

GEOECONOMIC PRESSURE, SOVEREIGN RISK, AND ASSET PRICES: EVIDENCE FROM MEXICO

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Job Market Paper

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INTRODUCTION

- ▶ Over the past decade, large economies increasingly exert **geoeconomic pressure** on smaller ones: tariffs, sanctions, and threats
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- ▶ How this form of pressure affects the **sovereign risk profile** of the targeted economies is largely **unstudied**
- ▶ **Threats** to restrict trade, investment, or migration can increase the **likelihood of bad outcomes**, repricing the **default risk** of the targeted economy

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► Once **exogenous variation** is extracted, the effect on **asset prices** and **welfare** can be studied

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- ✓ I build a sovereign default model with risk-averse lenders in which pressure tilts the income process, to price the shock and measure its welfare cost, alongside a complementary data-driven approach

PREVIEW OF FINDINGS

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- ③ A 1 bp increase in the premium depreciates the peso by 0.26% and lowers equity returns by 0.11% on impact
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 - ✓ Most exposed sectors: financial services (-0.17%), industrial (-0.15%), and non-basic goods and services (-0.12%)
- ④ Real cost of the episode:
 - ✓ Welfare: 0.02% of consumption (transitory), 0.06% if permanent
 - ✓ Consumption loss on impact: 0.20% (model), 0.35% (data-driven)

LITERATURE REVIEW AND CONTRIBUTION

- ① Geoeconomics and the politics of sovereign default Clayton et al. (2023), Clayton et al. (2025), Mohr and Trebesch (2025), Cuadra and Saprizza (2008)

Contribution: foreign geoeconomic pressure, not only domestic politics, moves sovereign default risk

- ② Sovereign default and its costs Hébert and Schreger (2017), Sagawa (2026), Arellano (2008), Aguiar and Gopinath (2006)

Contribution: I estimate the consumption response to foreign pressure and connect the reduced form to a structural default model

- ③ Trump's economic strategy Filippou et al. (2025), Caldara et al. (2020), Amiti et al. (2021), Bown (2017)

Contribution: most study the source economy (the U.S.); I study the targeted economy

- ④ Trump and Mexico Beard et al. (2017), Mao (2019), Matveev and Ruge-Murcia (2024)

Contribution: different identification and a longer sample; larger, persistent effects through default risk

- ⑤ Applied synthetic control Abadie et al. (2010), Abadie et al. (2015), Born et al. (2019), Goldsmith-Pinkham and Lyu (2025)

Contribution: apply synthetic control to high-frequency financial data (daily CDS)

EXTRACTING EXOGENOUS VARIATION IN SOVEREIGN RISK

SYNTHETIC CONTROL METHOD

- ▶ Following [Abadie and Gardeazabal \(2003\)](#), I estimate a [synthetic counterfactual](#) for the 5-year Mexican Credit Default Swap (CDS)

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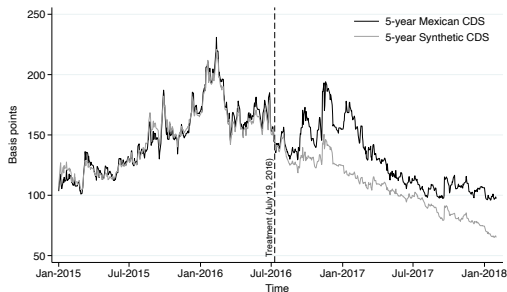
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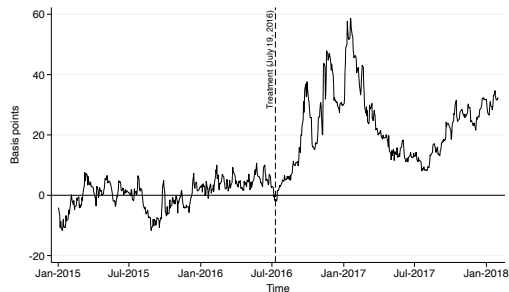
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 - ⇒ Difference between outcome and synthetic represents the [dynamic treatment effect](#)
- ▶ To construct the synthetic control, I use:
 - ✓ A [donor pool](#) of 18 economies with comparable macroeconomic [fundamentals](#)
 - ✓ A set of [predictors](#) of the outcome variable that include: exchange rates, GDP per capita, consumption per capita, capital stock per capita, and lagged observations of the CDS

SYNTHETIC CONTROL METHOD: EXTRACTING EXOGENOUS VARIATION

FIGURE. Observed CDS, synthetic control and treatment effect



(A) Observed and synthetic CDS

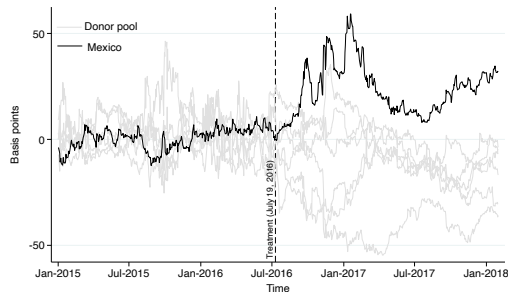


(B) Premium

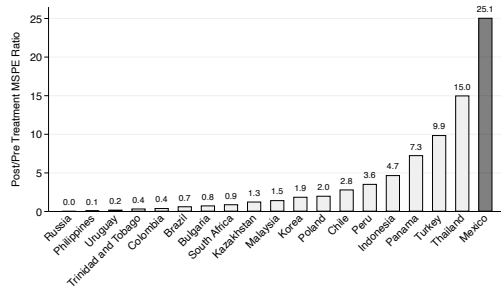
Note: For the estimation, I use daily data on sovereign 5-year CDS for Mexico and 18 other emerging market economies with comparable sovereign credit ratings. The estimated weights are: Panama ($w_2^* = 0.3771$), Colombia ($w_3^* = 0.3279$), and Poland ($w_4^* = 0.2950$), respectively.

PLACEBO RUNS: ECONOMIC AND STATISTICALLY SIGNIFICANT EFFECT

FIGURE. Placebo runs and treatment distribution



(A) Placebo runs



(B) Post-Pre MSPE ratio

Note: On the left, Figure 2a displays in gray the estimated premiums for the other countries in the donor pool while the superimposed black line is the premium for Mexico. To construct the gray lines, I move Mexico to the donor pool and estimate the synthetic control for all the countries. Following the literature, I only display those countries with a Mean Squared Prediction Error (MSPE) of, at most, κ times the MSPE of Mexico in the pre-treatment sample. I set $\kappa = 5$; however, the results are robust to different cutoff values. On the right, Figure 2b displays the post-pre-treatment MSPE ratio for all countries in the donor pool and Mexico.

BACKDATING: NO SIGN OF ANTICIPATION OR EXTRAPOLATION

FIGURE. Backdating



(A) 1 month



(B) 2 months



(C) 3 months



(D) 4 months



(E) 5 months

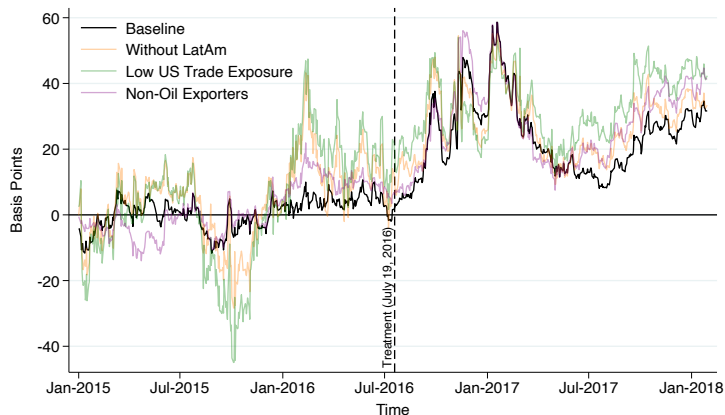


(F) 6 months

Note: I reassigned the treatment up to six months before the nomination of Donald Trump as the official candidate of the Republican Party. I get the same set of countries to build the synthetic 5-year CDS with almost identical weights.

SPILLOVERS: BASELINE GAP IS A LOWER-BOUND

FIGURE. Spillovers



Note: This Figure displays the dynamic treatment effect from applying the synthetic control method to a donor pool that excludes LatAm countries (i.e., orange), countries with above-average trade exposure to the US (i.e., green), and oil exporters (i.e., purple), respectively. The estimated weights for each restriction on the donor pool are: (Poland - $w_2^* = 0.3181$, Kazakhstan - $w_3^* = 0.0023$, South Africa - $w_4^* = 0.1196$, and Malaysia - $w_5^* = 0.5600$), (Malaysia - $w_2^* = 0.7655$ and Philippines - $w_3^* = 0.2345$), and (Panama - $w_2^* = 0.8731$ and Poland - $w_3^* = 0.1269$).

SYNTHETIC CONTROL METHOD: VALIDATION AND ROBUSTNESS

- ▶ To address concerns about **validity, inference, and significance**, I conduct several robustness checks
 - ✓ **Construction prediction intervals**
 - ✓ **Trimming donor pool**
 - ✓ **Leave-one-out estimators**
 - ✓ **Estimation with smoothed outcomes**
 - ✓ **Assessing the role of persistence**
 - ✓ **Estimation with residualized outcome variables**
- ▶ **Takeaway:** the shock is **unanticipated**, the estimated premium is **economically and statistically significant**, and likely constitutes a **lower bound on the true treatment effect**

DOES THE PREMIUM RESPOND TO OBSERVABLE PRESSURE?

RESPONSE TO TRUMP PRESSURES VIA SOCIAL MEDIA

- ▶ If the premium reflects pressure on Mexico, it should respond to observable realizations of that pressure (e.g., direct threats on a given platform)
- ✓ I test two properties: **sensitivity** (the premium responds to Trump's threats) and **targeting** (it moves only with pressure aimed at Mexico)

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- ▶ Using [Factba.se \(2023\)](#), I construct a dataset with detailed information (i.e., content, timestamp, and author) regarding Trump Tweets
 - ✓ Using **post-treatment** sample and a filter that contains the words: "Mexico", "Wall", "NAFTA", among others, identified **38** Tweets, **26** attributed to Trump and **12** to staff members

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- ▶ Only use Tweets attributed to Trump and, based on the timestamp and the trading hours of NYSE, I assign the Tweet to a given day
 - ✓ E.g., if the Tweet was made during the weekend or after 4:00 PM ET, I record it on the next **trading day**

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- ▶ Based on content I **classify the Tweets** as "good" (9%), "bad" (68%), and "neutral" (23%)

TRUMP SOCIAL MEDIA POSTS EXAMPLES

Good Tweet: "I received calls from the President of Mexico and the Prime Minister of Canada asking to renegotiate NAFTA rather than terminate. I agreed"

@realDonaldTrump (04/27/17 7:12 AM)

Bad Tweet: "Toyota Motor said will build a new plant in Baja, Mexico, to build Corolla cars for U.S. NO WAY! Build plant in U.S. or pay big border tax"

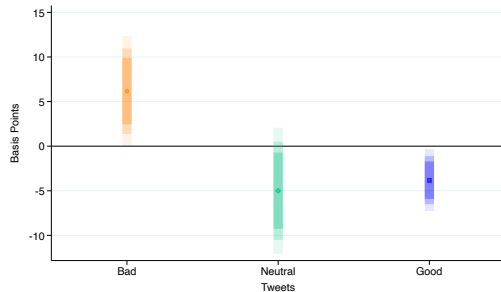
@realDonaldTrump (01/05/17 6:14 PM)

Neutral Tweet: "Former President Vicente Fox, who is railing against my visit to Mexico today, also invited me when he apologized for using the "f-bomb""

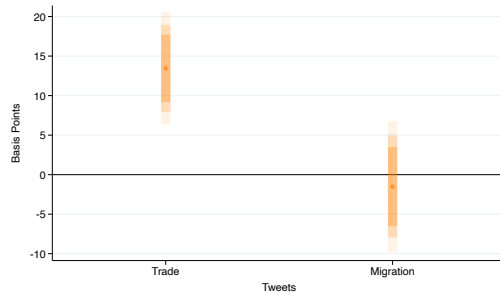
@realDonaldTrump (08/31/16 1:07 PM)

PREMIUM IS SENSITIVE TO SOCIAL MEDIA ACTIVITY

FIGURE. Effect of Trump announcements via Twitter



(A) Average effect

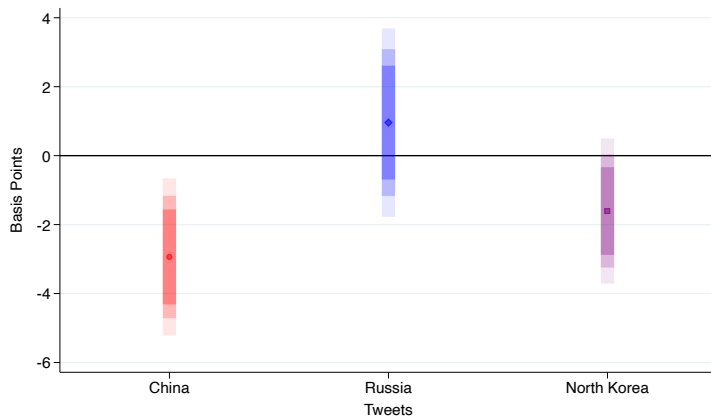


(B) By topic

Note: On the first panel, display estimates of: $\text{Premium}_t = \iota + \delta t + \beta \mathbb{1}_t\{\text{Bad Tweet}\} + \rho \mathbb{1}_t\{\text{Good Tweet}\} + \varrho \mathbb{1}_t\{\text{Neutral Tweet}\} + \gamma' \mathbf{X}_t + \eta_t$. On the second panel, the point estimates correspond to: $\text{Premium}_t = \iota + \delta t + \lambda \mathbb{1}_t\{\text{Trade}\} + \theta \mathbb{1}_t\{\text{Migration}\} + \psi \mathbb{1}\{\text{Other Tweets}\} + \gamma' \mathbf{X}_t + \epsilon_t$. Shaded areas correspond to the 90%, 80%, and 68%, respectively. I use HAC robust standard errors to compute CI.

ONLY THREATS TO MEXICO MOVE THE PREMIUM, EXCEPT CHINA

FIGURE. Estimated effect of tweets directed to other economies



Note: The panel displays the point estimates of: $\text{Premium}_t = \iota + \delta t + \beta_0 \mathbb{1}\{\text{China}_t\} + \beta_1 \mathbb{1}\{\text{N.Korea}_t\} + \beta_2 \mathbb{1}\{\text{Russia}_t\} + \zeta' \mathbf{z}_t + \varepsilon_t$. Shaded areas represent confidence intervals at 90%, 80%, and 68%, respectively. Standard errors are robust to heteroskedasticity and autocorrelation.

TRANSMISSION TO ASSET PRICES

ASSET-PRICE RESPONSES TO CHANGES IN SOVEREIGN RISK

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- ▶ Using **Jordà (2005)** local projections, I estimate impulse-response functions using the following linear specification:

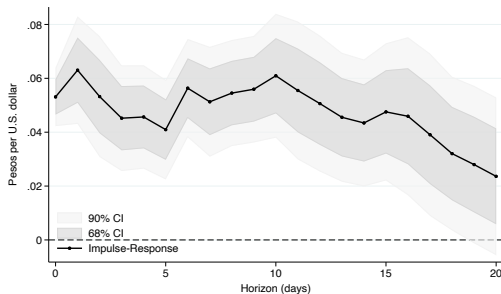
$$y_{t+h} - y_{t-1} = \gamma^h + \beta^h \text{Premium}_t + \mathbf{x}'_t \psi^h + u_{t+h}, \text{ with } h = 0, \dots, 20,$$

where y_{t+h} is the **USD-MXN exchange rate** or the **daily log IPC stock index**, Premium_t is the estimated gap between observed and synthetic control, $\mathbf{x}_t$ contains **controls** such as lagged observations, the VIX index, oil prices, daily changes in Fed funds rate, lagged domestic monetary policy rate, and u_{t+h} is the error term

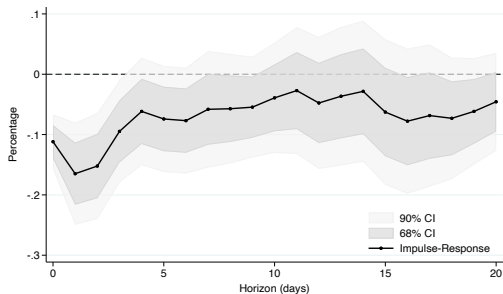
- ▶ I am interested in the sequence of point estimates $\{\hat{\beta}^h\}_{h=0}^{20}$

THE PESO WEAKENS AND EQUITIES DROP AS RISK REPRICES

FIGURE. Cumulative Impulse-Response Functions



(A) Exchange rate



(B) Stock returns

Note: I estimate the following local projection: $y_{t+h} - y_{t-1} = \gamma^h + \beta^h \text{Premium}_t + \mathbf{x}_t' \psi^h + u_{t+h}$, with $h = 0, \dots, 20$, Premium_t is the shock measure, $\mathbf{x}_t$ is a vector of controls, and u_{t+h} represents the error term. The first panel displays the cumulative impulse-response function of the exchange rate to an increase of 1 basis point in the premium while the second panel presents the cumulative impulse-response function of the daily log-return of the Mexican stock index to an increase in 1 basis point in $\hat{\alpha}_t$. The gray-shaded area corresponds to the 90% and 68% confidence intervals, respectively, computed using HAC robust standard errors.

ASSET PRICES RESPONSES TO CHANGES IN SOVEREIGN RISK: ROBUSTNESS

- ▶ I conduct different robustness exercises
 - ✓ **Forecastability of Premium_t and pre-trends**
 - ✓ **High-frequency identification**
 - ✓ **Subsamples and additional controls**
 - ✓ **Peso vis-à-vis other currencies**
 - ✓ **Role of estimation uncertainty and block wild bootstrap**
 - ✓ **Heterogeneity: Equity responses by sectors**
 - ✓ **Panel LP**
- ▶ **Takeaway:** Premium_t is **not predicted** by past movements in asset prices and **alternative** identification methods yield *almost* identical results

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 - ✓ **Forward-iteration** of the intertemporal efficiency condition + SCM premium
 - ✓ **Consumption loss** from comparing **implied** observed and counterfactual **consumption**

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 - ✓ **Forward-iteration** of the intertemporal efficiency condition + **SCM premium**
 - ✓ **Consumption loss** from comparing **implied** observed and counterfactual **consumption**
- ▶ The model delivers the **welfare cost** whereas the data-driven approach recovers the consumption response implied by **high-frequency financial data**

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 - ✓ Under **default**, there is a non-linear **output cost** $\phi(y_t)$ + **market exclusion** (re-entry with prob. θ)
- **Foreign lenders:** competitive **risk-neutral** lenders that price bond following **zero profit condition**

$$q(b_{t+1}, y_t) = \frac{1 - \pi(b_{t+1}, y_t)}{1 + r_f} \iff \text{Spread}_t = \frac{\pi(b_{t+1}, y_t)(1 + r_f)}{1 - \pi(b_{t+1}, y_t)}$$

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► I model geoeconomic pressure as an **unexpected** and **transitory regime switch** in the persistent income process y_t

- ✓ **Fatter left-tail** of persistent process for the next 7 quarters $\tilde{y}_t$
- ✓ $\tilde{y}_t$ is finite-state Markovian chain with **transition** $\Pi^{(1)}(y_{t+1}|y_t; \omega, \zeta)$
- ✓ Transition matrix is constructed in the following way:

$$\Pi^{(1)}(y_{t+1}|y_t; \omega, \zeta) = (1 - \omega)\Pi^{(0)}(y_{t+1}|y_t) + \omega \Pi^{\text{target}}(\zeta)$$

$$\text{with } \Pi^{\text{target}}(\zeta) = \frac{\zeta^{j-1}}{\sum_{k=1}^J \zeta^{k-1}} \mathbb{1}\{y_{t+1} \in \mathcal{L}\},$$

where ω governs **how much** mass to allocate in left-tail and $\zeta \in (0, \infty)$ **shape** of that tail

► Visuals

RECURSIVE FORMULATION

► **Value of repayment** (state $\mathbf{s} = (b, y, m)$):

$$V^R(\mathbf{s}) = \max_{b' \leq 0} \left\{ \frac{c^{1-\gamma}}{1-\gamma} + \beta \mathbb{E}_{y', m'|y} V(\mathbf{s}') \right\}, \quad c = y + m + \kappa(\delta) b - [b' - (1-\delta)b] q(b', y)$$

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$$X(y, m) = \frac{[y - \phi(y) + m]^{1-\gamma}}{1-\gamma} + \beta \mathbb{E}_{y', m' | y} [\theta V(0, y', m') + (1-\theta) X(y', m')]$$

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- **Risk-averse bond pricing** with SDF $\mathcal{M}_{t+1}$:

$$q_t = \mathbb{E}_t[\mathcal{M}_{t+1}(1 - d_{t+1})(\kappa(\delta) + (1-\delta) q_{t+1})], \quad \mathcal{M}_{t+1} = \exp\left\{-r - \chi(\varepsilon_{t+1}^y + \frac{1}{2}\chi\sigma^2)\right\}$$

CALIBRATION

Parameter	Description	Value	Target/Source	Method
<i>Fixed externally</i>				
γ	Risk aversion	2	Standard	Literature
r	Risk-free rate (qtrly.)	0.010	Johri et al. (2022)	Literature
ρ	AR(1) persistence	0.922	Mexican GDP	Estimated
σ	Innovation std. dev.	0.0144	Mexican GDP	Estimated
δ	Coupon decay	0.0742	$D \approx 12q$ duration	Literature
θ	Re-entry probability	0.0833	3-yr exclusion	Literature
χ	Price of income risk	8.75	Johri et al. (2022)	Literature
<i>Calibrated — Stage 1</i>				
β	Discount factor	0.968	Mean debt/GDP = 12.1%	SMM
d_0	Output cost (intercept)	-0.253	Mean spread = 2.23%	SMM
d_1	Output cost (curvature)	0.309	Std(spread) = 55 bp	SMM
σ_m	Transitory shock scale	0.0089	Default prob = 1.67%	SMM
<i>Calibrated — Stage 2</i>				
ω	Tilt intensity	0.0003	$\Delta s = 24$ bp	SMM
ζ	Within-tercile shape	0.513	Δ skew. = -0.036	SMM

Note: ρ and σ estimated from the cyclical component of log Mexican real GDP, 1993Q1–2016Q4. Duration $D = (1+r)/(\delta+r) \approx 12$ qtr. $\theta = 1/12$: average exclusion spell for Mexico [Gelos et al. \(2011\)](#). Stage-1 parameters ($\beta, d_0, d_1, \sigma_m$) calibrated by SMM; Stage-2 (ω, ζ) to the 24 bp SCM premium and the change in GDP skewness.

Moment	Data	Model
<i>Targeted moments</i>		
Mean external debt/GDP	12.13%	13.2%
Mean spread (ann.)	2.23%	2.04%
Std(spread, ann.)	55 bp	84 bp
Default prob. (ann.)	1.67%	1.16%
Spread increase	24 bp	23 bp
Skewness change	-0.036	-0.036
<i>Untargeted moments</i>		
Std(C)/Std(Y)	1.06	1.11
Corr(C , Y)	0.91	0.94
Corr(spread, Y)	-0.26	-0.69

Note: Model simulated for 15,000 quarters after a 2,000-quarter burn-in; moments are averages over non-default periods. Mean-spread and std targets (2.23%, 55 bp) are the EMBI Global Mexico average/std over 2013Q1–2016Q2; the default-probability target (1.67%) is the one-year risk-neutral implied probability from CDS; external debt/GDP from *SHCP*.

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 - ✓ Increase in spreads
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- ▶ For perspective
 - ✓ Lucas's estimated cost of business cycles $\in (-0.1\%, -0.05\%)$
 - ✓ Welfare cost of **world-interest rate uncertainty** is **-0.02%** following **Johri et al. (2022)**

▶ Impulse-Response Functions

USING FINANCIAL DATA TO MEASURE CONSUMPTION LOSS

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$$C_t = u'^{-1} \left(\frac{\beta}{q_t(1 + \eta_t)} \mathbb{E}_t [u'(C_{t+1})] \right), \text{ with } \eta_t \equiv \frac{\partial q(b_{t+1}, y_t)}{\partial b_{t+1}} \frac{b_{t+1}}{q(b_{t+1}, y_t)},$$

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- ▶ Under the assumptions of **short-term debt** (i.e., $\delta = 1$) and **log-normal consumption growth**, **log-consumption** is given by:

$$c_t = -\frac{(T+1)}{\gamma} \log(\beta) + \frac{1}{\gamma} \sum_{j=0}^T \mathbb{E}_t [\log(q_{t+j}) + \log(1 + \eta_{t+j})] - \frac{\gamma}{2} \sum_{j=0}^T \mathbb{E}_t [\text{Var}_{t+j}(\Delta c_{t+j+1})] + \mathbb{E}_t [c_{t+T+1}]$$

CONSUMPTION FALLS IN RESPONSE TO GEOECONOMIC PRESSURE

► Let $\tilde{c}_t$ be the counterfactual level of consumption. Under a **transitory** shock, the effect decomposes into two channels:

$$c_t - \tilde{c}_t = \underbrace{\frac{1}{\gamma} \left(\sum_{j=0}^T \mathbb{E}_t [\log q_{t+j} - \log \tilde{q}_{t+j}] \right)}_{(1a) \text{ Level subcomponent}} + \underbrace{\frac{1}{\gamma} \left(\sum_{j=0}^T \mathbb{E}_t [\log(1 + \eta_{t+j}) - \log(1 + \tilde{\eta}_{t+j})] \right)}_{(1b) \text{ Slope subcomponent}}$$

(1) Price component

$$- \underbrace{\frac{\gamma}{2} \left(\sum_{j=0}^T \mathbb{E}_t [\text{Var}_{t+j} (\Delta c_{t+j+1}) - \text{Var}_{t+j} (\Delta \tilde{c}_{t+j+1})] \right)}_{(2) \text{ Uncertainty component}}$$

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(1a) **Level**: observed vs. synthetic CDS (π_{t+j} , $q_{t+j} = (1 - \pi_{t+j}) / (1 + r_f)$)

(1b) **Slope**: at the relevant debt level the price schedule is locally flat ($\partial q / \partial b' \approx 0$)

(2) **Uncertainty**: $\text{Var}(\Delta c_{t+j}) \propto \Psi \text{Var}(r_{t+j})$ estimated with GARCH(1,1)

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▶ Filtering approach

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► **Takeaway:** geoeconomic pressure reprices sovereign risk through **threats alone**, with meaningful effects on asset prices, consumption, and welfare

THANK YOU!

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APPENDIX

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DONOR POOL

Country	Rating		Mean		Std. Dev.		Min		Max	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Brazil	BB	BB-	239.97	227.56	111.40	43.96	102.07	142.63	534.56	320.72
Bulgaria	BB+	BBB-	143.06	117.13	25.38	22.29	91.47	61.65	207.87	156.35
Chile	AA-	A+	90.25	70.26	20.73	13.73	60.29	42.24	153.35	107.45
Colombia	BBB	BBB-	149.66	141.10	58.32	27.90	74.25	89.49	326.44	210.09
Indonesia	BB+	BBB-	188.24	126.28	42.10	26.47	123.97	76.92	285.57	198.85
Kazakhstan	BBB-	BBB-	217.05	155.33	58.26	31.04	127.62	91.4	379.6	230.04
Malaysia	A-	A-	124.37	100.60	38.39	30.12	72.73	50.84	242.36	172.11
Mexico	BBB+	BBB+	118.51	129.55	35.15	25.63	64.17	95.44	231.99	193.01
Panama	BBB	BBB	127.40	106.29	34.41	26.79	73.94	55.58	223.43	157.13
Peru	BBB+	BBB+	131.90	93.19	33.41	16.35	76.76	65.79	230.49	131.31
Philippines	BBB	BBB	103.39	83.71	14.15	19.77	78.51	51.87	154.25	134.81
Poland	BBB+	BBB+	76.16	66.36	11.86	10.95	53.18	48.72	132.29	89.76
Russia	BB+	BBB-	264.56	174.39	104.84	39.67	119.03	106.55	628.39	241.33
South Africa	BBB-	BB	221.65	204.92	53.81	33.82	135.79	140.74	391.65	270.34
South Korea	AA-	AA	63.24	52.83	11.75	9.48	45.49	39.33	108.14	75.49
Thailand	BBB+	BBB+	116.30	65.47	21.41	17.23	80.84	40.36	177.00	104.83
Trinidad and Tobago	A-	BBB+	133.03	116.83	14.36	17.72	105.1	72.89	323.12	300.43
Turkey	BB+	BB	212.24	221.60	47.25	41.13	110.95	154.92	326.92	306.33
Uruguay	BBB	BBB	220.40	164.20	86.14	17.77	117.59	93.4	543.46	199.35

Note: Daily data on sovereign CDS from Markit. The data set covers the period from January 2, 2013, to February 28, 2018. The sample is divided into a pre-treatment period (i.e. January 2, 2013, up to July 18, 2016) and a post-treatment period (i.e. July 19, 2016, up to February 28, 2018.). Ratings correspond to the last one observed in each sub-sample.

TABLE: Descriptive statistics of sovereign 5-year CDS

SYNTHETIC CONTROL METHOD: CHOOSING THE WEIGHTS

- ▶ $\mathbb{Y}_1$ ($T \times 1$) and $\mathbb{X}_1$ ($K \times 1$): Mexico's CDS and predictors; $\mathbb{Y}_0$ ($T \times J$), $\mathbb{X}_0$ ($K \times J$): the donor pool
- ▶ The **weights** $\mathbb{W}$ match Mexico's pre-treatment predictors, given a diagonal $\mathbb{V}$:

$$\min_{\mathbb{W} \in \mathcal{W}} \|\mathbb{X}_1 - \mathbb{X}_0 \mathbb{W}\|_{\mathbb{V}}^2 = (\mathbb{X}_1 - \mathbb{X}_0 \mathbb{W})^T \mathbb{V} (\mathbb{X}_1 - \mathbb{X}_0 \mathbb{W}), \quad \mathcal{W} = \left\{ w_j \geq 0, \sum_j w_j = 1 \right\}$$

- ▶ As in [Abadie and Gardeazabal \(2003\)](#), $\mathbb{V}$ minimizes the **pre-treatment MSPE** of the outcome $\mathbb{Z}$ ($T_0 \times 1$) with $T_0 < T$:

$$\mathbb{V}^* = \arg \min_{\mathbb{V} \in \mathcal{V}} (\mathbb{Z}_1 - \mathbb{Z}_0 \mathbb{W}^*(\mathbb{V}))^T (\mathbb{Z}_1 - \mathbb{Z}_0 \mathbb{W}^*(\mathbb{V}))$$

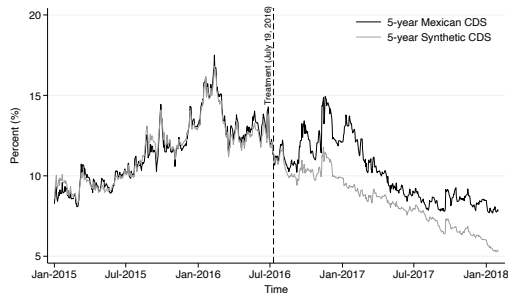
- ▶ **Premium:** the gap between observed and synthetic CDS

$$\text{Premium}_t = Y_{1,t} - \sum_{j=2}^{J+1} w_j^* Y_{j,t}, \quad t \in \{T_0 + 1, \dots, T\}$$

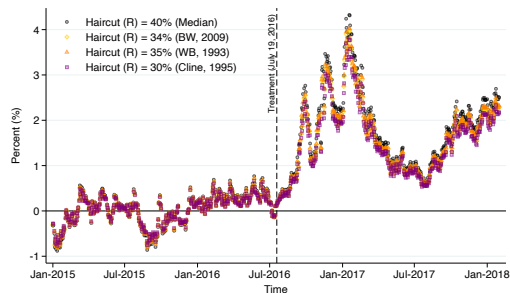
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SYNTHETIC CONTROL METHOD: IMPLIED DEFAULT PROBABILITY

FIGURE. Observed and synthetic risk-neutral default probabilities



(A) Observed and synthetic probabilities



(B) Premium for different R

Note: On the left, Figure 8a displays the implied risk-neutral default probabilities from the observed and synthetic 5-year CDS, respectively. To compute the implied risk-neutral default probabilities, I follow Hébert and Schreger (2017) assuming a constant hazard rate and a haircut of 39.5%. On the right, Figure 8b plots the treatment effect using different values for the haircut reported in Benjamin and Wright (2009) for the default episode of Mexico in 1982.

SYNTHETIC CONTROL METHOD: PRE-TREATMENT ADJUSTMENT

TABLE: CDS predictor means

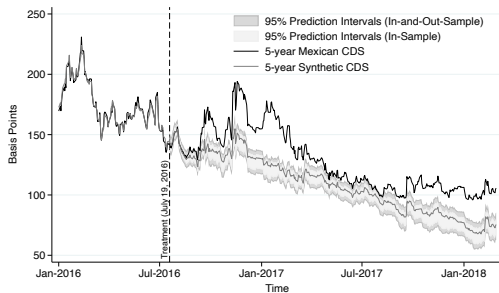
Variables	Observed	Synthetic	Average
Nominal exchange rate depreciation in 2013	-2.91	0.52	2.59
Nominal exchange rate depreciation in 2014	4.35	2.22	7.54
Nominal exchange rate depreciation in 2015	19.31	17.49	17.92
Log GDP per capita	9.80	9.94	9.82
Log consumption per capita	9.59	9.69	9.54
Log capital stock per capita	11.26	10.95	11.01
CDS at the beginning of 2013	97.23	91.28	105.95
CDS at the beginning of 2014	92.32	104.55	145.86
CDS at the beginning of 2015	103.45	107.66	158.87
CDS at the beginning of 2016	169.55	166.88	209.90

Note: The nominal exchange rate depreciation corresponds to the average depreciation observed that year. Log GDP per capita, log consumption per capita, and log capital stock per capita correspond to the average using data from 2013 to 2015.

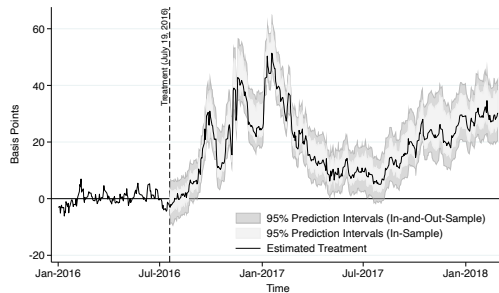
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SYNTHETIC CONTROL METHOD: PREDICTION INTERVALS

FIGURE. Prediction intervals



(A) Observed and synthetic CDS

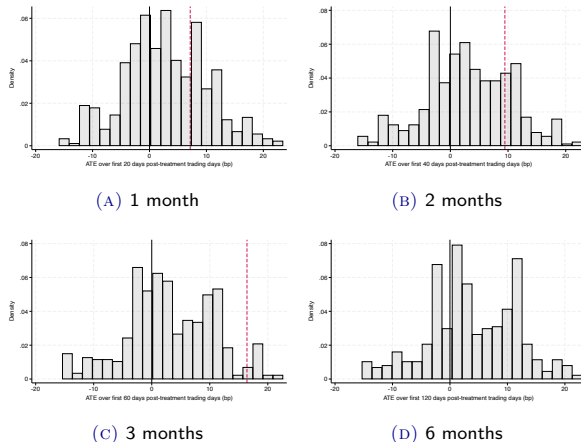


(B) Treatment effect

Note: I follow [Cattaneo et al. \(2021\)](#) and compute prediction intervals to assess statistical significance of the treatment. On the left, Figure 9a displays the daily evolution of the outcome variable and the synthetic control along with the 95% prediction intervals. On the right, Figure 9b presents the treatment effect and the 95% prediction intervals taking into account the in-sample uncertainty and the in-sample and out-of-sample uncertainty. To compute the prediction intervals for computational reasons, I re-estimated the synthetic control using a smaller pre-intervention sample, which spans from January 1, 2016, to July 18, 2016.

SYNTHETIC CONTROL METHOD: ACCOUNTING FOR SERIAL CORRELATION

FIGURE. Size of average $\hat{a}_t$ relative to alternative/random gaps



Note: This displays the histograms associated with the average treatment effects for 20, 40, 60, and 90 days, respectively, from the placebo runs using 500 simulations for each. The red-dashed line corresponds the ATE for the same number of days using the true treatment date.

SYNTHETIC CONTROL METHOD: TRIMMING DONOR POOL

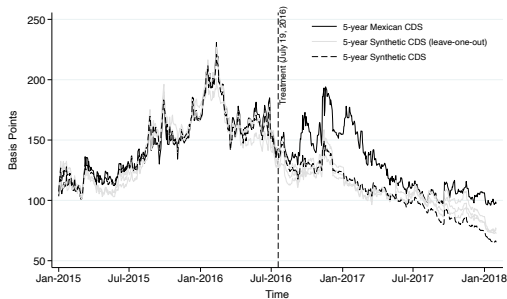
TABLE: CDS predictor means with trimmed donor pool

Variables	Observed	Synthetic	Average
Nominal exchange rate depreciation in 2013	-2.91	0.55	2.75
Nominal exchange rate depreciation in 2014	4.35	2.58	7.53
Nominal exchange rate depreciation in 2015	19.31	19.42	17.09
Log GDP per capita	9.80	9.92	9.68
Log consumption per capita	9.59	9.68	9.44
Log capital stock per capita	11.26	10.93	10.78
CDS at the beginning of 2013	97.23	91.06	108.33
CDS at the beginning of 2014	92.32	104.31	139.21
CDS at the beginning of 2015	103.45	107.92	144.37
CDS at the beginning of 2016	169.55	166.93	202.08

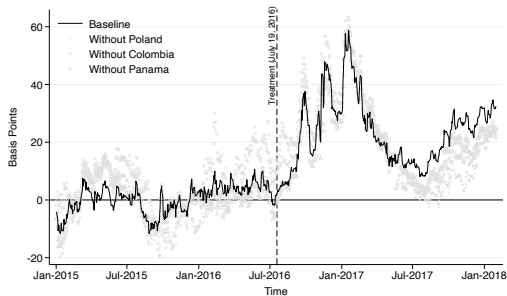
Note: The trimmed donor pool is constructed by keeping countries with a credit rating between BBB-, BBB, and BBB+ during the pre-treatment sample (i.e., Colombia, Kazakhstan, Panama, Peru, Philippines, Poland, South Africa, Thailand, and Uruguay). The nominal exchange rate depreciation corresponds to the average depreciation observed that year. Log GDP per capita, log consumption per capita, and log capital stock per capita correspond to the average using data from 2013 to 2015.

SYNTHETIC CONTROL METHOD: LEAVE-ONE-OUT ESTIMATOR AND EXTRAPOLATION BIAS

FIGURE. Robustness



(A) Leave-one-out estimator

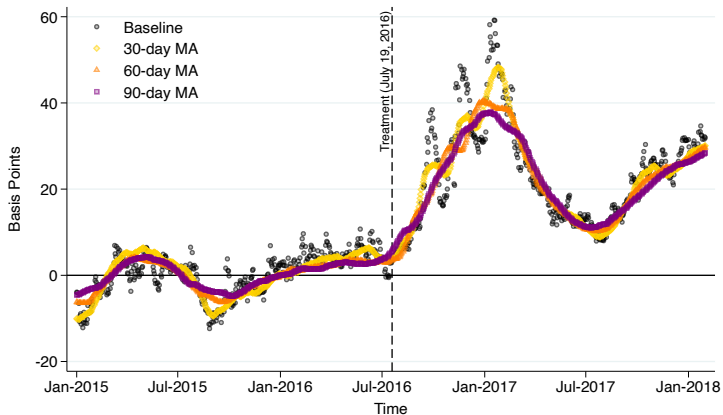


(B) Leave-one-out premiums

Note: On the left, Figure 11a displays the leave-one-out estimator that comes from estimating the synthetic control for Mexico using a donor pool that drops only one of the countries with positive weights in the baseline estimation. On the right, Figure 12 displays the treatment effect from applying the synthetic control method to smoothed data using a 30, 60, and 90 moving average, respectively.

SYNTHETIC CONTROL METHOD: SMOOTHED OUTCOME VARIABLE

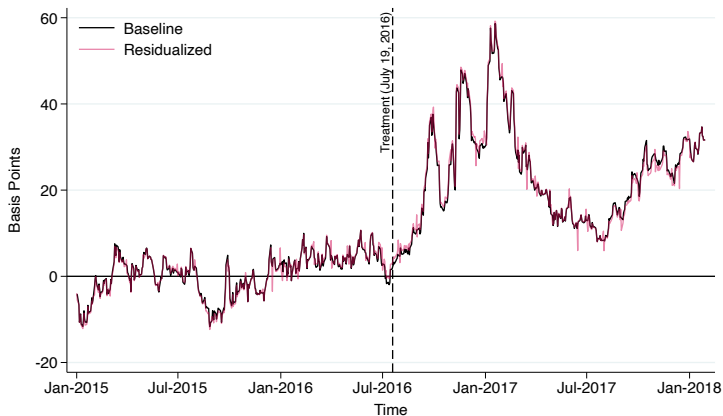
FIGURE. Moving average



Note: This Figure displays the treatment effect from applying the synthetic control method to smoothed data using a 30, 60, and 90 moving average, respectively.

SYNTHETIC CONTROL METHOD: US MONETARY POLICY

FIGURE. Residualizing CDS from changes in US Monetary Policy



Note: I residualize the CDS data for each country before estimating the synthetic control using the model: $CDS_{i,t} = \beta \Delta Fed_t + \varepsilon_{i,t}$, where $CDS_{i,t}$ is the 5-year CDS for country i at time t , and ΔFed_t is the daily change in the Fed funds rate. For the synthetic control estimation, I use $\hat{\varepsilon}_{i,t}$ instead of $CDS_{i,t}$. The black line shows the baseline estimate, and the red line displays the estimates using the residualized data.

RESPONSE TO TRUMP RHETORIC: SPECIFICATIONS

- First, to assess the impact of “good”, “bad”, and “neutral” Tweets on the **premium**, I estimate the following linear model:

$$\text{Premium}_t = \iota + \delta t + \beta \mathbb{1}\{\text{Bad Tweet}\} + \rho \mathbb{1}\{\text{Good Tweet}\} + \varrho \mathbb{1}\{\text{Neutral Tweet}\} + \gamma' \mathbf{X}_t + \eta_t,$$

- Second, I **decompose** the “bad” Tweets into two main topics: **trade** and **migration** by estimating the following linear model:

$$\text{Premium}_t = \iota + \delta t + \lambda \mathbb{1}\{\text{Trade}\} + \theta \mathbb{1}\{\text{Migration}\} + \psi \mathbb{1}\{\text{Other Tweets}\} + \gamma' \mathbf{X}_t + \epsilon_t,$$

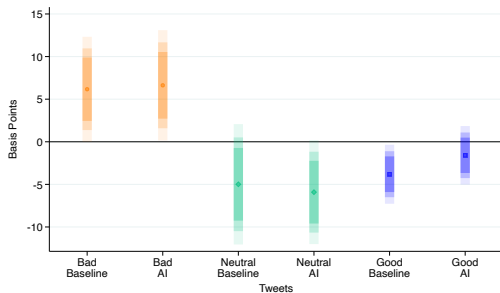
where Premium_t represents the gap between observed and synthetic 5-year CDS, t accounts for linear time trend, $\mathbb{1}\{x\}$ is an indicator function that takes the value of 1 if condition x is satisfied, $\mathbf{X}_t$ is a vector with controls, η_t and ϵ_t are error terms

SENSITIVITY TO TRUMP TWEETS: CLASSIFICATION USING AI

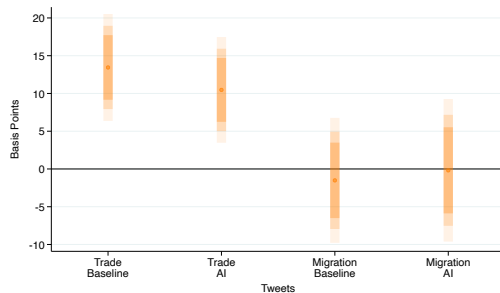
- ▶ Current classification might be biased due to subjectivity
 - ✓ **Alternative:** Use AI to classify tweets into the same three categories
- ▶ I use **ChatGPT-4o** to classify tweets based on the content (relies on **rule-based algorithm** to make classification)
 - ✓ **Prompt:** *"I am going to give you some "Tweets" made by President Trump regarding the Mexican economy during 2016-2018. Based on the content of such tweets and its potential impact for the Mexican economy, classify them as "positive", "negative", and "neutral"."*
- ▶ For classification, algorithm uses the following definitions:
 - Negative:** *"Tweets that criticize, blame, or undermine Mexico's economy, trade policies, or societal issues, or that propose actions harmful to its interests."*
 - Neutral:** *"Tweets that state facts, describe events, or focus on U.S. actions without directly praising or criticizing Mexico or its economy."*
 - Positive:** *"Tweets that express goodwill, praise, or acknowledge mutual benefits for Mexico, its people, or its economy, potentially fostering a constructive relationship."*

SENSITIVITY TO TRUMP TWEETS: CLASSIFICATION USING AI (CONT.)

FIGURE. Effect of Trump announcements via Twitter using AI classification



(A) Average effect



(B) By topic

Note: On the left, Figure 14a displays the point estimates with the respective CI at 90%, 80%, and 68%, respectively. On the right, 14b displays the point estimates of “bad” Tweets when they are separated by topic (i.e., “trade” and “migration”) with the corresponding CI at 90%, 80%, and 68%, respectively. We used HAC robust standard errors for both econometric specifications. To obtain AI classification of “trade” and “migration” related threats, I made the following prompt: “From the tweets that you classified as “negative”, now classify them as “trade related” and “migration related” based on their content.”

SENSITIVITY TO TRUMP TWEETS: “TARGETING” OTHER ECONOMIES

- ▶ How does the premium respond when Trump **shifts** his threats to **other economies**?
- ▶ Trump mentioned, on several occasions, three other economies: **China**, **North Korea**, and **Russia**
 - ✓ **33**, **28**, and **61** tweets, respectively
- ▶ To evaluate the **effect** of those tweets on the premium, I estimate the following **linear model**:

$$\text{Premium}_t = \iota + \delta t + \beta_0 \mathbb{1}\{\text{China}\} + \beta_1 \mathbb{1}\{\text{N.Korea}\} + \beta_2 \mathbb{1}\{\text{Russia}\} + \gamma' \mathbf{Z}_t + \epsilon_t,$$

where Premium_t represents the difference between the observed and synthetic Mexican 5-year CDS, $\mathbb{1}\{\text{Country}\}$ is an indicator function that takes the value of 1 if in day t there was a tweet directed to “Country”, $\mathbf{Z}_t$ is a vector that include the tweets about Mexico and other continuous controls, and ϵ_t represents the error term

TWEET EXAMPLES: OTHER COUNTRIES

- ✓ **China:** “The meeting next week with China will be a very difficult one in that we can no longer have massive trade deficits...”
@realDonaldTrump (03/30/17 6:16 PM)
- ✓ **Russia:** “Having a good relationship with Russia is a good thing, not a bad thing. Only “stupid” people, or fools, would think that it is bad! We have enough problems around the world without yet another one. When I am President, Russia will respect us far more than they do now and...”
@realDonaldTrump (01/07/17 10:02 AM)
- ✓ **North Korea:** “Military solutions are now fully in place,locked and loaded,should North Korea act unwisely. Hopefully Kim Jong Un will find another path!”
@realDonaldTrump (08/11/17 7:29 AM)

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LOCAL PROJECTIONS: TESTING EXOGENITY OF DYNAMIC TREATMENT EFFECT

► I estimate the following VAR with exogenous variables:

$$\mathbf{y}_t = \mathbf{C} + \mathbf{B}_1 \mathbf{y}_{t-1} + \dots + \mathbf{B}_p \mathbf{y}_{t-p} + \mathbf{\Theta} \mathbf{x}_t + \mathbf{u}_t, \quad \mathbf{u}_t \sim \mathcal{N}(\mathbf{0}, \mathbf{\Sigma})$$

with

$$\mathbf{y}_t = \begin{bmatrix} \text{Premium}_t \\ \Delta er_t \\ \Delta \log(IPC_t) \\ \Delta MP_t \end{bmatrix} \quad \mathbf{x}_t = \begin{bmatrix} VIX_t \\ Oil_t \\ \Delta Fed_t \end{bmatrix}, \quad \text{and} \quad \mathbf{u}_t = \begin{bmatrix} u_{1,t} \\ u_{2,t} \\ u_{3,t} \\ u_{4,t} \end{bmatrix}$$

► I compute [Granger causality tests](#), finding that the premium is, at least, [weakly exogenous](#) to the exchange rate, stock returns, and domestic monetary policy rate

Variable	<i>p</i> -value
Exchange rate	0.145
IPC Index	0.276
Monetary Policy	0.427
All	0.119

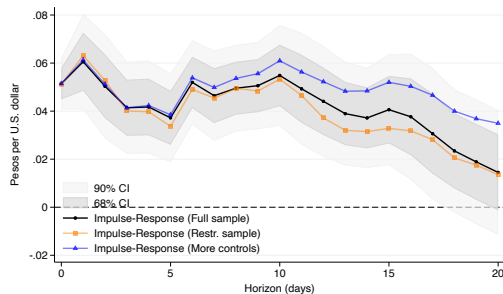
Note: This table displays the *p*-value associated with the null-hypothesis that the coefficients of variable *i* in the premium equation are zero. We allow for up to 5 lags to account for a business week.

► [Return](#)

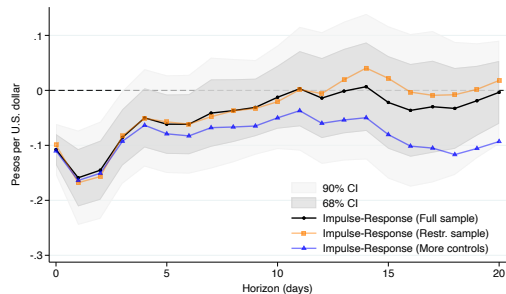
TABLE: Granger-causality Tests

LOCAL PROJECTIONS: SUBSAMPLES AND ADDITIONAL CONTROLS

FIGURE. Cumulative Impulse-Response Functions: Subsamples and Additional Controls



(A) Exchange rate

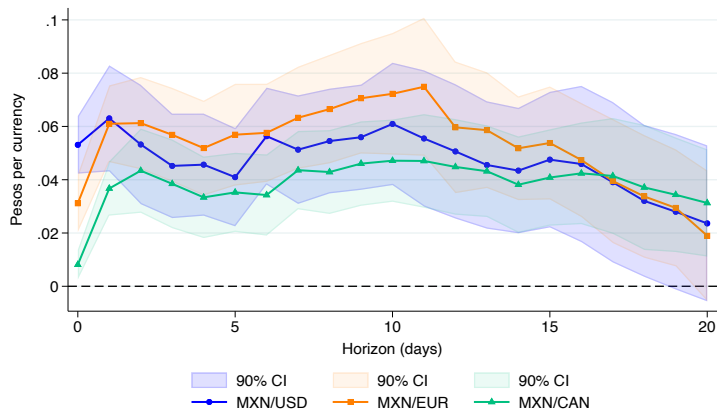


(B) Stock returns

Note: Figure 15a displays the cumulative impulse-response function of the first difference in the exchange rate to an increase of 1 basis point in the premium while Figure 15b presents the cumulative impulse-response function of the daily log-return of the Mexican stock index to an increase of 1 basis point in $Premium_t$. The shaded areas correspond to the confidence intervals at 68% and 90%, respectively, computed using HAC robust standard errors. Following Montiel Olea and Plagborg-Møller (2021), I also compute robust to heteroskedasticity standard errors using the Huber-White estimator.

LOCAL PROJECTIONS: COMPARISON BETWEEN USD/MXN AND EUR/MXN

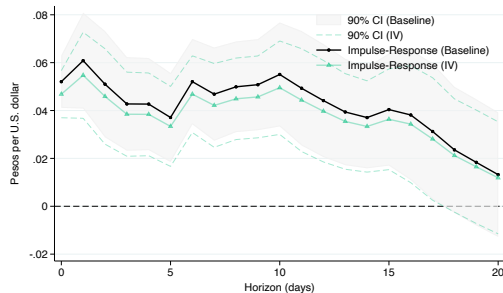
FIGURE. Cumulative Impulse-Response: Peso vis-à-vis the Euro and Canadian Dollar



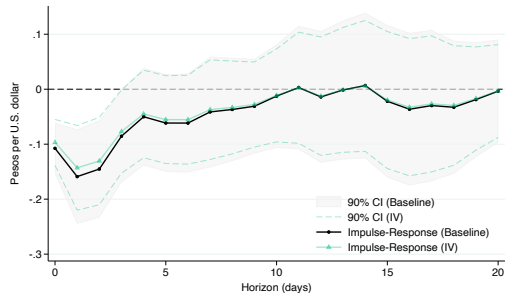
Note: The blue markers correspond to the response of the MXNUSD exchange rate to a 1 bp increase in $Premium_t$, the orange markers corresponds to the estimated response of the MXNEUR exchange rate, and the green markers corresponds to the MXNCAN exchange rate. The shaded areas represent the 90% confidence intervals computed using HAC robust standard errors.

LOCAL PROJECTIONS: ACCOUNTING FOR GENERATED REGRESSORS

FIGURE. Cumulative Impulse-Response Functions: LP-IV Approach



(A) Exchange rate

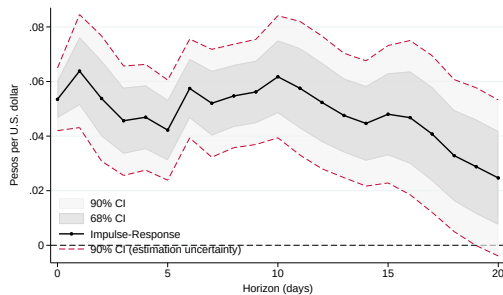


(B) Stock returns

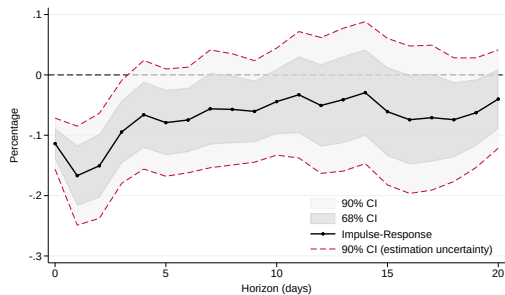
Note: Figure 17a displays the cumulative impulse-response function of the first difference in the exchange rate to an increase of 1 basis point in the instrumented EMBI spread while Figure 17b presents the cumulative impulse-response function of the daily log-return of the Mexican stock index to an increase of 1 basis point in the instrumented EMBI spread. The black markers correspond to the baseline estimates while the green markers are the estimates of the IV approach. The first-stage F statistic for the linear equation between the EMBI spread and $Premium_t$ is 20.96. The shaded areas correspond to the confidence intervals of the baseline estimation at 68% and 90%, respectively, while the green dashed line represents the 90% confidence intervals for the IV approach.

LOCAL PROJECTIONS: BLOCK WILD BOOTSTRAP

FIGURE. Cumulative impulse-response functions: Block wild bootstrap



(A) Exchange rate

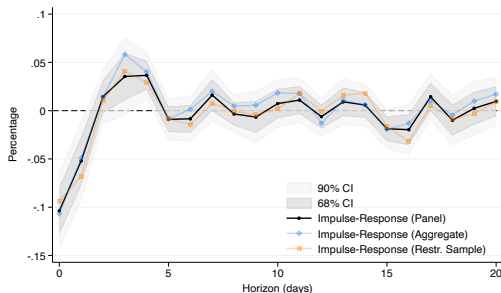


(B) Stock returns

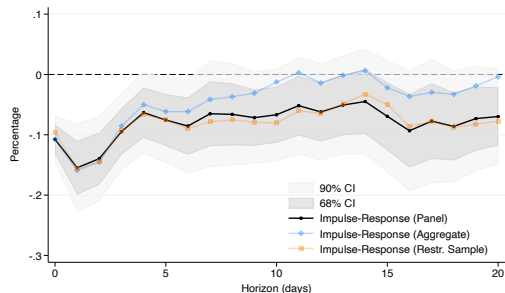
Note: Figure 18a displays the cumulative impulse-response function of the first difference in the exchange rate to a 1 basis point increase in $\hat{\alpha}_t$, and Figure 18b the response of the daily log-return of the Mexican stock index. The shaded areas are the baseline 68% and 90% confidence intervals computed with HAC robust standard errors; the dashed line is the 90% confidence interval that incorporates estimation uncertainty in $\hat{\alpha}_t$, obtained from a block wild bootstrap that re-estimates the synthetic control and re-runs the local projections ($B = 2,000$ replications). Across horizons the two intervals differ by less than three percent.

LOCAL PROJECTIONS: ACCOUNTING FOR FIXED UNOBSERVED CHARACTERISTICS

FIGURE. Average effect of Trump shock



(A) Impulse-Response

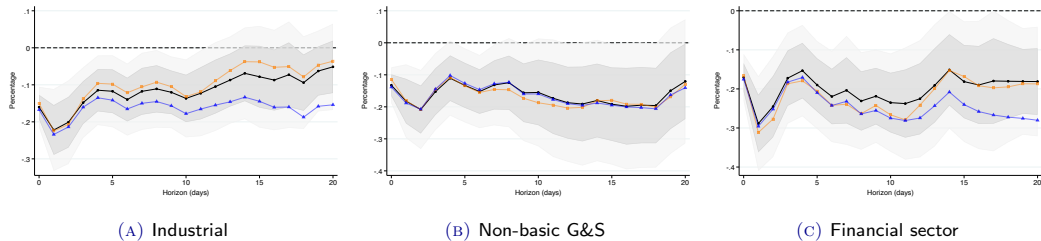


(B) Cumulative Impulse-Response

Note: I estimate $y_{i,t+h} = \gamma_i^h + \beta^h \text{Premium}_t + \mathbf{x}_t \boldsymbol{\rho}^h + u_{i,t+h}$, where $y_{i,t}$ represents the daily log-return of sector i in period t , γ_i is a fixed effect, Premium_t represents the dynamic treatment effect, $\mathbf{x}_t$ is a vector of controls, and $u_{i,t}$ stands for the error term. Figure 19a displays the impulse-response function of the daily log-return of the sectoral stock indices to an increase of 1 basis point in the premium while Figure 19b presents the cumulative impulse-response function. The black markers correspond to the average effect, the blue markers present the average effect estimated by removing from the sample the observations after July 2017, and the orange markers display the aggregate effect estimated using only the daily log-returns of the IPC. The shaded areas correspond to the confidence intervals at 68% and 90%, respectively, computed using Driscoll and Kraay (1998) standard errors.

LOCAL PROJECTIONS: INDUSTRY RESPONSES

FIGURE. Cumulative Impulse-Response Functions by Sectors



Note: This figure displays the estimated IRFs using local projections (LP) for the daily log return of the corresponding sectoral index. The shaded area corresponds to the 90% and 68% confidence intervals, respectively, computed using HAC robust standard errors.

► [Return](#)

HIGH-FREQUENCY IDENTIFICATION

- ▶ **Concern:** the $SCM\ Premium_t$ may be contaminated by non-geoeconomic shocks
- ▶ **Idea:** re-identify the responses from high-frequency movements of the Mexican CDS around “Trump days” (event windows E)
- ▶ Event days: Trump tweets about Mexico, the presidential debates, and the rounds of NAFTA renegotiation
- ▶ I instrument ΔCDS_t in $\Delta y_t = \beta \Delta CDS_t + \theta_1 X_{1,t} + \theta_2 X_{2,t} + \varepsilon_t$ with:
 - (1) a high-frequency external instrument, $z_t^{HF} = \mathbb{1}\{t \in E\} \times \Delta CDS_t$
 - (2) a heteroskedasticity-based instrument (Rigobon), as an alternative

where Δy_t is the first difference in the USD-MXN exchange rate (or the log *IPC* stock index) and $X_{1,t}, X_{2,t}$ are the VIX and oil price

HIGH-FREQUENCY IDENTIFICATION: HETEROSKEDASTICITY ALTERNATIVE

- ▶ Rigobon (2003): identify β from the difference in covariance matrices across “event” (E) and “non-event” (NE) windows, under a system with reverse causality φ
- ▶ Identifying assumption: **only** the variance of the CDS innovation η_t changes across regimes, so that:

$$\Delta\Sigma \equiv \Sigma_E - \Sigma_{NE} = \frac{(\sigma_\eta^E)^2 - (\sigma_\eta^{NE})^2}{(1 - \beta\varphi)^2} \begin{bmatrix} \beta^2 & \beta \\ \beta & 1 \end{bmatrix}$$

- ▶ Following Hébert and Schreger (2017), implemented by IV with the balanced ($|E| = |NE| = 41$) instrument:

$$z'_t = \frac{|E| + |NE|}{|E|} \mathbb{1}\{t \in E\} \times \Delta CDS_t - \frac{|E| + |NE|}{|NE|} \mathbb{1}\{t \in NE\} \times \Delta CDS_t$$

- ▶ Both instruments give **almost identical** estimates; the HF instrument has a much stronger first stage ($F \approx 1,028$ vs. 4.9)

HIGH-FREQUENCY IDENTIFICATION: ESTIMATES

TABLE: Estimates of the effect of the CDS on outcome

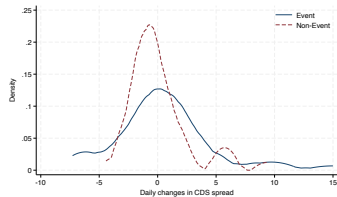
Outcome variable	IV (1)	ES (2)	OLS (3)	LP (4)
First difference in Mexican peso	0.06*** (0.02)	0.05*** (0.02)	0.03*** (0.004)	0.05*** (0.01)
Daily log-return of stock exchange	-0.12*** (0.02)	-0.11*** (0.02)	-0.08*** (0.02)	-0.11*** (0.03)
Sector 2: Materials	-0.06 (0.12)	-0.05 (0.07)	-0.05** (0.02)	-0.05 (0.04)
Sector 3: Industrial	-0.19*** (0.06)	-0.15*** (0.04)	-0.10*** (0.02)	-0.15*** (0.03)
Sector 4: Non-basic G&S	-0.09 (0.09)	-0.10** (0.05)	-0.09*** (0.02)	-0.12*** (0.03)
Sector 5: Frequent consumption	-0.08* (0.04)	-0.07*** (0.02)	-0.06*** (0.02)	-0.08*** (0.03)
Sector 6: Health	-0.15** (0.06)	-0.12*** (0.04)	-0.05*** (0.01)	-0.09*** (0.02)
Sector 7: Financial services	-0.21*** (0.08)	-0.19*** (0.05)	-0.11*** (0.02)	-0.17*** (0.04)
Sector 9: Telecommunications	-0.11 (0.07)	-0.08** (0.03)	-0.04** (0.02)	-0.04 (0.03)
Events				41
Obs.				417
F-stat				15.884
F-stat (robust)				4.90

Note: ***, **, * represents statistical significance at 1%, 5% and 10 %, respectively. Robust standard errors are reported in parenthesis. F-stat corresponds to the [Cragg and Donald \(1993\)](#) F-statistic, and F-stat (robust) displays the [Kleibergen and Paap \(2006\)](#) rk F-statistic allowing for heteroskedasticity.

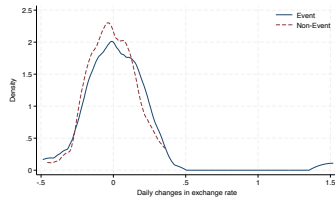
► Return

HETEROSKEDASTICITY ALTERNATIVE: RELATIVE VARIANCE TEST

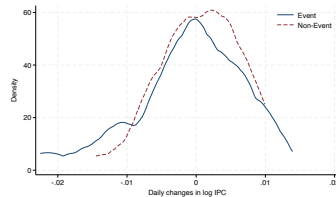
FIGURE. Distributions during event and non-event windows



(A) CDS



(B) Exchange rate



(C) Equity returns

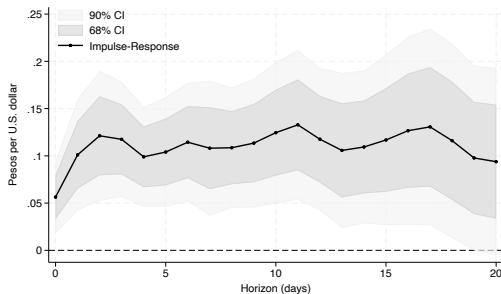
TABLE: Tests of differences in variances

Test	CDS	Exchange Rate	Stock Returns
Levene	4.14**	1.21	2.94*
Brown-Forsythe (median)	4.27**	1.17	2.76
Brown-Forsythe (trimmed mean)	4.26**	1.16	2.80*

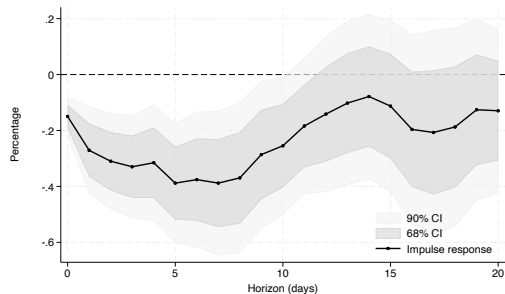
Note: “Test” column displays the F -statistic being computed for the test of equal variances. The sample used corresponds to the balanced sample of 41 observations for event windows and 41 observations for non-event windows.

HIGH-FREQUENCY IDENTIFICATION: DYNAMIC RESPONSE

FIGURE. Cumulative Impulse-Response Functions



(A) Exchange rate



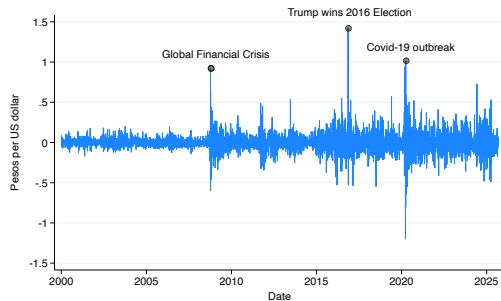
(B) Stock returns

Note: For comparison purposes, the black line corresponds to the LP estimates using $\hat{a}_t$, the blue line corresponds to the CIRF that comes from estimating $\mathbf{y}_t = \mathbf{C} + \mathbf{B}_1 \mathbf{y}_{t-1} + \dots + \mathbf{B}_p \mathbf{y}_{t-p} + \boldsymbol{\Theta} \mathbf{x}_t + \mathbf{u}_t$, where $\mathbf{y}_t$ includes the first difference in the 5-year CDS, the daily change in the peso-dollar exchange rate, the daily returns on the S&P 500, and the daily changes in domestic monetary policy rate (in basis points), and $\mathbf{x}_t$ includes global controls such as the VIX index, oil prices, and the daily changes in the Fed funds rate. Identification requires that:

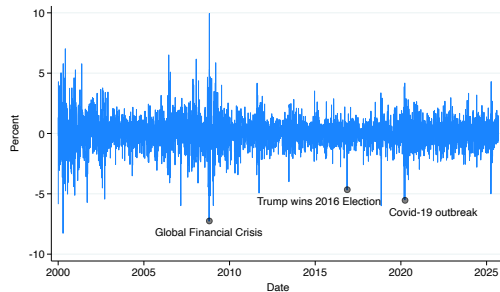
$$\mathbb{E}[z_t \varepsilon_t^{\Delta CDS}] = \alpha, \text{ and } \mathbb{E}[z_t \varepsilon_t^{2:n}] = \mathbf{0} \text{ where } z_t = \frac{|E|+|NE|}{|E|} \mathbb{1}\{t \in E\} \times \Delta CDS_t - \frac{|E|+|NE|}{|NE|} \mathbb{1}\{t \in NE\} \times \Delta CDS_t.$$

TIME SERIES FOR MXNUSD AND STOCK RETURNS

FIGURE. Historical evolution of MXNUSD exchange rate and stock returns



(A) Exchange rate



(B) Stock returns

Note: On the first panel, I display the first difference in the daily MXNUSD exchange rate. On the second panel, the daily log-returns of the Mexican stock index are displayed. The sample covers the period 2000 to 2025. Figures elaborated with data from *Banco de México*.

CONSTRUCTION OF $\Pi^{(1)}$

- ▶ In normal times, y_t follows a finite-state Markov chain with **transition matrix** $\Pi^{(0)}(y'|y)$ obtained from discretizing $\log(y_{t+1})$
- ▶ Under **geoeconomic pressure**, the **actual distribution of future tradable income shifts**: the likelihood of bad states increases

▶ **Tilted transition matrix:**

$$\Pi^{(1)}(y'|y; \omega, \zeta) = (1 - \omega) \Pi^{(0)}(y'|y) + \omega \Pi^{\text{target}}(y'|y; \zeta),$$

with $\Pi^{\text{target}}(y'|y; \zeta) = \lambda_j(\zeta) \mathbb{1}\{y' \in \mathcal{L}\}$ and $\lambda_j(\zeta) = \frac{\zeta^{j-1}}{\sum_{k=1}^{|\mathcal{L}|} \zeta^{k-1}}$

Target distribution:

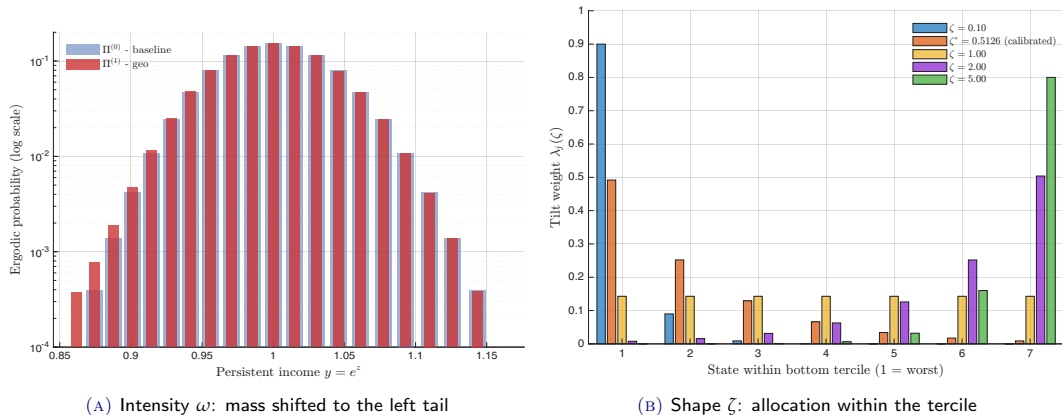
- ✓ Concentrates mass on **bottom tercile** of income grid (states 1–7 with $N = 21$)
- ✓ $\zeta = 1$: **uniform**
- ✓ $\zeta < 1$: more mass on **worst** states

Properties:

- ✓ Row-stochastic $\forall \omega \in [0, 1]$
- ✓ $\omega = 0$ captures normal times
- ✓ **Both** government and lenders use $\Pi^{(1)}$
- ✓ Rational-expectations equilibrium under the post-shock measure

- ▶ ω and ζ are calibrated to the **24 bp** SCM premium and the change in income **skewness**

ROBUSTNESS: ALTERNATIVE WAYS OF ALLOCATING MASS



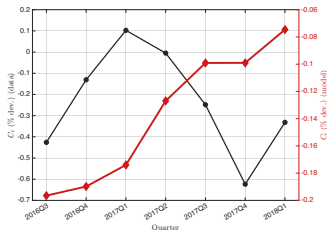
(A) Intensity ω : mass shifted to the left tail

(B) Shape ζ : allocation within the tercile

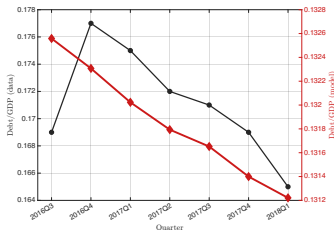
Note: Panel a: ergodic distribution of the persistent income component $y = e^z$ under the baseline transition matrix $\Pi^{(0)}$ (blue) and under the post-shock matrix $\Pi^{(1)}$ (red) at $\omega = \omega^* = 0.0003$ and $\zeta = \zeta^* = 0.513$; ω controls how much mass is reallocated toward the left tail. Panel b: tilt weights $\lambda_j(\zeta)$ across the seven states of the bottom tercile for $\zeta \in \{0.1, 0.51, 1, 2, 5\}$; $\zeta < 1$ concentrates the additional mass on the worst states, $\zeta = 1$ spreads it uniformly, and $\zeta > 1$ shifts it toward the least-bad states. [Return](#)

FIGURE. The two margins of the regime switch: intensity ω and within-tercile shape ζ .

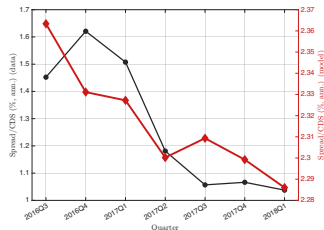
EXPERIMENT I: MIT SHOCK AND MACRO DYNAMICS



(A) Consumption C_t



(B) External debt/GDP

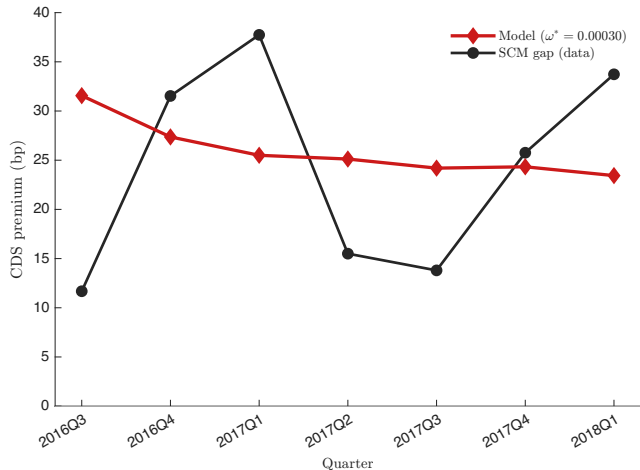


(C) Sovereign spread (CDS)

Note: Impulse responses to the regime switch, conditioning on non-default periods. Red lines with diamond markers: model average over $S = 10,000$ paths (right axis). Black lines with circle markers: Mexican data (left axis). Output and consumption are in percent deviation from the pre-shock mean (two-quarter moving average); external debt/GDP and the CDS spread are in levels. The window is 2016Q3–2018Q1.

FIGURE. Impulse responses to a geoeconomic regime switch

EXPERIMENT II: COMPUTE MODEL-EQUIVALENT PREMIUM



Note: Black circles display the SCM quarterly premium (basis points), while red diamonds correspond to the model-implied premium from matched-pairs simulation under constant $\omega^* = 0.0003$ and $\zeta^* = 0.513$. [► Return](#)

FIGURE. Model-implied CDS spread premium vs. SCM estimate.

AGGREGATE CONSUMPTION: DERIVATION DETAILS

► From the **intertemporal efficiency condition** of a SOE maximization problem, we can write **present consumption** as

$$C_t = u'^{-1} \left(\frac{\beta}{q_t(1 + \eta_t)} \mathbb{E}_t [u'(C_{t+1})] \right), \text{ with } \eta_t \equiv \frac{\partial q(b_{t+1}, y_t)}{\partial b_{t+1}} \frac{b_{t+1}}{q(b_{t+1}, y_t)}$$

► Under the **assumptions**:

(A1) CRRA instantaneous utility function (i.e., $u(C_t) = \frac{C_t^{1-\gamma}}{1-\gamma}$)

(A2) Log-normal consumption growth (i.e., $\Delta c_{t+1} \sim \mathcal{N}(\mu_{c,t}, \sigma_{c,t}^2)$)

(A3) Constant risk-free rate (i.e., $r_{f,t} = r_f$)

(A4) Default probability priced in CDS data (i.e., $q_t = (1 - \pi_t)(1 + r_f)^{-1}$)

and **iterating forward** $T + 1$ periods (e.g., number of periods in post-treatment sample), we can express **log-consumption** as:

$$\log(C_t) \equiv c_t = -\frac{(T+1)}{\gamma} \log(\beta) + \frac{1}{\gamma} \sum_{j=0}^T \mathbb{E}_t [\log(q_{t+j}) + \log(1 + \eta_{t+j})] - \frac{\gamma}{2} \sum_{j=0}^T \mathbb{E}_t [\text{Var}_{t+j}(\Delta c_{t+j+1})] + \mathbb{E}_t [c_{t+T+1}],$$

where $\Delta c_{t+1} = \log(C_{t+1}) - \log(C_t)$

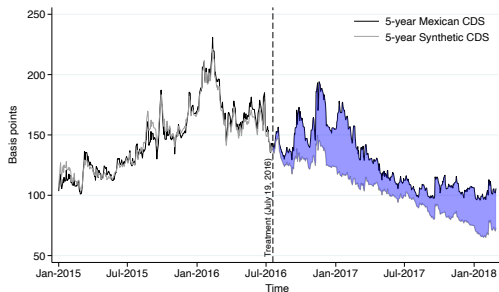
AGGREGATE CONSUMPTION: DERIVATION DETAILS (CONT.)

- Let $\tilde{c}_t$ represent the counterfactual log-level of consumption (in the absence of geoeconomic pressures)
- The implied effect on consumption is given by:

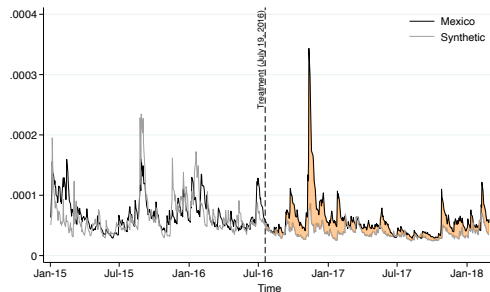
$$\begin{aligned}
 c_t - \tilde{c}_t = & \underbrace{\frac{1}{\gamma} \left(\sum_{j=0}^T \mathbb{E}_t [\log q_{t+j} - \log \tilde{q}_{t+j}] \right)}_{(1a) \text{ Level subcomponent}} + \underbrace{\frac{1}{\gamma} \left(\sum_{j=0}^T \mathbb{E}_t [\log(1 + \eta_{t+j}) - \log(1 + \tilde{\eta}_{t+j})] \right)}_{(1b) \text{ Slope subcomponent}} \\
 & \underbrace{\hspace{15em}}_{(1) \text{ Price component}} \\
 & - \underbrace{\frac{\gamma}{2} \left(\sum_{j=0}^T \mathbb{E}_t [\text{Var}_{t+j} (\Delta c_{t+j+1}) - \text{Var}_{t+j} (\Delta \tilde{c}_{t+j+1})] \right)}_{(2) \text{ Uncertainty component}} \\
 & + \underbrace{(\mathbb{E}_t [c_{t+T+1}] - \mathbb{E}_t [\tilde{c}_{t+T+1}])}_{(3) \text{ Transitory vs. permanent component}} ,
 \end{aligned}$$

AGGREGATE CONSUMPTION: DECOMPOSITION

FIGURE. Decomposition of log-consumption



(A) Default channel



(B) Uncertainty channel

Note: Panels show observed and counterfactual CDS spreads and stock return volatility used to construct the consumption decomposition.

► [Return](#)

AGGREGATE CONSUMPTION: HANDLING VARIANCE OF Δc_{t+j}

- ▶ Given the lack of daily data on Δc_{t+1} , I assume that the variance of log-consumption growth is **proportional** to the **variance of log stock returns**:

$$\text{Var}_t(\Delta c_{t+1}) \propto \Psi \text{Var}_t(r_{t+1}), \quad \text{with } \Psi < 1$$

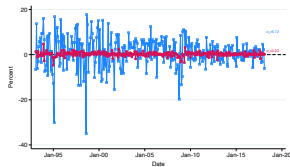
- ▶ Historical data at different **frequencies** (e.g., month, quarter, year) suggest that $\Psi \approx 2\%$
- ▶ The variance of log-returns is then estimated using **Bollerslev (1987)** GARCH(1,1) model
- ▶ As for the counterfactual variance, I use the estimated **weights** of the synthetic control for the CDS data and construct it as the **convex combination** of the variances of **Panama**, **Colombia**, and **Poland** stock returns

$$\text{Var}_t(\Delta \tilde{c}_{t+1}) \propto \Psi \left[\sum_{i=2}^4 w_i^* \text{Var}_t(r_{i,t+1}) \right]$$

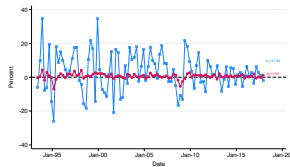
▶ Return

RELATION BETWEEN STOCK RETURNS AND CONSUMPTION GROWTH

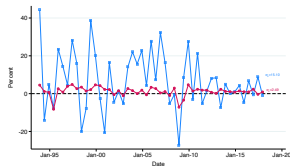
FIGURE. Stock returns and consumption growth by frequency



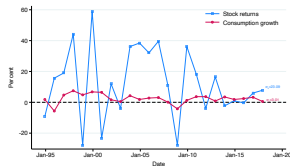
(A) Monthly frequency



(B) Quarterly frequency



(C) Semi-annual frequency



(D) Annual frequency

Note: In each panel, we display the Mexican stock returns (blue-shaded markers) and the log-consumption growth (red-shaded markers) at four different frequencies, respectively. On average, we get that the ratio of log-consumption growth variance to stock return variance is approximately 2%.

RELATION BETWEEN STOCK RETURNS AND CONSUMPTION GROWTH (CONT.)

TABLE: Comparison of variances across frequencies

Statistic	Frequency			
	Month	Quarter	Semiannual	Year
$\sigma_{\text{stock returns}}$	6.72	11.34	15.10	23.10
$\sigma_{\text{cons. growth}}$	0.93	1.54	2.49	3.01
$\sigma_{\text{cons. growth}}^2 / \sigma_{\text{stock returns}}^2$	0.02	0.02	0.03	0.02
$\text{Cov}(r_t, \Delta c_t)$	0.64	6.72	16.05	18.57
$\hat{\beta}_{OLS}$	0.01	0.05	0.07	0.03
N	301	99	49	24

Note: Monthly data from January 1993 to February 2018 was used to construct the statistics. Data on stock returns come from Bloomberg while data on the private consumption index comes from *Banco de México*. Lower frequency observations represents the corresponding EOP of the monthly observations (i.e., Q1 = M3, S1 = M6, and YYYY = YYYYM12). $\hat{\beta}_{OLS}$ corresponds to the estimate of the slope of the linear model $\Delta c_t = \alpha + \beta r_t + \varepsilon_t$.

► Return

RELATION BETWEEN STOCK RETURNS AND CONSUMPTION GROWTH (CONT.)

► We can **posit** that the variance of consumption growth is **proportional** to the variance of stock returns by using **Bansal and Yaron (2004)** Long-Run Risk framework

► We have that:

$$\begin{aligned}\Delta c_{t+1} &= \mu_c + x_t + \sigma \eta_{t+1}, \\ x_{t+1} &= \rho x_t + \varphi_e \sigma e_{t+1}, \\ r_{t+1} &= \mu_r + \phi x_t + \varphi_r \sigma u_{t+1},\end{aligned}$$

with η_{t+1} , e_{t+1} , and $u_{t+1} \stackrel{i.i.d}{\sim} \mathcal{N}(0, 1)$

► By **combining** the previous equations, we get that

$$\Delta c_{t+1} = \tilde{\mu} + \frac{1}{\phi} r_{t+1} + \sigma \varepsilon_{t+1}, \quad \text{with } \tilde{\mu} = \left(\mu_c - \frac{\mu_r}{\phi} \right) \text{ and } \varepsilon_{t+1} = \left(\eta_{t+1} - \frac{\varphi_r}{\phi} u_{t+1} \right),$$

► This implies that

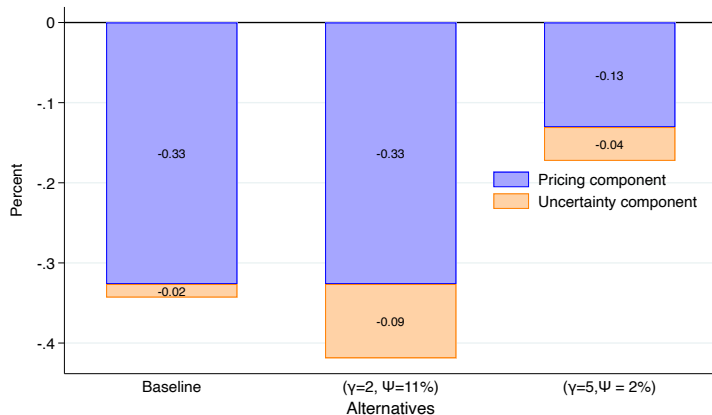
$$\text{Var}_t(\Delta c_{t+1}) \propto \underbrace{\frac{1}{\phi^2}}_{\equiv \Psi} \text{Var}_t(r_{t+1})$$

► In standard **calibrations**, we have that $\phi > 1$ thus $\Psi < 1$

► [Return](#)

AGGREGATE CONSUMPTION: COMPARATIVE STATICS

FIGURE. Overall effect on consumption



Notes: The blue shaded bars correspond to the first component of the difference of log consumption, while the orange shaded bars represent the second component. The calculation relies on the assumption that Trump's actions and rhetoric are a transitory shock to the Mexican economy.

AGGREGATE CONSUMPTION: FILTERING METHOD

- I recover a **daily measure of consumption** by combining **stock returns** and **low-frequency consumption data**
- Following **Bansal and Yaron (2004)**, both variables are driven by a **latent persistent component**
- **State-space representation:**

$$\begin{aligned} \mathbf{z}_{t+1} &= \boldsymbol{\mu}_z + \mathbf{A}\mathbf{z}_t + \mathbf{B}\mathbf{u}_{t+1}, & \mathbf{u}_{t+1} &\sim \mathcal{N}(0, \mathbf{I}), \\ r_{t+1} &= \mu_r + \mathbf{H}\mathbf{z}_t + \sigma_r \varepsilon_{t+1}, & \varepsilon_{t+1} &\sim \mathcal{N}(0, 1), \\ \Delta c_M &= \sum_{i \in M} \Delta c_i + \sigma_c \xi_M, & \xi_M &\sim \mathcal{N}(0, 1), \end{aligned}$$

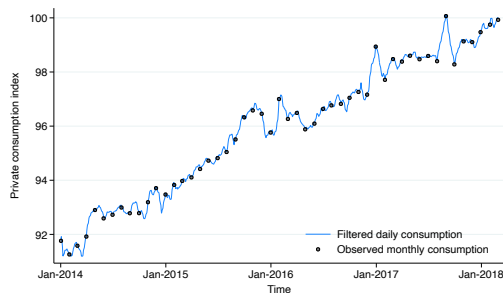
with

$$\mathbf{z}_t = \begin{bmatrix} \Delta c_t & x_t \end{bmatrix}^T$$

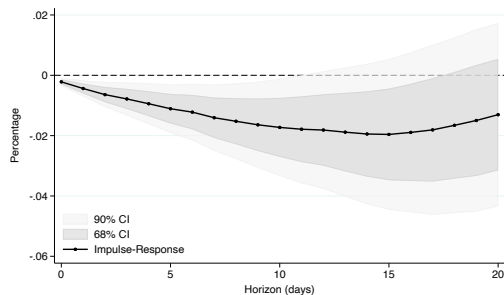
- Parameters are estimated via **maximum likelihood** and daily consumption growth is extracted using the **Kalman filter**
- I recover the level of log-consumption by cumulating filtered consumption growth
- This approach delivers a **high-frequency measure of consumption** that complements the Euler equation results

AGGREGATE CONSUMPTION: FILTERING METHOD (CONT.)

FIGURE. Estimating marginal effects



(A) Observed vs. filtered



(B) Consumption response

Note: On the left panel, the black markers represents the observed monthly observations of the private consumption index reported by *Instituto Nacional de Estadística, Geografía, e Información* (INEGI). The blue line corresponds to the interpolated series using the Kalman filter with daily stock returns and monthly consumption growth. On the right panel, the CIRF is computed using local projections:

$c_{t+h} - c_{t-1} = \gamma^h + \hat{\alpha}_t \beta^h + \mathbf{x}_t \psi^h + u_{t+h}$, with $h = 0, \dots, 20$. The black markers represent the point estimates $\{\hat{\beta}^h\}_{h=0}^{20}$. The shaded areas represent the 68%, and 90% confidence intervals, respectively, constructed using HAC robust standard errors.

AGGREGATE CONSUMPTION: COMPARISON WITH LITERATURE

- ▶ Are these numbers **consistent** with what the **literature** has documented?
 - ✓ In particular, literature that **highlights** the role of stochastic **country-specific spreads** driving **business cycles** of small open economies
- ▶ **Neumeyer and Perri (2005)** using a DSGE model calibrated to the Argentinean economy, estimates a contraction of **1%** of consumption, relative to the steady-state level, to a **one-standard-deviation shock** to country-specific spread (i.e., first moment shock)
- ▶ **Fernández-Villaverde et al. (2011)** provide evidence that **uncertainty** regarding country-specific spreads also matters for **business cycle fluctuations** (i.e., second moment shocks)
 - ✓ On average, a **one-standard-deviation shock** to the volatility of spreads yields a contraction in the level of consumption of **-0.21%**
 - ✓ **Humped-shaped response** to such innovations to volatility
- ▶ Both **magnitudes** and **shape** of the response of consumption are **in line** with estimates of other studies

▶ [Return](#)