Writing Sample

Inflation Risk Management with Global Supply Disruptions*

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Abstract

Global supply chain disruptions were a major driver of the inflation surge in the pandemic era. In this paper, I investigate how key macroeconomic indicators shape inflation risk in Mexico and whether global supply chain pressures affect it. Using a quantile augmented Phillips Curve, I show that global supply chain pressures shift the entire 1-year-ahead predictive distribution of inflation to the right, having a higher effect on upper percentiles. Then, I ask whether monetary policy can manage inflation risk. Using high-frequency identified monetary policy shocks, I find a non-linear effect across the predicted inflation distribution. Policy shocks can curb right-tail inflation risks but have a small effect on the lower part of the distribution. My findings suggest that policymakers have room to maneuver to reduce tail risks, even when these are driven by external factors, such as global supply chain disruptions.

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*"The 2021-2022 inflationary period was clearly different from the previous ones, characterized by atypical shocks that led to **tail risks**. Given this scenario, fifteen consecutive hikes were made, accumulating 725 basis points and raising the policy rate to record highs."*[1]

Banxico Board Member, *March 2024 Minutes.*

1 Introduction

Central banks have faced a remarkably complex scenario in recent years. The economic disruptions caused by the COVID-19 pandemic, including an unprecedented mix of fiscal stimulus, widespread lockdowns, and geopolitical conflicts increased the uncertainty around inflation dynamics and the likelihood of extreme outcomes, or "tail risks".

Risks around inflation forecasts are crucial for monetary policy. In an inflation-targeting regime, a central bank's credibility is partially based on its ability to forecast inflation accurately and manage expectations (Svensson (1997); Bernanke et al. (2001)). Uncertainty around inflation forecasts can also influence market expectations regarding interest rates and inflation risk premia, impacting asset prices, financial conditions, and market volatility (Söderling (2011)). Moreover, higher inflation risks can complicate central banks' communication and affect price-setting decisions, feeding back into realized inflation.

As central bankers themselves have acknowledged, their policy response to the inflation surge in the pandemic era was driven not only to combat inflation but also to address tail risks. In this paper, I focus on inflation risk for Mexico and ask three questions: *How do key macroeconomic indicators shape inflation risk? How do global supply chain disruptions affect it? Can policymakers effectively manage inflation tail risks with monetary policy shocks?*

To address these questions, I follow a two-step approach. First, I estimate a quantile Phillips curve for Mexico, which allows me to examine how macroeconomic factors influence the conditional distribution rather than the conditional mean. This framework is useful for understanding potential asymmetries in the effects of different factors on inflation risk, particularly at the tails of the distribution. In line with the standard literature, I augment the Phillips curve by incorporating key elements relevant to a small open economy, such as inflation inertia, exchange rate fluctuations, and oil prices. Additionally, given Mexico's deep integration into global trade and the increasing complexity of global value chains, I include a Global Supply Chain Pressure Index,[2] recognizing the growing relevance of global supply chain disruptions in shaping inflation dynamics, particularly in the post-pandemic context (Benigno et al. (2022); Ascari et al. (2024)).

[1] Minutes number 107. Meeting of Banco de México's Governing Board on the occasion of the monetary policy decision announced on March 21, 2024 (available at Banxico website).

[2] I use the Federal Reserve Bank of New York's Global Supply Chain Pressures Index (GSCPI). It summarizes global supply chain disruptions by integrating various metrics that capture factors that put pressure on global supply chains.

Second, I analyze the dynamic effect of monetary policy shocks on inflation tail risks. Following the literature on growth and inflation at risk (Adrian et al. (2019), López-Salido and Loria (2024)), the 10th and 90th percentiles of the 1-year-ahead predicted inflation distribution are considered as measures of tail risks. Using the corresponding predicted quantiles from the previous step, I estimate local projections Jordà (2005) using the Solís (2023) high-frequency identified monetary policy shocks for Mexico as an instrument, controlling for an ample set of macroeconomic variables and lags to address potential communication effects as stressed by Miranda-Agrippino and Ricco (2021) and Jarociński and Karadi (2020).

My findings are threefold. First, focusing on the quantile regression estimates, I found a negligible effect on the conditional median for almost all key indicators but for inflation expectations and the GSCPI. An increase in inflation expectations is nearly one-to-one passed-through to the 1-year-ahead predicted median inflation, while an increase of one standard deviation in the GSCPI rises it by 0.71pp. In contrast, the remaining variables do not have a significant effect on the conditional median. This implies that in a world with no supply chain disruptions, the 1-year-ahead predicted median inflation would align with the professional forecasters' median expectation, providing a measure of conditional risk around their point estimates.

Second, the quantile Phillips curve does provide a rich characterization of the conditional distribution. I find that the GSCPI has a significant and positive effect on the whole distribution. That is, an increase in global supply chain disruptions shifts the distribution to the right, with a more pronounced effect on upper percentiles. Moreover, the impact of a nominal exchange rate depreciation exhibits a U-shaped asymmetry across the conditional quantiles. In other words, an exchange rate depreciation compresses the lower part of the distribution towards the median (narrowing the $\mathcal{Q}_{50} - \mathcal{Q}_{10}$ interquantile range) while simultaneously expanding the upper part in a convex manner (widening the $\mathcal{Q}_{90} - \mathcal{Q}_{50}$ range). In the case of financial conditions, a tightening would add a negative skew since it decreases predicted inflation only for lower quantiles but has no further effect on the rest of the distribution.

Third, despite being short-lived, monetary policy can manage inflation risk. That is, monetary policy shocks do affect the 1-year-ahead inflation predicted distribution. After an unexpected 25bp interest rate hike, the predicted 90th percentile falls by 0.14pp, having a maximum effect of 0.66pp around the fourth month after the shock. Noteworthy, the impact on the median is smaller than on the 90th percentile and even smaller on the 10th percentile. To understand how the median moves relative to tail-risks, I study the dynamic response of the $(\mathcal{Q}_{90-50}, \mathcal{Q}_{50-10})$ interquantile ranges as single statistical objects. The $\mathcal{Q}_{50-10}$ interquantile shrinks while the $\mathcal{Q}_{90-50}$ range expands after the policy shock. Altogether, my results imply that after an unexpected policy tightening, the predicted inflation distribution moves to the left and has more right skew than before the shock.

Related Literature. My paper contributes to the following strands of the literature.

Macroeconomic Tail Risk. My work primarily contributes to the literature that studies macroeconomic tail risk, which started with the seminal contributions of Giglio et al. (2016), Adrian et al. (2019) and Adrian et al. (2022) on "Growth-at-Risk".[3] In particular, it relates to the scarce but growing literature on Inflation-at-Risk (IaR, hereafter), which examines the predicted conditional inflation distribution using quantile regression techniques. These studies have shown a significant variation in the shape and measure of inflation tail risks over time. Existing literature has focused on inflation risks for the United States and the euro zone (López-Salido and Loria (2024); Busetti et al. (2015)) or used panel quantile regressions with fixed effects for a cross-country pool of advanced and emerging economies (Queyranne et al. (2022); Banerjee et al. (2023); Makabe and Norimasa (2022)). Advanced economies face downside inflation risks due to the constraint of the zero lower bound, whereas emerging market economies experience upside risks associated with large exchange rate depreciations Banerjee et al. (2023). Further, tighter financial conditions add both upside and downside risks for emerging market economies, a pattern that contrasts with the evidence for the US and euro area that documents only downside risk from tighter financial conditions López-Salido and Loria (2024). While much of the existing literature relies on quarterly data from the 'Great Moderation' period, beginning in the 1980s, Makabe and Norimasa (2022) extends the analysis back to the late 1960s to encompass the 'Great Inflation' period. This broader temporal scope allows for a more comprehensive assessment of upside inflation risks, finding a time-varying effect from unit labor costs, government spending, and import prices.

My contribution to this literature is twofold. First, my work is the first to examine the role of global supply chain disruptions on Inflation-at-Risk.[4] This analysis is particularly relevant given the increasing complexity and integration of global value chains, which may be synchronizing inflation cycles across countries, as highlighted by Auer et al. (2017) and Ciccarelli and Mojon (2010). From a policy perspective, understanding how global supply chain disruptions influence inflation risk is crucial for effective monetary policy communication and strategy. Second, to the best of my knowledge, this is the first study to analyze IaR for Mexico using monthly data. This allows us to capture high-frequency shifts in macroeconomic conditions, providing timely information for risk management.

[3]Recent studies have extended this literature in several dimensions, by analyzing whether domestic or foreign developments drive growth tail risk Lloyd et al. (2022), studying the extent to which macroprudential policies can mitigate recessions Aikman et al. (2019), and assessing the forecasting performance of financial variables on the GDP growth distribution Reichlin et al. (2020). Besides the focus on growth, the methodology has been applied to investigate the key factors characterizing macroeconomic risk, as for exchange rate returns Eguren-Martin and Sokol (2022), capital flows Eguren-Martin et al. (2024), and inflation.

[4]López-Salido and Loria (2024) extend their baseline model by incorporating the personal savings rate and the Philadelphia Fed's Current Delivery Time Diffusion Index to capture key pandemic-era inflation drivers such as fiscal stimulus and supply chain disruptions. However, the Delivery Time Index provides a localized view of delivery delays specific to Philadelphia's manufacturing sector, offering limited insights into global inflationary pressures and broader systemic risks.

Phillips Curve. The theoretical framework followed for the quantile regressions is based on the New Keynesian Phillips Curve (NKPC) in an open economy context, which started with the seminal work of (Clarida et al. (2001); Clarida et al. (2002)) and Galí and Monacelli (2005). I contribute to this literature by extending the framework to allow for a parsimonious but rich Phillips curve that entails both backward and forward-looking components, domestic factors, financial conditions, external inflation, and global supply factors. It aims to capture the most relevant aspects shaping inflation for small-open economies in a globalized world.

Monetary Policy Shocks. My paper also contributes to the growing empirical literature on the effects of monetary policy shocks in emerging market economies (EMEs) (Brandao-Marques et al. (2020); Deb et al. (2023); Checo et al. (2024); Aguilar et al. (2024)). Until recently, the assessment of monetary policy in EME has shown limited progress since most novel approaches to identify monetary policy shocks in advanced economies are hard to replicate for emerging market economies.[5] Most of the existing literature has focused on the transmission mechanism of monetary policy, tracing out its effect on financial markets (sovereign bond yields, stock prices, exchange rates), real activity (industrial production, unemployment rate), inflation, and inflation expectations. Granted, the scarcity of works focusing on the effects of monetary policy shocks on inflation tail risks is remarkable. My paper provides the first empirical evidence in this regard. Adapting Loria et al. (2024) approach to IaR, I show that policy shocks can shift the 1-year ahead inflation predicted distribution to the left, having a non-linear effect across the predicted distribution. My findings suggest that policymakers can reduce tail risks, even when external factors, such as global supply chain disruptions, drive these.

Outline. The rest of the paper is organized as follows. Section 2 introduces the econometric framework used to study inflation-at-risk. Section 3 presents the econometric estimates and examines how each factor influences the 1-year-ahead predicted inflation distribution. Section 4 assesses the role of global supply chain disruptions in capturing tail risks. Section 5 explores whether the central bank can mitigate tail risk through monetary policy shocks. Finally, Section 6 concludes the paper.

2 Characterizing Inflation-at-Risk

This section presents the framework used to characterize inflation tail risks. Following the literature on IaR, I combine theoretical-based determinants of inflation with quantile regressions to estimate the one-year-ahead inflation conditional distribution. This approach is very useful to assess how these factors shape inflation risk and whether they exhibit an asymmetric effect

[5]Intra-day data for EMEs is limited, and when available, short-term bond yields often include counter-cyclical risk premia, complicating their use as proxies for monetary policy stance De Leo et al. (2023). Additionally, significant differences in timing, language, and communication strategies make it impractical to rely on a narrative approach Deb et al. (2023).

along the conditional distribution. To formally characterize the relationship between future inflation and these factors, let us denote π_{t+12} the growth rate of headline inflation between t and $t+12$, and x_t a vector containing the conditioning variables, including a constant.[6] In a quantile regression of π_{t+12} on x_t, the regression slope β_τ is chosen to minimize the absolute value of errors, weighted by the corresponding quantile:

$$\hat{\beta}_\tau = \underset{\beta_\tau \in \mathbb{R}^k}{\arg\min} \sum_{t=1}^{T-h} \left(\tau \cdot \mathbb{1}_{(\pi_{t+12} \geq x_t \beta)} \left| \pi_{t+12} - x_t \beta_\tau \right| + (1-\tau) \cdot \mathbb{1}_{(\pi_{t+12} < x_t \beta)} \left| \pi_{t+12} - x_t \beta_\tau \right| \right) \quad (1)$$

where $\mathbb{1}_{(.)}$ denotes the indicator function, taking the value of one if the condition is satisfied. As shown by Koenker and Bassett (1978), the predicted value from that regression

$$\hat{\mathcal{Q}}_\tau \left(\pi_{t+12} \mid x_t \right) = x_t \hat{\beta}_\tau, \quad (2)$$

is a consistent linear estimator of the quantile function of π_{t+12} conditional on x_t, where $\tau \in (0,1)$ is the quantile of interest, x_t is a $1 \times k$-dimensional vector of conditioning (risk) variables, and $\hat{\beta}_\tau$ is a $k \times 1$-dimensional vector of quantile-specific coefficients.

To discipline how to model the conditional inflation quantiles, I follow a theory-based approach as López-Salido and Loria (2024) and modify an open-economy version of a New Keynesian Phillips Curve:

$$\hat{\mathcal{Q}}_\tau \left(\pi_{t+12} \mid x_t \right) = \hat{\mu}_\tau + (1-\hat{\lambda}_\tau)\pi_t + \hat{\lambda}_\tau \pi^E_{t+12} + \hat{\theta}_\tau \hat{x}_t + \hat{\phi}_\tau \Delta e_t + \hat{\alpha_\tau} \pi^F_t + \hat{\delta}_\tau f_t + \hat{\gamma}_\tau \pi^O_t + \hat{\psi}_\tau s_t \quad (3)$$

where the risk factors shaping the predictive inflation distribution are chosen as follows.

Regarding the first three risk factors, π_t, π^E_{t+12} and $\hat{x}_t$ respectively represent the current annual inflation rate; professional forecasters' inflation expectations over the next 12 months and a measure of domestic demand pressures. Including current inflation aims to capture the role of inflation persistence in price-setting mechanisms. From a theoretical stance, lagged inflation can arise in models with adaptive expectations, staggered contracts or price stickiness, indexation to past inflation, or by a simple rule of thumb from informationally constrained agents. To incorporate an informed gauge of inflation risk, I introduce the one-year ahead inflation forecast of professional economists at time t and impose a homogeneity constraint for the coefficients of the previous two variables to add up to one.[7] If $\hat{\lambda_\tau} = 1$, the model would be centered around professional forecasters' median expected inflation, in a spirit close to Adams et al. (2021).[8] For a measure of demand pressures, I proceed by demeaning the quarter-over-quarter growth rate of the rolling 3mma monthly economic activity index. Then,

[6] The model periodicity is monthly, thus, future inflation represents the year-over-year growth rate.

[7] In particular, I impose $(1-\lambda_\tau) + \lambda_\tau = 1, 0 \leq (1-\lambda_\tau) \leq 1$ and $0 \leq \lambda_\tau \leq 1$ and implement them using the inequality constrained quantile regression method by Koenker and Ng (2005).

[8] In fact, notice that if $\hat{\mu_\tau} = 0$ and $\hat{\lambda_\tau} = 1$, professional economists' forecasts will be passed one-to-one to predicted inflation across quantiles, centering risk around their expectation.

a positive value implies that the economy has grown quarter-over-quarter above its historical average, on a rolling monthly basis.[9]

The next two risk factors, Δe_t and π_t^F, represent nominal exchange rate depreciation and a measure of foreign inflation, respectively. Exchange rate pass-through (ERPT) to inflation is particularly relevant in Mexico, given its high trade openness and reliance on imported goods. Although several studies indicate that ERPT in Mexico is relatively small and has decreased since the formal adoption of the inflation targeting regime, evidence suggests an asymmetric effect on the conditional mean, particularly when the economy is growing above potential, as well as variations in the sign and magnitude of the effect (Jaramillo et al. (2019); Angeles et al. (2019); Kochen and Sámano (2016); Capistrán et al. (2012)). In equation (3), I capture ERPT effects on the inflation distribution by examining the cross-quantile variation in the parameters $\hat{\phi}_\tau$. On the other hand, foreign inflation is included since it influences the price of imported intermediate and final goods, shaping domestic inflation dynamics.[10]

The next factor, f_t, represents a measure of financial conditions. Studies such as Christiano et al. (2015) and Gilchrist et al. (2017) argue that financial frictions and the working capital channel were crucial to understanding why U.S. inflation did not decline sharply alongside GDP during the Great Recession. In a quantile regression framework using credit spreads as a measure of financial stress, López-Salido and Loria (2024) found that higher credit spreads are associated with increased downside risks for inflation in the U.S. and Europe, not only widening the inflation distribution but also skewing it to the left. Although financial conditions are less meaningful in Mexico due to high informality rates and low financial deepening, Alberola and Urrutia (2020) find that inflation tends to rise following an exogenous tightening of credit spreads. I include the country risk premium as a proxy for financial conditions to capture this potential influence on inflation risk.

Finally, the last two risk factors, π_t^O and s_t, account for oil price inflation and global supply chain disruptions, respectively. Oil prices play a significant role in inflation dynamics in Mexico due to the country's dependence on energy products, its position as both an oil producer and importer of refined oil products, and the impact of global oil price fluctuations on exchange rates. Oil price changes directly influence the cost of gasoline, diesel, and fuels, which significantly weights CPI inflation. Further, there has been historically a tight link between oil prices and the exchange rate in Mexico, given its role in public finances André et al. (2023). Thus, oil price swings have an indirect effect through the nominal exchange rate,

[9]By differencing monthly GDP, this approach implicitly assumes a stochastic trend with at least one unit root, uncorrelated with the cyclical component. This method is chosen over HP filtering to address well-documented limitations, such as real-time data inaccuracies Orphanides and Van Norden (2002), failure to capture structural breaks, and the introduction of spurious dynamics Hamilton (2018).

[10]The United States is by far Mexico's largest trading partner, with a substantial share of Mexico's imports originating from the U.S. To put it in perspective, as of August 2024, over the last 10 years, 45% of Mexico's total imports come from the United States. Consequently, I consider both the bilateral nominal exchange rate between the Mexican peso and the US dollar, as well as the U.S. inflation rate, in the analysis.

the country's risk premium, and inflation expectations.[11] Global supply chain disruptions can be particularly relevant for countries like Mexico, which are deeply integrated into global value chains. As a major exporter of manufactured goods, Mexico relies heavily on a consistent flow of intermediate inputs from international suppliers. Consequently, disruptions—whether from trade restrictions, logistical bottlenecks, or production delays—can significantly affect its industrial output. For the case of Europe, Ascari et al. (2024) found that augmenting a Phillips curve with the Global Supply Chain Pressure Index (GSCPI) by Benigno et al. (2022) improves inflation modeling and yields a higher estimate of the Phillips curve slope. I analyze the impact of global supply chain disruptions on Mexico's inflation at risk through the cross-quantile coefficient $\hat{\psi}_\tau$ in equation (3).

2.1 Inflation-at-Risk: Evidence from Mexico

To analyze how these risk factors shape Inflation-at-Risk for Mexico, I estimate the quantile regression (3) for headline inflation using monthly data from December 2001 to June 2024. This period begins with Mexico's formal adoption of the inflation-targeting regime.[12]

In terms of data, both π_t and π_{t+12} represent realized headline inflation at month t and one year ahead, respectively, with the latter serving as the dependent variable. π^E_{t+12} indicates the one-year-ahead median inflation expectation of professional forecasters,[13] while $\hat{x}_t$ represents the demeaned quarter-over-quarter growth rate of the 3-month rolling IGAE. Δe_t denotes the year-over-year depreciation of the nominal exchange rate, π^F_t is the US CPI inflation rate, and f_t represents the normalized Emerging Markets Bond Index Global (EMBIG) for Mexico by JP Morgan,[14] π^O_t is the annual inflation rate of WTI oil prices, and s_t represents the Global Supply Chain Pressure Index (GSCPI) by the New York Fed, as previously described. Additional details on the data can be found in Appendix A.

Figure 1 presents the estimated quantile regression (QR) coefficients for headline inflation, accompanied by 90% confidence bands generated using the "blocks-of-blocks" bootstrap method from Politis and Romano (1994). Notice that inflation expectations are a crucial determinant of inflation risk, exhibiting an almost one-to-one transmission effect across the predictive distribution. Specifically, a one percentage point increase in median inflation ex-

[11] Even though fuel prices have been regulated and subsidized in Mexico for some periods, the indirect effects may still be present. The higher the fuel subsidies, the higher the vulnerability to public finances, increasing the importance of indirect effects.

[12] The sample is limited to this period to focus on a single monetary regime. Notably, Chiquiar et al. (2008) found that inflation dynamics became more stationary following the adoption of inflation targeting in 2001, and Gaytan and Gonzalez-García (2006) provide evidence of a structural change in the monetary transmission mechanism after this period.

[13] This survey is conducted by the Central Bank of Mexico every month.

[14] The EMBIG Mexico, developed by J.P. Morgan, measures the risk premium associated with Mexican sovereign debt. It reflects the yield differential between Mexican government bonds denominated in US dollars and US Treasury bonds.

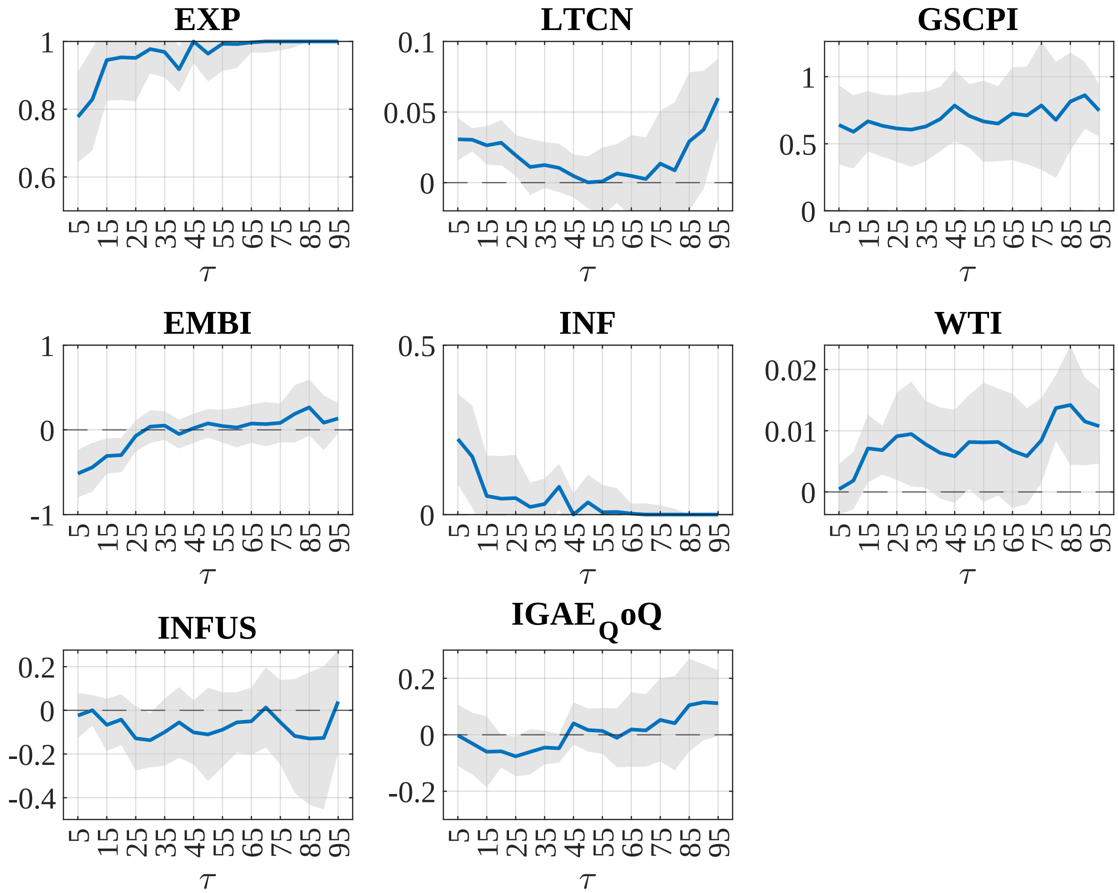


Figure 1: Quantile regression for headline inflation. Estimated coefficients and 90% confidence intervals were obtained via Politis and Romano (1994) "blocks-of-blocks" bootstrap procedure.

pectations results in an 80 basis point rise in the predicted 5th percentile of inflation, with the impact growing across higher quantiles. This indicates that higher inflation expectations shift the entire inflation distribution to the right and introduce greater right skewness. From a policy perspective, these findings highlight the importance of anchoring inflation expectations. An increase in median inflation expectations is associated not only with a higher conditional mean inflation but also with an increased likelihood of extremely high inflation outcomes.

The depreciation of the nominal exchange rate has a clear asymmetric effect on the predictive inflation distribution. A 1pp depreciation raises the predicted 5th percentile by 0.04pp. Interestingly, the effect vanishes as we move towards the median, but then it increases in a convex way, having an effect of 0.06pp on the 95th percentile. That is, leaving the median unchanged, a nominal exchange rate depreciation shrinks the $\mathcal{Q}_{50-10}$ interquantile range but expands the corresponding $\mathcal{Q}_{90-50}$ range.

In terms of magnitudes, my results are in line with previous studies that have documented an ERPT on the conditional mean between 0.02-0.05pp Angeles et al. (2019) but shed light on the underlying probability distribution.

As to financial conditions, an increase in credit spreads results in higher downside risks, not only widening the entire distribution but also becoming more left-skewed. A one-standard-deviation increase in credit spreads decreases the predicted inflation 5th percentile by 50 basis points, with this relationship weakening as we move across higher quantiles. For instance, although not statistically significant at the 90% confidence level, tighter financial conditions are associated with increases of 8 and 13 basis points in the predicted 50th and 95th percentiles, respectively. These findings suggest that tighter financial conditions are predominantly linked to modest increases in inflation—potentially through a working capital channel—while also carrying the possibility of significantly reducing inflation, likely via a weak demand channel.[15]

The effect of economic activity on inflation is asymmetric along the conditional distribution, having a negative slope for all percentiles below the 45th and a positive effect afterward. This implies that an expansion of economic activity above mean spreads out the predictive inflation distribution. Notice that the positive effect dominates along the distribution, implying an effect on the conditional mean of 0.0073pp. Interestingly, this number lies close to the 0.0077-0.0094 estimates by Ramos-Francia and Torres (2006), one of the few studies examining the slope of the NKPC for Mexico.

Oil price inflation has a positive but asymmetric effect on the inflation distribution, pushing up the upper tail nearly twice as much as the lower tail, thereby increasing upside risks. In contrast, after accounting for the risk factors in equation (3), foreign inflation does not have a significant impact across the predicted inflation distribution. Although not statistically significant, the effect of foreign inflation remains consistently negative across quantiles. This could be explained by the possibility that foreign demand shocks lead to higher domestic output, while foreign supply shocks are captured separately through the GSCPI, washing out the predictive power of foreign inflation.[16]

The impact of global supply chain pressures on the predictive inflation distribution is both significant and increasing across quantiles. A one-standard-deviation increase in the

[15] These findings are consistent with López-Salido and Loria (2024), which showed that credit spreads are associated with an increase in downside risks to inflation for the 10th quantile but with a positive relationship for the 90th quantile using simulated data from a nonlinear DSGE model. The model features two equilibria, one with and one without a financial panic. In normal times when shocks are small, a capital quality shock reduces capital, increasing the rental rate of capital and marginal costs. In contrast, bad times can trigger a financial panic, ultimately dropping economic activity and pushing down inflation.

[16] In fact, if the correlation between foreign inflation and global supply chain pressures is positive, by excluding the GSCPI from the quantile regression (3), we would expect a higher effect coming from foreign inflation. In Appendix D, I estimate the quantile regression excluding it and show that, in fact, the effect of foreign inflation turns positive for almost all quantiles. I further discuss the relevance of including the GSCPI to better identify the slope of the Phillips curve.

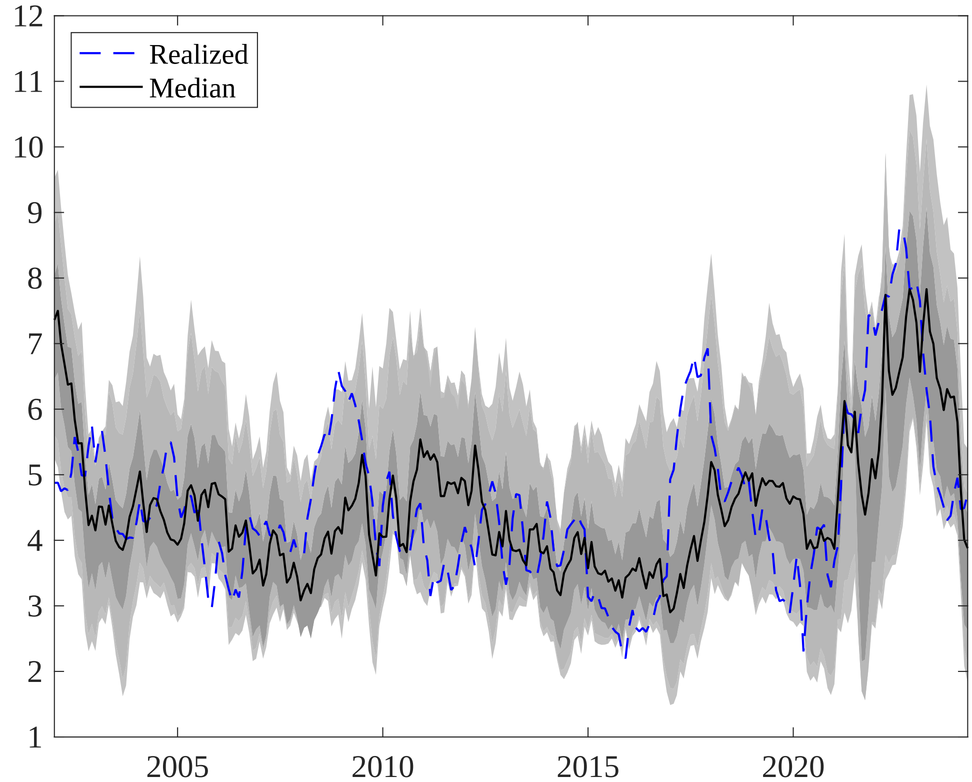


Figure 2: One year ahead inflation predicted percentiles and realized headline inflation.

GSCPI raises the predicted 5th, 50th, and 95th inflation quantiles by 60, 71, and 75 basis points, respectively. This indicates that periods of stress in global supply chains lead to an upward shift in inflation risk, with the upper tail of the distribution spreading more noticeably. Interestingly, aside from the effects of global supply chain disruptions and inflation expectations, other variables have little to no influence on the conditional median inflation. Consequently, in the absence of supply chain disruptions, the median predicted inflation would align with the professional forecasters' median expectations.

Figure 2 illustrates the time series evolution of the predicted distribution for one-year-ahead inflation. Notably, the quantile Phillips curve from Equation 3 performs well in capturing inflation risks in probabilistic terms. Even during highly challenging episodes—such as the Great Recession of 2007-2008, the liberalization of fuel prices in Mexico in 2017, and the pandemic—the predictive distribution consistently assigns a positive probability to nearly all observed inflation outcomes in the sample.

3 Global Supply Chain Disruptions

In this section, I examine the role of global supply disruptions in shaping inflation risk during periods of remarkable stress. Understanding these disruptions is essential for designing effective monetary policy, as they act as cost-push shocks that exacerbate the trade-off between stabilizing inflation and output. Their global nature further complicates monetary policy, reducing its effectiveness in mitigating inflation pressures in an environment of stressed supply chains Hernández et al. (2024). This dynamic ultimately raises the sacrifice ratio, increasing the economic costs of controlling inflation.

Given these challenges, the ability to forecast inflation accurately and communicate inflation risks effectively becomes critical. For central banks operating under an inflation-targeting regime, transparent communication plays a central role in anchoring expectations and sustaining credibility. By clearly outlining the implications of supply chain disruptions and the reasoning behind policy decisions, central banks can strengthen their commitment to inflation targets. This approach not only mitigates uncertainty but also reassures the public and markets during periods of heightened volatility.

In the following analysis, I address the question: *How would the assessment of inflation risk have differed if global supply chain disruptions were not incorporated?* To explore this, I compare the predictive inflation densities derived from the quantile Phillips curve (3), excluding the Global Supply Chain Pressure Index.

However, as noted by Adrian et al. (2019), while the quantile regression provides approximate estimates of the quantile function, these are difficult to map into a probability distribution function because of approximation error and estimation noise. Thus, to recover the probability density function, I follow them fitting the *skewed t-distribution* developed by Azzalini and Capitanio (2003) to smooth the quantile function:

$$f(y;\mu,\sigma,\alpha,\nu)=\frac{2}{\sigma}t\left(\frac{y-\mu}{\sigma};\nu\right)T\left(\alpha\frac{y-\mu}{\sigma}\sqrt{\frac{\nu+1}{\nu+\frac{y-\mu}{\sigma}}};\nu+1\right) \tag{4}$$

where $t(\cdot)$ and $T(\cdot)$ denote, respectively, the PDF and the CDF of the Student t-distribution.[17] The four parameters of the distribution pin down the location μ, scale σ, fatness ν, and shape α. For each month, I choose the four parameters to minimize the squared distance between the estimated quantile function $\hat{\mathcal{Q}}_\tau$ (eq. 3) and the quantile function of the *skewed t-distribution* $F^{-1}\left(\tau;\mu_t,\sigma_t,\alpha_t,\nu_t\right)$ to match the 5, 25, 75 and 95 percentiles:

$$\{\hat{\mu}_{t+h},\hat{\sigma}_{t+h},\hat{\alpha}_{t+h},\hat{\nu}_{t+h}\}=\underset{\mu,\sigma,\alpha,\nu}{\operatorname{argmin}}\sum_{\tau}\left(\hat{\mathcal{Q}}_\tau\left(\pi_{t+12}\mid x_t\right)-F^{-1}(\tau;\mu,\sigma,\alpha,\nu)\right)^2 \tag{5}$$

where $\hat{\mu}_{t+h}\in\mathbb{R}$, $\hat{\sigma}_{t+h}\in\mathbb{R}^+$, $\hat{\alpha}_{t+h}\in\mathbb{R}$, and $\hat{\nu}_{t+h}\in\mathbb{Z}^+$. This could be interpreted as an exactly identified nonlinear cross-sectional regression of the predicted quantiles on the quantiles of the *skewed t-distribution*.

[17] For more details, see Adrian et al. (2019).

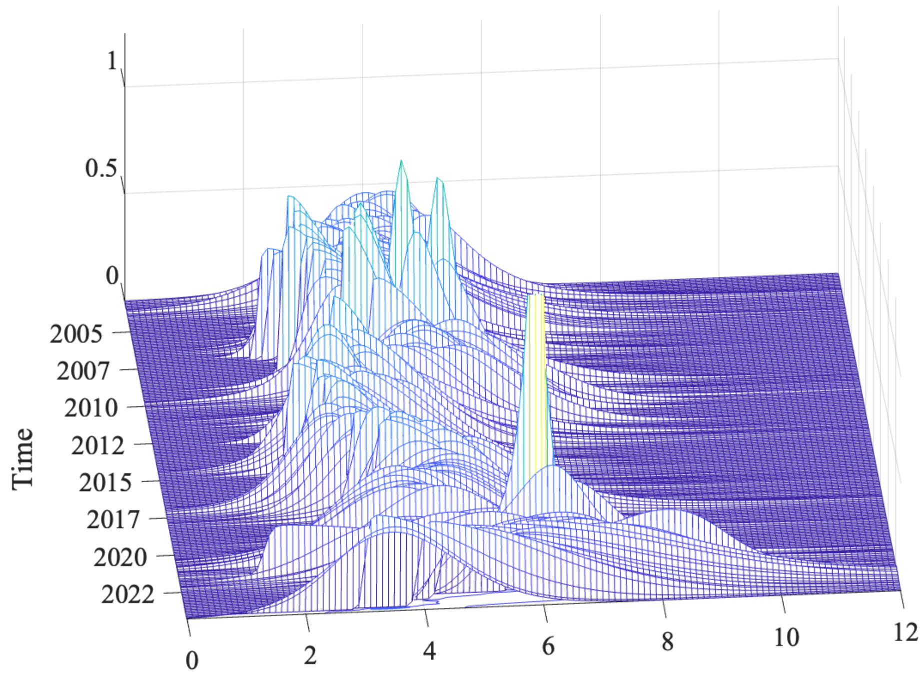


Figure 3: One-year-ahead predictive distribution of headline inflation, based on the quantile Phillips Curve.

Figure 3 illustrates the evolution of the smoothed predicted inflation density over time, revealing several noteworthy features. First, the one-year-ahead predicted inflation density is centered around 4.5%. This is not only above the 3% inflation target but also outside the central bank's permissible 2–4% variability band, typically allowed for supply-side factors beyond monetary control.[18] In fact, hitting the inflation target appears more like a downside risk than a baseline scenario. Second, in line with the opening quote, the COVID-19 period was indeed characterized by an unusually elevated inflation risk, in which the variance of predicted inflation reached its largest value. Finally, notice that there is a pattern suggesting that the inflation density skews to the right before shifting leftwards. This could inspire further research into the time-varying properties of the inflation distribution, as highlighted by Reis (2022).

To further explore the role of global supply chain disruptions shaping inflation risk, figure 4 presents the predicted densities (left column) and cumulative distribution functions (right column) by the quantile Phillips curve (3), with and without the inclusion of the GSCPI. Each row focuses on a key episode characterized by significant stress in global supply chains: the China–U.S. trade disputes in 2017, the onset of COVID-related lockdowns in China, and the start of the Ukraine-Russia armed conflict.

[18] See Banxico's Monetary Policy Programs.

In each plot, the solid blue line represents the smoothed estimates from the quantile Phillips curve that includes the GSCPI, while the orange dashed line corresponds to estimates excluding it. These lines' differences highlight the bias introduced across the conditional distribution when global supply chain disruptions are omitted from equation 3. Additionally, the plots include realized inflation (black line) and the professional forecasters' median expectation (dash-dotted blue line) for reference.

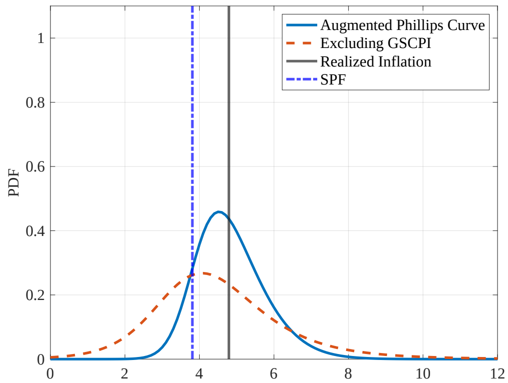
First and foremost, the GSCPI provides additional information that has important implications for inflation risks. These span from rescaling the predicted inflation distribution to modifying its variance and central location measures. For instance, the first row of Figure 4 displays the predicted inflation probability density function (PDF) and cumulative distribution function (CDF) for November 2017, a month marked by the peak of the GSCPI amid the China-US trade disputes. Notice that by including the GSCPI in our main quantile regression, the predicted inflation distribution not only shifts upwards but also exhibits reduced variance. This indicates that the one-year-ahead inflation risks are more tightly concentrated around a higher level. Notably, the quantile-augmented Phillips curve achieves a peak density closer to realized inflation, thereby enhancing its median (and mean) forecast accuracy.

The second row of the figure (4) focuses on April 2020, the month when China implemented its major lockdown policy. Incorporating the GSCPI into the analysis reveals a markedly different scenario. The predicted inflation distribution shifts upward, skews to the left, and exhibits greater variance, reflecting a significantly more uncertain environment with risks tilted to the upside. Notably, the CDF shows that the quantile-augmented Phillips curve assigns a higher probability to the realization of observed inflation.

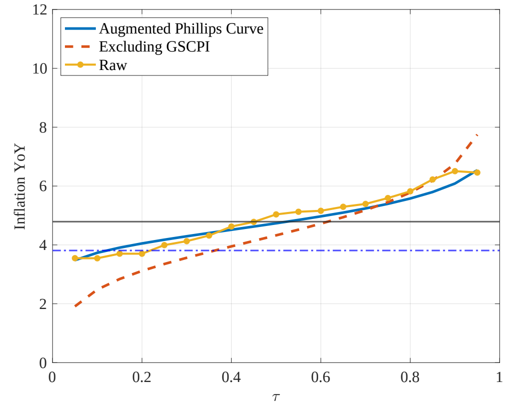
The last row of Figure 4 highlights April 2022, during the peak escalation of the armed conflict between Russia and Ukraine. The implications are critical from a policymaking perspective. The distribution of inflation risks shifts upward, exhibiting a pronounced positive skew. Compared to the dotted orange line, the predicted distribution assigns an almost negligible probability to inflation rates below 5.75% and a relative fat right-tail, showing how upside risks mounted in this period.

As illustrated across all panels, it is worth mentioning that professional forecasters' errors were sizable during these episodes. To what extent forecast errors were driven by not internalizing the disruptions on global value chains promptly is out of the scope of this paper since it requires performing a dynamic out-of-sample forecast; granted, Figure (4) provides preliminary evidence on this front.

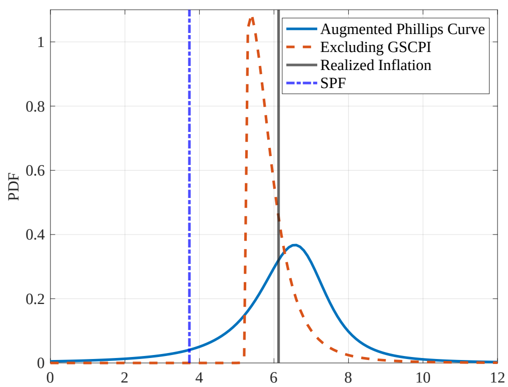
These findings highlight the key role of global supply chains in influencing inflation dynamics. During periods of significant supply chain disruptions, such as trade disputes, incorporating global supply factors provides a more accurate and comprehensive picture of the conditional inflation distribution. As the global economy becomes increasingly fragmented and protectionist, these factors are likely to gain more relevance in shaping inflation trends.



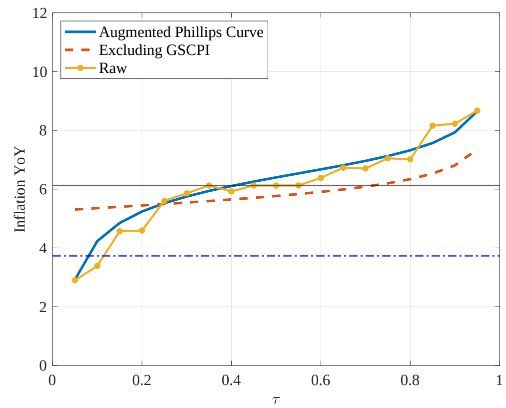
(a) Predicted Density: November 2017.



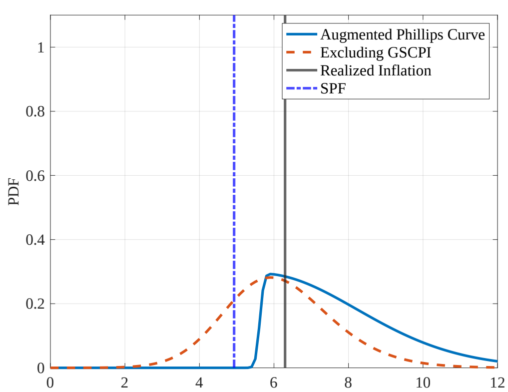
(b) Predicted CDF: November 2017.



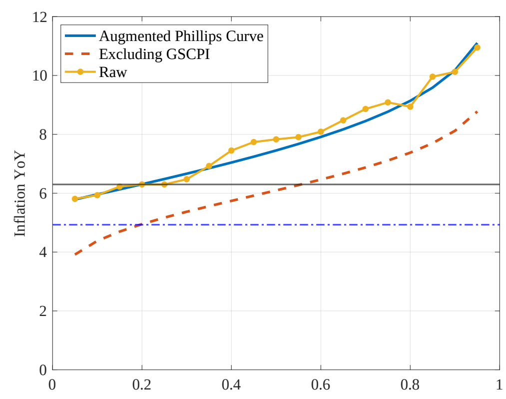
(c) Predicted Density: April 2020.



(d) Predicted CDF: April 2020.



(e) Predicted Density: April 2022.



(f) Predicted CDF: April 2022.

Figure 4: Predicted densities and cumulative distribution function for selected periods.

4 Inflation Risk Management

In this section, I shift the focus from characterizing inflation-at-risk to asking if the central bank can mitigate tail risks through monetary policy shocks. In particular, I follow the two-step approach proposed by Loria et al. (2024). Since the fitted quantiles from section (3) characterize the inflation conditional distribution, I estimate the responses of the predicted 10th, 50th, and 90th percentiles to a monetary policy shock using Jordà (2005) local projections. That is, for each predicted percentile $\hat{\mathcal{Q}}_\tau$, I estimate the following linear model:

$$\hat{\mathcal{Q}}_{\tau,t+s} = \delta^s_\tau + \sum_{\ell=1}^{p} \gamma^s_{\tau,\ell} \hat{\mathcal{Q}}_{\tau,t-\ell} + \theta^s_\tau \,\text{shock}_t + \Psi^s_\tau(L)\,\text{controls}_t + u^s_{\tau,t+s}, \quad s = 0, \ldots, S \tag{6}$$

where shock_t is a proxy measure of the aggregate shock, $\Psi(L)^s_\tau \text{controls}_t$ is a lag polynomial of order p with control variables including the lagged percentiles and other relevant factors. Further, to deal with very persistent endogenous variables, I use lag augmentation which provides a robust inference approach as pointed out by Montiel-Olea and Plagborg-Møller (2021). Notice that in equation (6), s is the horizon of the local projection. Therefore, the estimated coefficient vector $\hat{\theta}^s_\tau = (\hat{\theta}^0_\tau, \hat{\theta}^1_\tau, \hat{\theta}^2_\tau, ..., \hat{\theta}^S_\tau)$ will trace out the dynamic effect of the aggregate shock on the predicted conditional percentiles.[19] The proxy for the monetary policy shock is the surprise in the 3-month TIIE28D swap rate around a 30-minute window of the monetary policy announcements by Solís (2023).[20]

Identifying the dynamic causal effect of a monetary policy shock in equation (6) requires that the proxy (shock_t): *i)* is correlated with the true monetary policy shock (relevance); *ii)* is contemporaneously uncorrelated with other structural shocks (contemporaneous exogeneity); and *iii)* remains uncorrelated with all structural shocks at any lead or lag (lead-lag exogeneity).

By construction, the high-frequency market-based surprise is likely to meet conditions *i)* since it captures immediate market reactions directly linked to the unexpected policy announcement, ensuring a strong correlation with the true shock, and *ii)*, as it isolates the shock's impact within a narrow time window, minimizing the systematic influence of other structural shocks.

Regarding the lead-lag exogeneity condition, Stock and Watson (2018) argue that the requirement for the instrument to be uncorrelated with future ε's is generally not restrictive when the instrument only includes variables realized at or before date t, as this follows from defining shocks as unanticipated structural disturbances. However, the requirement to be uncorrelated with past ε's is both restrictive and challenging.

[19] I follow the bootstrap procedure of Loria et al. (2024) to create the confidence bands of the impulse-response functions, which controls for serial correlation in the error terms and the estimation error in the quantiles. More details can be found in Appendix B.

[20] The 3-month TIIE28D swap rate is the most liquid swap in the Mexican market and serves as the primary local derivative. See Appendix C for more details.

For example, Miranda-Agrippino and Ricco (2021) and Jarociński and Karadi (2020) emphasize that commonly used high-frequency instruments for monetary policy shocks likely mix the true policy shock with information about the state of the economy revealed through the policy action itself. If this occurs, where information asymmetries exist between policymakers and market participants, market-based monetary policy surprises would exhibit serial correlation, be predictable using other macroeconomic variables, and correlate with the central bank's private information set.

If market-based surprises are predictable by other macroeconomic variables or exhibit serial correlation, it follows directly from their Wold representation that omitting them from equation (6) would violate condition *iii)*. This motivates the following specification:

$$\hat{\mathcal{Q}}_{\tau,t+s} = \delta_\tau^s + \sum_{\ell=1}^{p} \gamma_{\tau,\ell}^s \hat{\mathcal{Q}}_{\tau,t-\ell} + \theta_\tau^s \, \mathrm{shock}_t + \Psi_\tau^s(L) \, [\mathrm{mex}_t, \mathrm{us}_t, \mathrm{g}_t]' + u_{\tau,t+s}^s, \quad s = 0, \ldots, S \tag{7}$$

where I control for an ample set of macroeconomic variables, $\mathrm{controls}_t = [\mathrm{mex}_t, \mathrm{us}_t, \mathrm{g}_t]'$ represented by the blocks mex_t, us_t, and g_t. These blocks are based on theory, resembling the specification of *state-of-the-art* two-country VAR models with block-exogeneity assumptions, used in the literature of small-open economies (see Canova (2005); Carrillo et al. (2020); Alba et al. (2024)). Specifically, this approach assumes that the U.S. economy is block-exogenous to the Mexican economy.[21]

The us_t vector incorporates key information from traditional models that estimate U.S. monetary policy shocks using a structural VAR approach.[22] This vector includes variables such as industrial production, the unemployment rate, the consumer price index, the excess bond premium (EBP) from Gilchrist and Zakrajšek (2012), and the Wu and Xia (2016) shadow rate. To allow flexibility in the number of possible lags for these controls, I use the first two principal components of the us_t vector as a data-reduction technique.

The mex_t vector includes Mexico-specific variables: the nominal interest rate, CPI inflation, the country risk premium, the monthly economic activity index, the nominal exchange rate depreciation, and the lagged value of the proxy for the monetary policy shock. Finally, the g_t vector gathers information about the state of global supply, such as the NYFED Global Supply Chain Pressure Index (GSCPI) and the annual change in oil prices.[23]

This specification is estimated using data from January 2011 to June 2024, which aligns with the monetary policy shock sample period.[24] I control for twelve lags of the endogenous variable and six lags for the control variables. The upper panel of Figure (5) shows the main

[21] Carrillo et al. (2020) provide evidence supporting this assumption, as Mexican variables do not Granger-cause U.S. variables.

[22] See Coibion (2012) and Gertler and Karadi (2015).

[23] An alternative approach would be to include the g_t vector as part of the us_t control vector, allowing the data-reduction technique to be applied to this set as well. The results remain robust under this approach.

[24] The Local Projections with External Instruments (LP-IV) were estimated using the Empirical Macro Toolbox by Canova and Ferroni (2021).

results of the local projections. In particular, it shows the estimated impulse-response functions of the one-year-ahead predicted inflation 10th, 50th, and 90th percentiles to a normalized 25 basis points hike monetary policy shock in Mexico.

Focusing on the dynamics of the one-year-ahead predicted 90th percentile (red line), notice that it falls both at impact and over time, having a maximum effect of almost 60 basis points around four months after the shock. This effect is both relevant and statistically significant. That is, monetary policy can curve high inflation risk.

Before moving to the responses of the one-year ahead predicted median and 10th percentiles, it is worth clarifying how these estimated impulse responses read. These give us the response of the monetary policy shock on the level of the predicted quantiles. Suppose the one-year-ahead inflation 90th predicted percentile is at 9%, the median at 6%, and the 10th percentile at 4%. According to the previously explained dynamic on the 90th percentile, this implies the shock moves high inflation risk from 9% to around 8.4% after four months of the shock. Therefore, we can have scenarios in which the impulse responses of the quantiles cross, but by construction, the quantiles themselves cannot cross as we directly model changes in the entire distribution.[25]

Focusing on the blue line in Figure 5, which represents the one-year-ahead median predicted inflation response, we observe a slight increase upon impact, followed by a decline around the third month. The 25 basis point contractionary monetary policy shock has its largest negative effect on the predicted median, approximately 30 basis points, around the third and fourth months.

Finally, the grey line in Figure 5 represents the impulse response function of the predicted 10th percentile, which captures downside inflation risks. Although it initially falls by the same magnitude as the 90th percentile (red line), its response over time is muted, declining by only about 15 basis points from months three to seven. This indicates that the effect of a contractionary monetary policy shock on downside inflation risks is nearly four times smaller than its effect on upside risks.

There are two main takeaways: *i)* Although short-lived, monetary policy shocks can reduce inflation risks, as the predicted 10th, median, and 90th percentiles all decline following an unexpected monetary tightening. That is, the policy shock shifts left the one-year-ahead predictive inflation distribution. *ii)* The response to the monetary policy shock is clearly asymmetric, with monetary policy having a greater capacity to curb upside inflation risk than downside risk.

However, the impact of the monetary policy shock on the skewness of the predicted distribution is not immediately clear. For example, the confidence bands for the one-year-ahead median predicted inflation response overlap with those of the 10th and 90th percentiles. This suggests that analyzing individual percentiles in isolation may be misleading, as it overlooks

[25] Loria et al. (2024) provide a graphical analysis to better understand this approach.

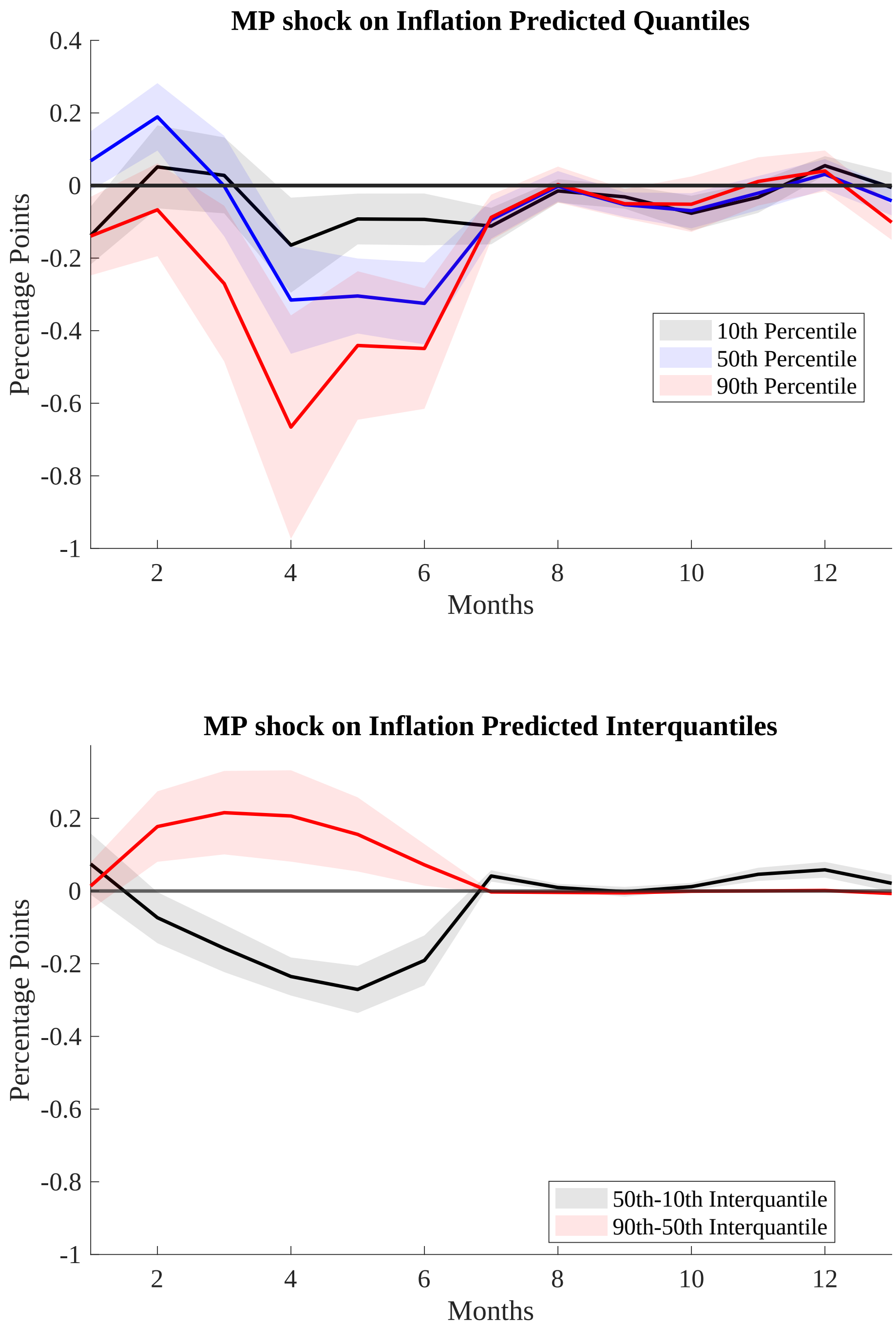


Figure 5: Impulse Responses of Quantiles and Interquantile Ranges of the one-year-ahead inflation predictive distribution. 90% confidence bands.

the correlation between responses across different quantiles.

By instead examining interquantile ranges as single statistical objects, we account for the fact that these quantiles are generated from a common data process, providing deeper insights into potential shifts in skewness. Thus, I study the dynamics of the joint behavior with the following specifications:

$$\hat{\mathcal{Q}}_{\tau_1-\tau_2,t+s} = \delta^s_\tau + \sum_{\ell=1}^{p} \gamma^s_{\tau,\ell} \hat{\mathcal{Q}}_{\tau_1-\tau_2,t-\ell} + \theta^s_\tau \, \text{shock}_t + \Psi^s_\tau(L) \, [\text{mex}_t, \text{us}_t, \text{g}_t]' + u^s_{\tau,t+s}, \tag{8}$$

where $\hat{\mathcal{Q}}_{\tau_1-\tau_2,t+s} = \hat{\mathcal{Q}}_{\tau_1,t+s} - \hat{\mathcal{Q}}_{\tau_2,t+s}$ is the difference between any two given quartiles. The lower panel of Figure 5 shows the impulse-response functions of both the $\mathcal{Q}_{90-50}$ and $\mathcal{Q}_{50-10}$ interquantile ranges. Interestingly, when considered as single statistical objects, the $\mathcal{Q}_{50-10}$ interquantile shrinks while the $\mathcal{Q}_{90-50}$ range expands after the policy shock. To sum up, my results imply that after an unexpected policy tightening, the predicted inflation distribution moves to the left and has more right skew than before the shock until eventually converging towards the initial distribution.

4.1 Inflation Risk Management: An Application

To illustrate the previous findings, this section presents an application of how policymakers can use this framework for inflation risk management. Suppose we were the central bankers in September 2021 and were interested in forecasting inflation risk one year ahead. Using our estimated quantile Phillips curve, the black line in Figure (6) shows the predicted inflation distribution for September 2022, conditional on the September 2021 information set.

The question of interest is, *how would a 25-basis-point monetary policy shock have affected the predicted inflation distribution?* Using specification (7), I estimate the dynamic effect for a monetary policy shock on the 10th, 25th, 50th, 75th and 90th predicted percentiles. Since the quantile regression approximates an inverse cumulative distribution function, I fit a skewed *t-distribution* for each period to smooth the quantile function and recover a probability density function as suggested by Adrian et al. (2019).

The gray line in Figure (6) represents the predicted inflation distribution four months after a 25-basis-point monetary policy shock, which corresponds to the time when the impulse-response functions show the highest effect. Compared to the initial distribution (black line), the mode shifts from an expected inflation rate of 7.8% to 7.49%, reflecting a significant decline. Additionally, the distribution compresses to the left, reducing the likelihood of extremely high inflation values—an outcome that is particularly desirable for policymakers. Moreover, consistent with our earlier findings, the interquantile range $\mathcal{Q}_{50-10}$ narrows, indicating reduced uncertainty in the lower half of the distribution. However, the $\mathcal{Q}_{90-50}$ range expands, introducing a somewhat adverse trade-off by increasing uncertainty in the upper half of the distribution.

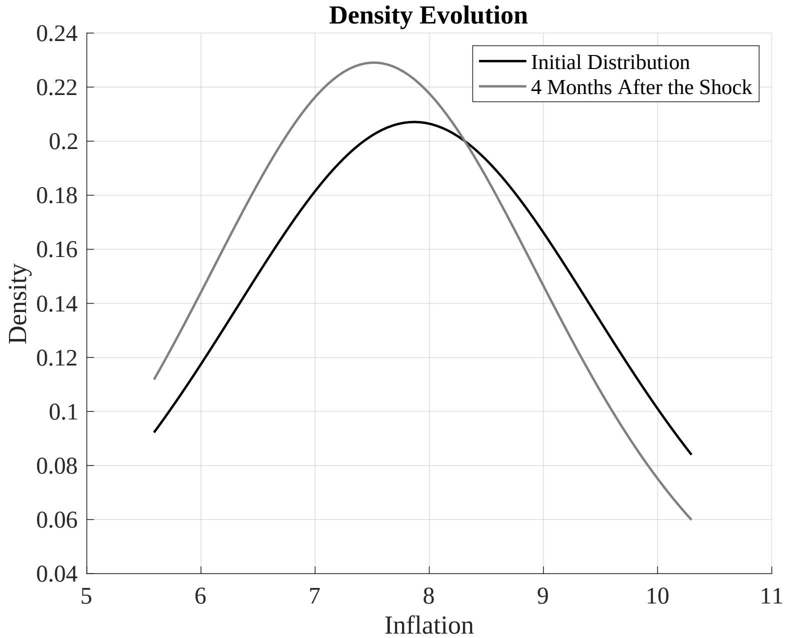


Figure 6: Effect of a 25bp monetary policy shock on the one-year-ahead predicted distribution.

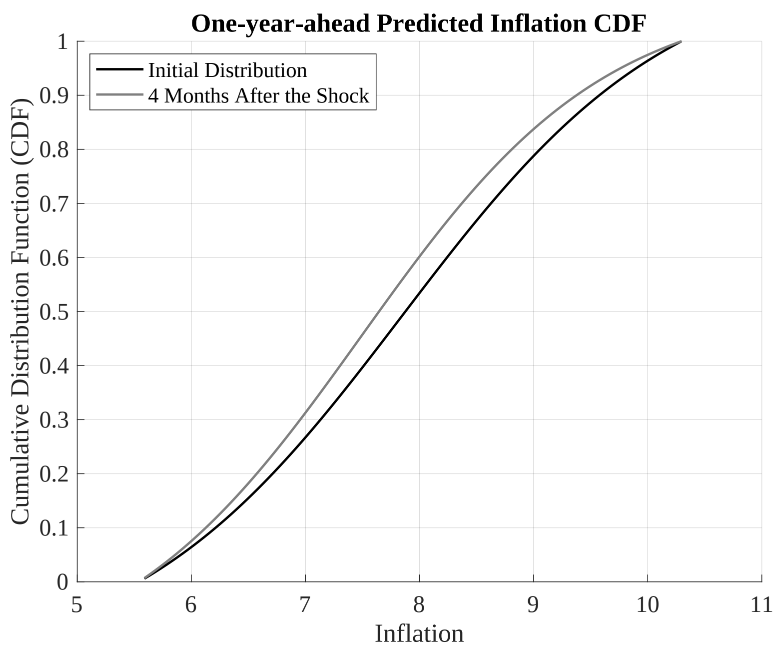


Figure 7: Effect of a 25bp monetary policy shock on the cumulative density function.

To provide an alternative perspective, Figure (7) presents the corresponding cumulative density functions (CDFs). The monetary policy shock shifts the CDF to the left, indicating that, for any given cumulative probability, the resulting *"shocked"* distribution predicts a lower inflation rate. Notably, the differences are more pronounced in the upper tail of the distribution, underscoring the asymmetric impact of the policy shock. These findings highlight the potential for policymakers to address tail risks, even when these risks are largely driven by external factors, such as global supply chain disruptions observed during the pandemic inflation peak.

5 Conclusion

As the opening quote highlights, managing tail risks is a critical priority for policymakers. This paper represents a first attempt to understand how key macroeconomic indicators influence inflation risk in Mexico and to assess whether monetary policy shocks can shape its distribution. The findings are particularly relevant, as they emphasize the significant role of external factors—such as oil prices and the state of global value chains—in driving inflation risks, which are often beyond policymakers' control. More importantly, the results highlight the impact of internal factors, which policymakers can influence to some extent, on the distribution of inflation risks. For instance, the analysis underscores the critical role of anchoring inflation expectations in mitigating tail risks. Most notably, the findings suggest that policymakers have scope for action to reduce tail risks, even when these are driven by external factors such as global supply chain disruptions.

A Data Appendix

This section gives a brief overview of the data used throughout this paper.

A.1 Inflation-at-Risk

- Headline CPI Inflation
  - Source: INEGI.
  - Details: *Índice Nacional de Precios al Consumidor (INPC).*
- Professional Forecasters' Inflation Expectations
  - Source: *Encuesta Sobre las Expectativas de los Especialistas en Economía del Sector Privado.*
  - Details: *Inflación General, Para los Próximos 12 meses (en t), Mediana.*
- Monthly Economic Activity Index
  - Source: INEGI.
  - Details: *Indicador Global de la Actividad Económica, Series desestacionalizadas.*
- Bilateral Nominal Exchange Rate
  - Source: Banxico.
  - Details: *Tipo de cambio Pesos por dólar E.U.A., (FIX) Cotizaciones promedios.*
- Foreign Inflation
  - Source: FRED.
  - Details: Consumer Price Index for All Urban Consumers: All Items in U.S. City Average, Percent Change from Year Ago.
- Financial Conditions
  - Source: *J.P. Morgan - Banco Central de Reserva del Perú.*
  - Details: Normalized Emerging Markets Bond Index Global (EMBIG) for Mexico.
- Oil Price Inflation
  - Source: FRED.
  - Details: Crude Oil Prices: West Texas Intermediate (WTI).
- Global Supply Chain Pressures
  - Source: Federal Reserve Bank of New York.
  - Details: Global Supply Chain Pressures Index (GSCPI).

A.2 Inflation Risk Management

- Industrial Production
  - Source: FRED.
  - Details: Industrial Production: Total Index, Index 2017=100, Monthly, SA.
- Unemployment Rate
  - Source: FRED.
  - Details: Unemployment Rate, Percent, Monthly, Seasonally Adjusted
- Excess Bond Premium (EBP)
  - Source: Board of Governors of the Federal Reserve System.
  - Details: Updating the Recession Risk and the Excess Bond Premium
- Shadow Rate
  - Source: Federal Reserve Bank of Atlanta.
  - Details: Wu-Xia Shadow Federal Funds Rate
- Nominal Interest Rate, Mexico
  - Source: Banxico.
  - Details: *TIIE a 28 días, Tasa de interés promedio mensual, en por ciento anual*

B Bootstrap Procedure Appendix

This section provides a brief overview of the bootstrap procedure used to obtain the confidence bands. The procedure is designed to capture the uncertainty involved both with the quantile regression and with the local projection step, following directly Loria et al. (2024).

Quantile Regression. The initial step in the bootstrap process is to assess the uncertainty around the quantile regression estimates. This is achieved by applying the stationary "blocks-of-blocks" bootstrap method from Politis and Romano (1994), which preserves the time-series dependency in the data that would otherwise be lost with a naive bootstrap. With a total of $K = 100$ bootstrap replications, blocks of data are randomly drawn to form a new sample matching the original data's size. Importantly, these blocks are resampled in the same sequence for both the dependent variable y and the regressors X. This procedure is asymptotically valid for stationary processes if the block size m grows at an appropriate rate as $T \to \infty$. Here, the block size is set to $m = \sqrt[3]{T}$, where T is the sample size. Notably, this bootstrap approach preserves the key feature of quantile regression by remaining agnostic about the error term's underlying distribution, as it does not rely on residuals.

Local Projection Step. To account for the uncertainty around the predicted quantiles from the first stage, a local projection is estimated at each horizon for each resampled dataset of quantiles obtained in the prior step. The local projection coefficient $\hat{\theta}_{\tau,k}$ then captures the impact of the shock on quantile τ at horizon s for each bootstrap replication k. To integrate estimation uncertainty in this second stage, 100 parameter values for the local projection parameters are generated for each k by drawing impulse response coefficients from their asymptotic distribution. This distribution is known and defined as $\theta^s_\tau \sim \mathcal{N}\left(\hat{\theta}^s_{\tau,k}, \hat{\Sigma}^s_{u,k}\right)$, where $\hat{\theta}^s_{\tau,k}$ is the point estimate for bootstrap sample k, and $\hat{\Sigma}^s_{u,k}$ is the estimated variance-covariance matrix of the local projection residuals $u^s_{t+s,k}$ in sample k. The variance-covariance matrix is estimated using the Newey and West (1987) method with a lag order of $s-1$ to account for serial correlation in the error term induced by the successive leading of the dependent variable in the t-step ahead direct forecasting regression.

C High-frequency identified monetary policy surprises

This section explains the methodology followed by Solís (2023) to estimate the high-frequency monetary policy surprises for Mexico used in this paper.

Solís (2023) uses the difference in the 3-month swap rate in a short 30-minute window around monetary policy announcements to identify monetary policy surprises. The window starts 10 minutes before and ends 20 minutes after each announcement. As he stresses, an ideal instrument to measure the market surprises would be an overnight index swap (OIS), but the swap market in Mexico instead references the 28-day interbank interest rate (TIIE28D) - an interbank interest rate denominated in local currency that closely follows the policy rate denominated, being the benchmark rate for banking loans in Mexico.

The 3-month swap, which references the TIIE28D, is the most liquid swap in the Mexican market and serves as the primary local derivative. While Banxico calculates the TIIE28D rate once daily based on quotes from commercial banks, the 3-month swap trades continuously throughout the day, allowing for the measurement of intraday rate changes around key announcement windows. Changes in the 3-month swap rate reflect shifts in expectations for the policy rate around these announcements and can be broken down into expectations of the policy rate itself and a risk premium component. Evidence suggests that the risk premium varies at the business-cycle frequency, impacting medium-term but not short-term horizons. Thus, taking the difference in the 3-month swap rate over a 30-minute window around the announcement effectively cancels out any risk premium effect.

A potential concern is that changes in the 3-month swap rate may capture surprises not only about the current policy rate level but also about its future path, given that the contract may span multiple policy meetings. However, the high correlation (around 0.9) between this market-based measure and an alternative based on the difference between the actual policy

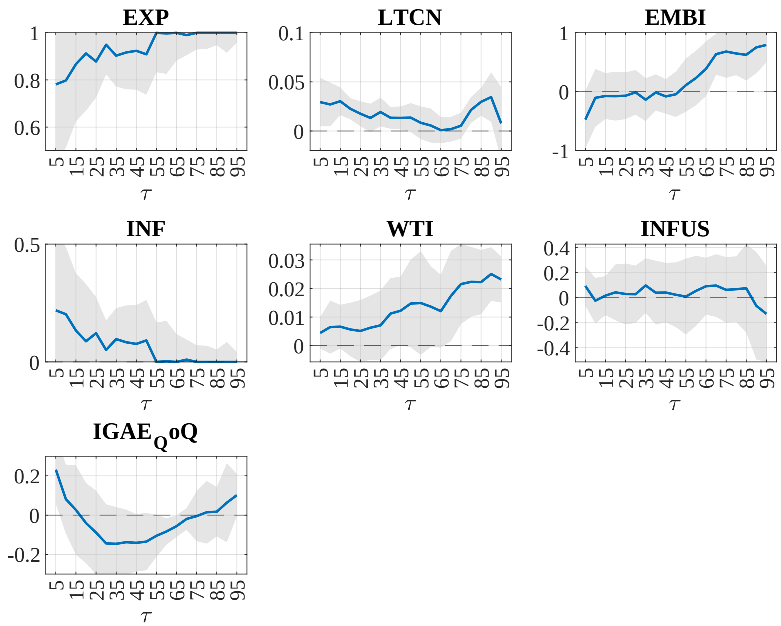


Figure 8: Quantile regression for headline inflation excluding the GSCPI.

rate change and Bloomberg survey expectations supports its validity. Although a 1-month swap referencing the TIIE28D is also available and could more directly reflect current rate surprises without accounting for future expectations, it has lower liquidity and a shorter history, with a daily change correlation of 0.7 relative to the 3-month swap.

Finally, Solis finds that changes in the 1-year swap rate, which are uncorrelated with changes in the 3-month swap, closely align with shifts in expectations about Banxico's future policy path as communicated in official statements. Therefore, while the 3-month swap may reflect expectations extending beyond a single policy meeting, it effectively captures the current monetary stance.

D QR Without the GSCPI

This section presents the QR estimated coefficients from equation (3) by excluding the global supply chain pressures index. Comparing Figure (1) with (8) helps us to understand the bias coming from excluding the GSCPI. By introducing more supply factors, we could better identify the slope of the Phillips Curve that otherwise confounds the correlation between economic activity and inflation since we cannot disentangle the effects coming from pure structural demand or supply shocks. Notice that this has important implications for financial conditions also, as periods of stressed supply chains are historically correlated with global risk aversion. It also overestimates the effect of oil prices and foreign inflation.

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