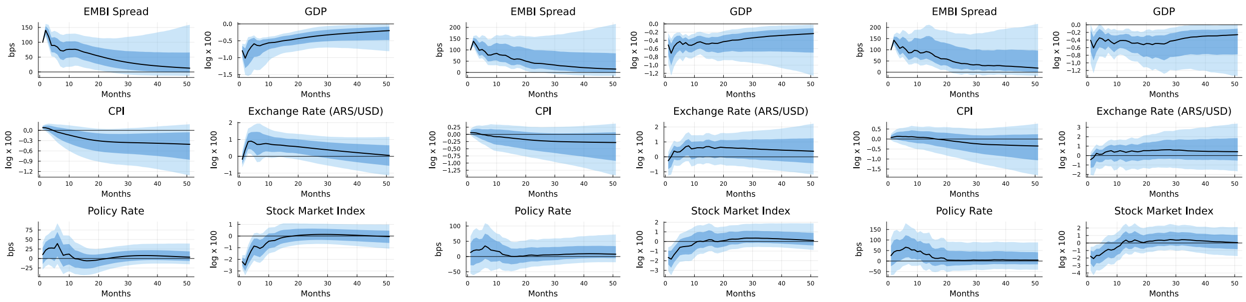
This section presents a series of robustness checks to examine whether the main results still hold. In Figure C.2a, I estimate impulse responses using an alternative exchange rate measure called the Blue Dollar rate as a substitute for the Blue Chip Swap rate. In Figures C.2b and C.2c, I estimate the impulse responses using 9 and 12 monthly lags respectively.

I examine whether the main results are robust to a series of sample restrictions. Recall that in the baseline analysis, the sample used to estimate the reduced-form VAR differs from the sample used to estimate the structural impact vector. This is due to data limitations, as the data on CDS spreads are only available from July 2005 onwards. In Figure C.2d, I estimate the impulse responses using the sample from July 2005 onwards for both the reduced-form VAR and the structural impact vector. Given that the sample period in the baseline analysis includes the COVID pandemic, I examine whether the main results are also robust to a sample restriction limited to periods before 2020. In Figure C.2e, I estimate the impulse responses using the sample up to December 2019.

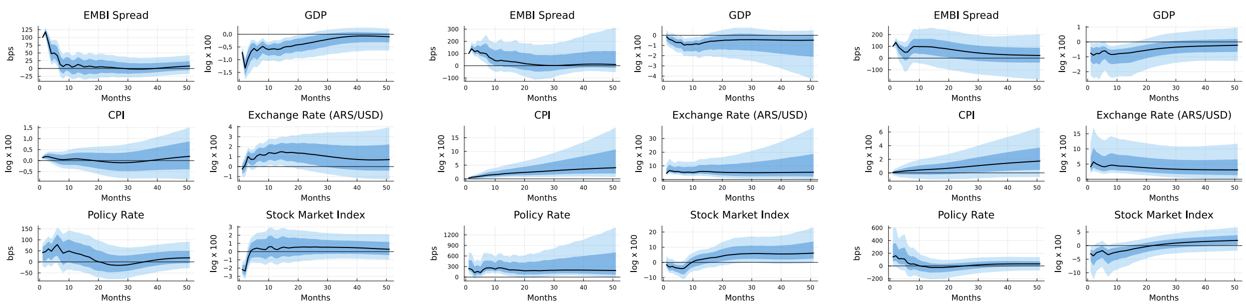
To address any concerns that particular subsets of the surprises may influence the results, I exclude a number of surprises from the analysis. In Figure C.2f, I estimate impulse responses using a surprise series that sets all values during 2020 to zero. In C.2l, I estimate impulse responses using a surprise series that replaces the largest value of the series in May 2018 with zero. As shown in Figure 2, May 2018 exhibits the largest surprise in the monthly series.

I also examine whether the baseline results are robust to alternative methods of decomposing the surprise series. Figure C.2i shows the estimated impulse responses using the factor analysis decomposition explained in Appendix B.3. Figure C.2j shows the estimated impulse response using the narrative zero restriction method outlined in Appendix B.4.

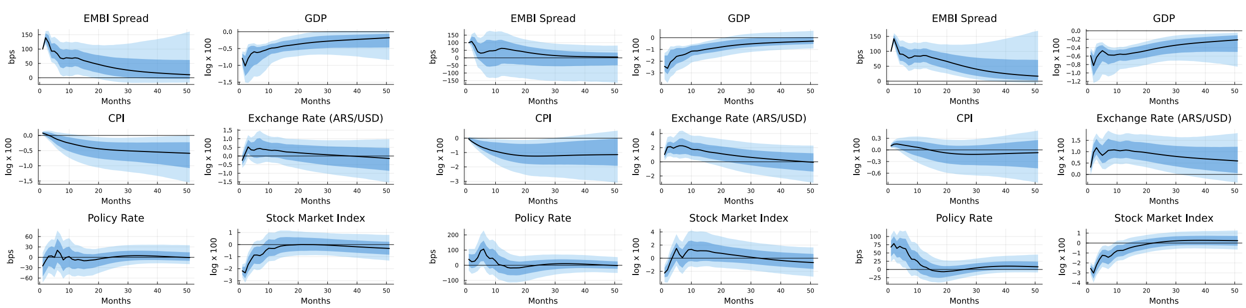
Finally, I examine whether the results are robust to alternative methods of aggregating the surprise series to the monthly level. Figure C.2g shows the estimated impulse responses using a surprise series that is aggregated by taking the sum of surprises without any day-of-month correction. Figure C.2h shows the estimated impulse responses using a surprise series that is aggregated following the methodology from Gertler and Karadi (2015). This method features a day-of-month correction that carries over across multiple calendar months. As mentioned in Footnote 11 of Gertler and Karadi (2015), this involves two steps. First, for each day of the calendar month, I cumulate the surprises on any announcement days during the last 31 days. Second, I average these monthly surprises across each day of the calendar month. One concern of this approach is that it can induce autocorrelation of the monthly series, as discussed in Ramey (2016). In fact, without any correction, I find that this methodology results in a monthly surprise series that exhibits serial correlation. To address this autocorrelation, I use the residual from an AR(1) model of the monthly surprise series.



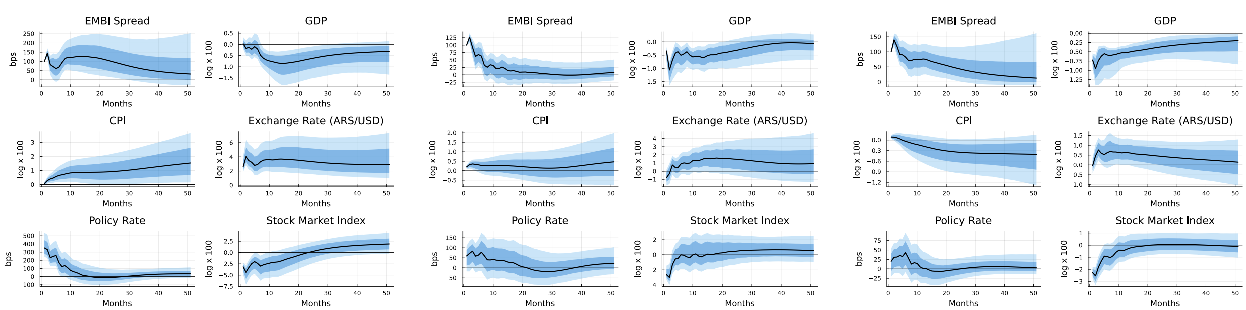
(a) Blue Dollar Rate (b) 9 Lags (c) 12 Lags



(d) Overlapping Sample (e) Pre-COVID (f) Excluding 2020 Surprises



(g) Simple Sum Aggregation (h) Aggr. from GK (2015) (i) Factor Analysis



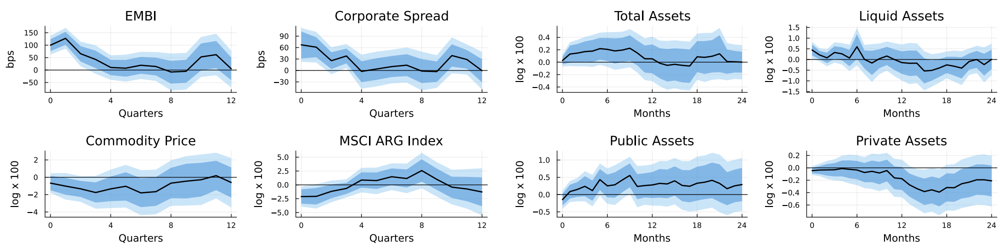
(j) Narrative Zero Restriction (k) RS (2004) Identification (l) Excl. May 2018 Surprise

Figure C.2: Impulse Responses - Robustness Checks

Notes: This figure shows the impulse responses to a sovereign liquidity shock estimated using the external instruments approach. The shock is scaled such that it corresponds to a 100-basis-point increase in the Argentine EMBI spread on impact. The solid lines represent the point estimates; the dark and light shaded areas correspond to the 68 and 90 percent confidence intervals respectively.

C.6 Financial and Trade Channels

Figure C.3a shows impulse responses estimated using local projections for additional financial variables. The corporate spread is option-adjusted spread from the ICE BofA Emering Markets Corporate Plus Argentina Issuers (EARH) index. The EARH index is constructed using USD-denominated bonds issued by Argentine non-sovereign entities. The commodity price is the Argentine commodity price index (IPMP) constructed by the Central Bank of Argentina. The MSCI Argentina Index is a USD-denominated index of American Depositary Receipts (ADRs) for 18 of the largest publicly listed companies in Argentina. Figure C.3b shows impulse responses estimated using local projections for variables from the consolidated bank balance sheets of all domestic banks in Argentina, focusing on types of assets. Figure C.4 shows the impulse response estimates for types of exports using quarterly data from INDEC.



(a) Financial Market Responses (b) Bank Asset Responses

Figure C.3: Financial Responses

Notes: This figure shows the impulse responses to a sovereign liquidity shock estimated using local projections. The shock is scaled such that it corresponds to a 100-basis-point increase in the Argentine EMBI spread on impact. The solid lines represent the point estimates; the dark and light shaded areas correspond to the 68 and 90 percent confidence intervals respectively.

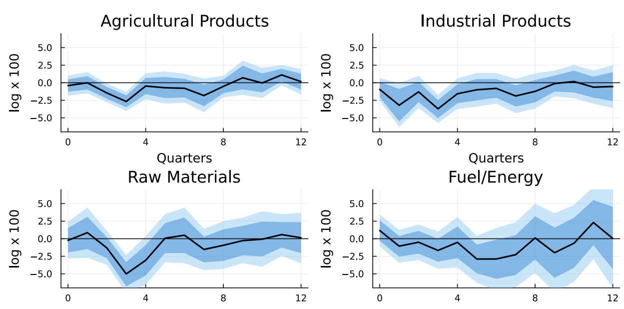


Figure C.4: Export Responses

Notes: This figure shows the impulse responses to a sovereign liquidity shock estimated using local projections. The shock is scaled such that it corresponds to a 100-basis-point increase in the Argentine EMBI spread on impact. The solid lines represent the point estimates; the dark and light shaded areas correspond to the 68 and 90 percent confidence intervals respectively.

C.7 Sectoral Responses

I examine how the sovereign liquidity shocks propagate to various sectors. I use quarterly data on a sectoral breakdown of GDP, also known as value added by industry, from INDEC. Figure C.5 shows impulse responses estimated using local projections.

Figure C.5: Sectoral Responses

Notes: This figure shows the impulse responses to a sovereign liquidity shock estimated using local projections. The shock is scaled such that it corresponds to a 100-basis-point increase in the Argentine EMBI spread on impact. The solid lines represent the point estimates; the dark and light shaded areas correspond to the 68 and 90 percent confidence intervals respectively.

Note that the gross value added of the financial services sector does not decrease as much as other sectors. This may be due to the fact that the current methodology of measuring financial sector output can overstate the operating surplus of financial institutions, especially when assets suddenly depreciate in value. This measurement issue is not specific to Argentina, as it arises from international statistical conventions used for national accounts. Haldane et al. (2010) and Everett et al. (2013) discuss the issue in the context of the United Kingdom and Ireland respectively, where the gross value added of the financial sector peaked in the fourth quarter of 2008 for both countries during the Great Recession.