BANCO CENTRAL DE RESERVA DEL PERÚ

Economic Uncertainty from Business Tendency Surveys:

The Peruvian case

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DT. N°. 2025-024
Serie de Documentos de Trabajo
Working Paper Series
December 2025

Economic Uncertainty from Business Tendency Surveys: The Peruvian case*

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This version December 10, 2025

First version May 13, 2025

Abstract

We develop novel survey-based measures of economic uncertainty using firm-level data from Peru's Survey of Macroeconomic Expectations. These proxies, based on forecast dispersion and forecast errors, rise sharply during major domestic and global shocks, particularly the COVID-19 pandemic. Using Vector Autoregressions (VAR), we identify uncertainty shocks and estimate their macroeconomic effects. Such shocks are contractionary, leading to declines in output, investment, and employment, as well as currency depreciation and lower interest rates. Investment exhibits the largest and most immediate response, while employment adjusts more gradually. The results underscore the macroeconomic relevance of survey-based uncertainty measures in emerging market economies.

JEL classification: C53, C83, D81, E23, E27, E32, E37.

Keywords: Uncertainty, Survey of Expectations, Vector Autoregressions.

*We thank comments and helpful suggestions from seminar participants at the research seminar of the Central Reserve Bank of Peru and the Annual Conference of the Peruvian Economic Association. The views in this paper are the responsibility of the authors and should not be interpreted as reflecting the views of the Central Reserve Bank of Peru or any other person associated with the Central Reserve Bank of Peru.

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1 Introduction

Periods of heightened uncertainty are often associated with significant macroeconomic downturns. In the case of Peru, major global events such as the Global Financial Crisis of 2008–2009 and the COVID-19 pandemic, along with recurrent domestic disturbances - ranging from political instability to climate shocks - have coincided with marked contractions in economic activity. These episodes underscore the importance of understanding the role of uncertainty in shaping macroeconomic dynamics in small open emerging economies like Peru.

This paper quantifies the macroeconomic effects of uncertainty shocks in Peru by constructing novel, firm-level uncertainty measures derived from the Central Bank's Survey of Macroeconomic Expectations. Following the methodology of Bachmann *et al.* (2013), we construct two uncertainty proxies: an ex-ante measure based on cross-sectional forecast disagreement, and an ex-post measure based on the dispersion of forecast errors. We then estimate their aggregate effects using vector autoregressions (VARs) with standard identification assumptions.

We document three main findings. First, our uncertainty measures are countercyclical and spike during periods of economic and political distress, most prominently during the COVID-19 pandemic. Second, structural shocks to uncertainty are contractionary: they generate persistent declines in output, investment, and employment. Investment exhibits the largest and most immediate response; employment adjusts more gradually. Third, in extended VAR specifications, we find that uncertainty shocks also induce a depreciation of the domestic currency and a decline in inflation and domestic interest rates. These results are consistent with the theoretical mechanisms highlighted in the literature, whereby uncertainty suppresses aggregate demand through precautionary savings, delayed investment, and tighter financial conditions (Bloom *et al.*, 2018; Alessandri and Mumtaz, 2019; Fernández-Villaverde and Guerrón-Quintana, 2020).

A key challenge in identifying the effects of uncertainty is the simultaneous onset of the COVID-19 pandemic and the associated economic collapse. To address this, we estimate alternative VAR specifications that include controls for pandemic-related disruptions, namely a time dummy for the initial outbreak and the Oxford Stringency Index (Hale *et al.*, 2021). These adjustments attenuate—but do not eliminate—the estimated effects of uncertainty shocks, indicating that our findings are not entirely driven by COVID-specific dynamics.

However, we also note that the pandemic itself likely operated as a major source of uncertainty (Baker *et al.*, 2020; Caggiano *et al.*, 2020), making clean identification inherently difficult.

Our contribution is twofold. First, we provide new measures of economic uncertainty in Peru based on firm-level survey data, which are closely aligned with the theoretical concept of uncertainty (Jurado *et al.*, 2015). Second, we show that these measures are economically significant predictors of macroeconomic fluctuations in Peru. This complements recent work on uncertainty in emerging markets (Carrière-Swallow and Céspedes, 2013; Bhattarai *et al.*, 2020; Miescu, 2023; Llosa *et al.*, 2025; Giraldo *et al.*, 2023; Alvarado and Rodríguez, 2025), and provides new evidence on the role of survey-based indicators in capturing economically relevant uncertainty (Bachmann *et al.*, 2013; Bush and López Noria, 2021; Bachmann *et al.*, 2023; Bloom *et al.*, 2024).

The rest of the paper is organized as follows. Section 2 describes the data and the construction of the uncertainty measures. Section 3 presents the empirical results. Section 4 concludes.

2 Data description

Our analysis is based on firm-level data from the Survey of Macroeconomic Expectations (SME), conducted monthly by the Central Reserve Bank of Peru (BCRP). The survey collects qualitative and quantitative forecasts from a sample of non-financial private firms, covering expectations about both macroeconomic conditions and firm-level performance. The current version of the SME includes 32 qualitative and 17 quantitative questions, with responses used internally by the BCRP to monitor economic sentiment.

The survey targets the 10,000 largest firms by nominal sales (hereafter, Top 10k), stratified across seven major sectors (agriculture and fishing, mining and oil & gas, manufacturing, utilities, construction, commerce, and services). Participation in the survey is nonmandatory, which reduces its sample size and introduces turnover. According to the latest data, the number of respondents per month is 290 on average. To improve representativeness at the sectoral level, the sampling design combines proportional-to-size and purposive sampling techniques, consistent with recommended practices (OECD, 2003).

Table 1 reports the distribution of nominal gross output by industry. The first column presents the distribution in the SME of December 2022. The two columns on the right

Table 1: Distribution of sales by industry – 2022

Sector	SME	(a)	(b)
Construction	1.4	4.0	2.2
Services	10.6	21.6	18.0
Wholesale trade (incl. retail)	26.5	36.8	35.1
Utilities	2.7	3.1	3.1
Agriculture & fishing	3.6	3.7	4.6
Manufacturing	29.5	19.9	19.4
Mining (incl. oil & gas)	25.7	12.8	17.6
Total	100.0	100.0	100.0
SEM total gross output as % of :	100.0	12.7	20.5

Note: The distribution of nominal gross output by sector in the SME was constructed from the sample of December 2022. Column (a) presents the distribution of nominal gross output in the official tax records of 2022. Column (b) presents the distribution nominal gross output in the top 10k firms in 2022.

show the distribution in the official tax records (column a) and the Top 10k sample (column b). Compared to columns (a) and (b), the SME underrepresents the service and wholesale trade industries while overrepresents the manufacturing and mining industries. The last row reports the SME's total gross output in December 2022 as a percentage of total gross output in the official tax records (column a) and Top 10k (column b). The SME accounts for 12.7 percent of national gross output and 20.5 percent of the total gross output by the 10k largest firms.

To construct firm-level measures of uncertainty, we follow the approach of Bachmann *et al.* (2013). Specifically, we use responses to two questions on expected and realized production: a forward-looking question ("Do you expect your production level to increase, remain the same, or decrease over the next three months?") and a contemporaneous retrospective question ("Has your production increased, remained the same, or decreased relative to the previous month?"). Responses are encoded numerically as +1 (increase), 0 (no change), and -1 (decrease).

We define two uncertainty proxies. The ex-ante uncertainty measure ($FDISP$) is based on the cross-sectional dispersion of expectations across firms in a given month:[1]

$$FDISP_t = \sqrt{Frac_t^+ + Frac_t^- - (Frac_t^+ - Frac_t^-)^2}$$

[1]As noted by Bachmann *et al.* (2013), this formula is the standard deviation of a random variable that takes the values of +1, -1 or 0, with probabilities $Frac_t^+$, $Frac_t^-$ and $1 - Frac_t^- - Frac_t^+$, respectively.

where $Frac_t^+$ and $Frac_t^-$ are the sales-weighted fraction of firms reporting expected increases or decreases in production, respectively. The weighting factor is computed every month.

The ex-post uncertainty measure ($FEDISP$) is based on the cross-sectional dispersion of realized forecast errors over a three-month horizon. We approximate a firm's realized production over that period using its responses to the retrospective question in months $t+1$ to $t+3$, and compute the error as the difference between the forecast and the realized production path (normalized to lie in the interval $[-4/3, 4/3]$).[2]

Let ω_i denote the firm i's share of total sales. Then, the ex-post uncertainty measure is defined as the (sales-weighted) cross-sectional standard deviation of the forecast errors:

$$FEDISP_t = \frac{1}{N_t - 1}\sqrt{\sum_{i=1}^{N_t} \omega_{i,t} \left(e_{i,t+3} - \mu_t\right)^2}$$

where $e_{i,t+3}$ denotes the forecast error, μ_t is the cross-sectional average of such errors, and N_t is the number of firms with valid responses in all relevant months.

We acknowledge two limitations inherent in our data. First, variation in the sample composition over time may confound changes in measured uncertainty. Second, the construction of the ex-post measure requires a four-month balanced panel, which restricts the effective sample size and may reduce precision.

3 Results

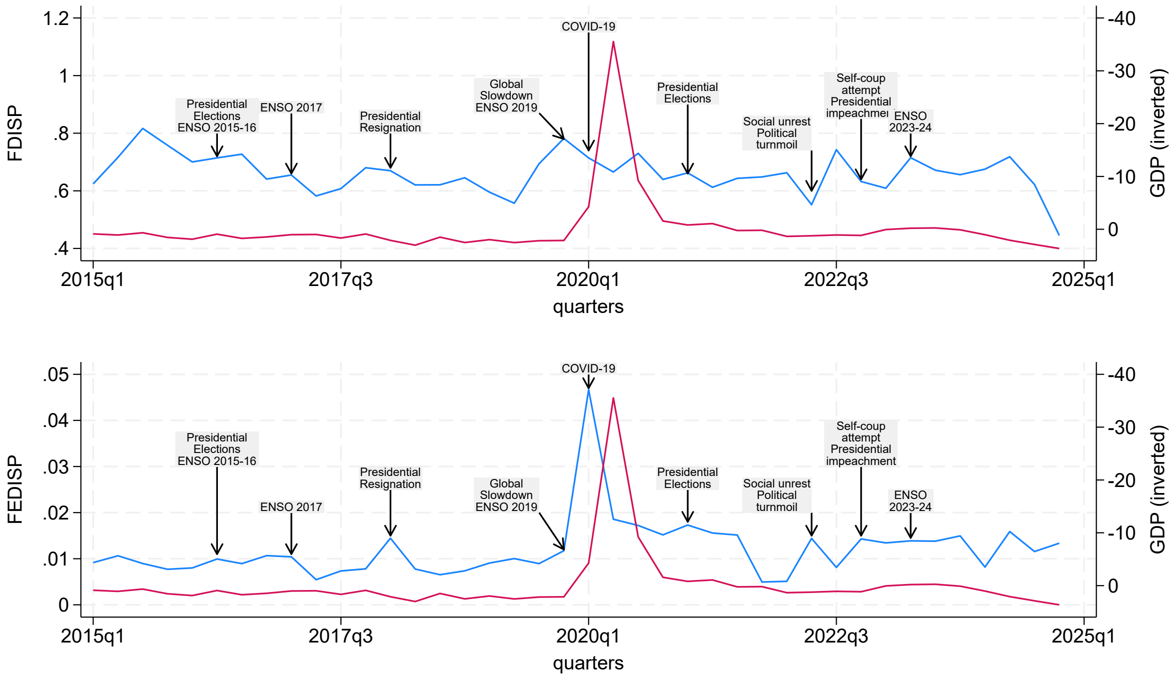
This section presents the empirical properties of the uncertainty measures and quantifies their macroeconomic effects using structural VAR models. We begin by documenting the comovement of uncertainty with major economic and political events. We then explore the statistical characteristics and cyclicality of the measures. Finally, using standard VAR models, we estimate their dynamic impact on key macroeconomic variables, including output, investment, employment, interest rates, inflation, and the exchange rate.

3.1 Uncertainty and Historical Events

To better understand the behavior of our uncertainty measures, we examine their evolution around major historical events that have affected Peru over the period 2015–2024. These

[2] Specifically, we approximate the production realization as the sum of encoded answers to the retrospective question in months $t+1$ to $t+3$. Then we compute the difference with the answers to the forward-looking question in month t and divide the result by 3.

Figure 1: Uncertainty Measures and Main Events



Note. Top (bottom) panel plots the quarterly series for ex-ante (ex-post) uncertainty and the timeline of events. Seasonally adjusted log GDP times 100 (linear-quadratic detrended) is depicted by red line and in an inverted scale. The timeline of events is as follows: Presidential Elections and ENSO 2015-16 (second quarter of 2016), ENSO 2017 (first quarter of 2017), Presidential resignation (first quarter of 2018), Global Slowdown and ENSO 2019 (fourth quarter of 2019), COVID-19 (first quarter of 2020), Presidential Elections (first quarter of 2021), Social unrest and political turmoil (second quarter of 2022), Self-coup attempt and presidential impeachment (fourth quarter of 2022), and ENSO 2023-24 (second quarter of 2023).

include global shocks, domestic political disruptions, and climate-related phenomena. Figure 1 plots the quarterly dynamics of the ex-ante and ex-post uncertainty measures, alongside a detrended series of GDP, and annotates key events over the sample period.

One of the most salient global events is the COVID-19 pandemic, which triggered an abrupt and unprecedented rise in both uncertainty proxies in early 2020. The Peruvian economy experienced one of the sharpest contractions in Latin America, as authorities implemented strict lockdowns in response to rising infections. The government closed non-essential businesses, restricted internal mobility, and suspended economic activity across multiple sectors. These policies were among the most stringent globally, as reflected in the Oxford Stringency Index (Hale *et al.*, 2021). The crisis also exposed institutional weaknesses in Peru's healthcare system and was accompanied by high excess mortality (Gianella *et al.*, 2021). Unsurprisingly, our ex-post uncertainty measure reaches its maximum during this episode.

Beyond global events, a defining feature of the Peruvian economic environment during this period has been persistent political instability. Since 2016, Peru has experienced an unusually high rate of presidential turnover, with six presidents in less than a decade. Notable episodes include:

- The resignation of President Pedro Pablo Kuczynski in March 2018, following allegations of corruption linked to the Odebrecht scandal.
- The dissolution of Congress by President Martín Vizcarra in September 2019, and his subsequent impeachment and removal in November 2020 on charges of "permanent moral incapacity."
- The brief presidency of Manuel Merino, who resigned after less than a week in office amid widespread protests and fatalities.
- The election of Pedro Castillo in 2021, which was followed by high political polarization, ministerial turnover, and growing tensions with Congress.
- The self-coup attempt by President Castillo in December 2022, during which he attempted to dissolve Congress and rule by decree — an act that was immediately nullified by constitutional authorities and followed by his arrest and impeachment.
- The subsequent impeachment proceedings against President Dina Boluarte, amid ongoing political fragmentation and declining public trust in democratic institutions.

These events have repeatedly undermined policy credibility and generated uncertainty over the direction of economic policy (Barrenechea and Vergara, 2023). Several of the spikes in both $FDISP$ and $FEDISP$ align closely with these moments of political crisis, suggesting that the measures are sensitive to shifts in political risk and institutional volatility.

A third source of recurrent macroeconomic disruption is climate-related shocks, especially those linked to the El Niño Southern Oscillation (ENSO). The Peruvian economy, particularly in coastal regions, is highly exposed to weather anomalies. The 2017 Coastal El Niño caused widespread flooding, infrastructure damage, and disruptions to agricultural and fishing activity. Similar events occurred in 2015–2016, 2019, and again in 2023–2024. These episodes coincide with elevated levels of uncertainty in the data, although the correlation is less pronounced than for political or pandemic-related shocks. The irregular and

Table 2: Quarterly Summary Statistics

A. Moments	*FDISP*	*FEDISP*	*VIX*	*EPU*	*MU*
Standard deviation	10.24	56.09	30.52	55.40	11.74
Skewness	-0.43	3.50	0.96	2.77	1.08
Kurtosis	4.42	18.98	3.44	11.96	3.69
First order autocorrelation	0.32	0.27	0.68	0.69	0.73
Second order autocorrelation	-0.04	0.16	0.43	0.40	0.48

B. Cross-correlations	*FDISP*	*FEDISP*	*VIX*	*EPU*	*MU*
FDISP	1.00				
FEDISP	0.08	1.00			
VIX	0.05	0.52	1.00		
EPU	-0.07	0.45	0.73	1.00	
MU	0.27	0.36	0.48	0.48	1.00

Notes. All statistics are computed using the common sample from 2015 to 2024. To normalize the scales, all series are percent changes from their sample means.

often unpredictable timing of El Niño episodes continues to pose a risk to Peru's short-run economic outlook (Ledesma *et al.*, 2023).

Finally, global macro-financial developments - including the 2015–2016 commodity price slowdown, heightened global risk aversion in late 2018, and episodes of international financial volatility — have affected Peru as a small open economy. However, our uncertainty measures appear less sensitive to these external disturbances, possibly reflecting the relative resilience of Peru's macroeconomic policy framework and the limited direct exposure of surveyed firms to international financial markets.

In sum, the temporal alignment of our survey-based uncertainty indicators with major episodes of political turmoil, climate disruption, and global shocks suggests that they capture economically meaningful variation in the perceived risk environment. This provides empirical validation of the measures and motivates the structural analysis presented in the following sections.

3.2 Statistical Properties of the Uncertainty Measures

To assess the empirical behavior of our survey-based uncertainty measures, we analyze their statistical properties and compare them with standard proxies commonly used in the literature. Table 2 reports descriptive statistics for the ex-ante uncertainty measure ($FDISP$), the ex-post measure ($FEDISP$), and three benchmark indicators: the VIX index, the U.S. Economic Policy Uncertainty index (EPU; Baker *et al.*, 2016), and a macroeconomic uncertainty index for Peru (MU; Llosa *et al.*, 2025). All series are sampled quarterly for the period 2015–2024 and are transformed into percent changes from their respective means.

Both survey-based measures exhibit substantial variability over time. The standard deviation of $FEDISP$ is particularly high (56.1), reflecting the greater dispersion in realized production forecast errors relative to ex-ante disagreement. This is consistent with the idea that realized forecast errors capture both uncertainty and unexpected shocks that affect firm-level outcomes post-forecast. $FDISP$, though less volatile (standard deviation of 10.2), still displays significant fluctuations.

The distributional moments indicate that $FEDISP$ is positively skewed and exhibits substantial excess kurtosis, implying frequent occurrences of extreme values - likely driven by tail events such as the COVID-19 crisis. In contrast, $FDISP$ has slightly negative skewness and more moderate kurtosis. These features suggest that firms' expectations become highly dispersed during crises, but such episodes are relatively rare. The benchmark uncertainty indicators also show high skewness and kurtosis, reinforcing the view that uncertainty is heavily influenced by tail risk.

First-order autocorrelations indicate moderate persistence in both $FDISP$ and $FEDISP$, suggesting that uncertainty levels are somewhat sticky, but not strongly persistent over time. This is in contrast with the VIX, EPU, and MU indices, which exhibit higher autocorrelation (ranging from 0.68 to 0.73), consistent with more prolonged periods of elevated uncertainty in financial markets and macroeconomic aggregates.

Panel B of Table 2 reports pairwise correlations among the five uncertainty indicators. $FEDISP$ is moderately correlated with the VIX (0.52), the EPU index (0.45), and MU (0.36), indicating that the ex-post forecast error measure shares common movements with global financial volatility and US policy uncertainty, as well as with domestic macroeconomic uncertainty. $FDISP$, by contrast, shows weak correlations with all other measures - most notably, just 0.08 with $FEDISP$ and 0.05 with the VIX. This result suggests that the ex-ante measure captures distinct, firm-level expectations not necessarily aligned with the common definition of uncertainty.

While the low correlation between $FDISP$ and standard measures may raise questions about its representativeness, it may instead reflect a more micro-founded dimension of uncertainty - specifically, the forward-looking dispersion of beliefs across firms that is not driven by financial conditions or macroeconomic aggregates alone. Moreover, as noted by Bachmann *et al.* (2023), survey-based measures are more tightly linked to the theoretical

Table 3: Dynamic cross-correlations with GDP

Lag/lead: $j =$	-4	-3	-2	-1	0	+1	+2	+3	+4
FDISP	0.27	-0.16	-0.39	-0.24	-0.12	-0.23	0.04	0.02	0.12
FEDISP	-0.01	-0.03	-0.27	-0.91	-0.34	-0.17	-0.10	-0.10	-0.06
VIX	0.03	0.02	-0.03	-0.50	-0.59	-0.35	-0.26	-0.15	-0.01
EPU	-0.02	-0.06	-0.08	-0.41	-0.89	-0.58	-0.35	-0.10	0.09
MU	0.07	-0.06	-0.20	-0.40	-0.54	-0.28	-0.35	-0.50	-0.34

Notes. Pairwise correlations are computed using the common sample from 2015 to 2024. Each column reports the correlation between the logarithm of GDP - detrended using the linear-quadratic method - and the uncertainty indicators - in percentage deviations from their sample means - at various lags and leads j.

notion of Knightian uncertainty rather than ex-post realized volatility.

To examine the cyclical behavior of uncertainty, Table 3 presents dynamic pairwise correlations between detrended GDP and the uncertainty indicators at various leads and lags, from -4 to +4 quarters. All measures exhibit negative contemporaneous correlations with GDP, consistent with the standard view that uncertainty is countercyclical. The strongest contemporaneous relationship is found for EPU (-0.89), followed by the VIX (-0.59) and MU (-0.54). $FEDISP$ also shows a significant negative correlation at contemporaneous and lagged values (-0.91), suggesting that uncertainty derived from realized forecast errors rises just prior to or during downturns.[3]

$FDISP$, however, exhibits weaker and more delayed correlations with output. Its maximum (in absolute value) correlation with GDP occurs at lag 2 (-0.39), indicating that disagreement among firms' expectations may build gradually in anticipation of declining economic conditions, rather than reacting immediately. This is in line with the view that changes in forward-looking disagreement may operate through anticipatory channels different from uncertainty (Zohar, 2024).

These findings collectively highlight important differences in the nature and timing of uncertainty across measures. While standard indicators tend to rise in tandem with economic downturns, our survey-based measures - particularly the ex-ante proxy - capture a distinct dimension of uncertainty arising from dispersed beliefs about the future.

[3]Heterogeneous information models predict that higher uncertainty about fundamentals leads to higher expectational errors (Arslan *et al.*, 2015).

3.3 Uncertainty and Economic Activity

This section quantifies the dynamic effects of uncertainty shocks on key macroeconomic aggregates using vector autoregression (VAR) models. We begin with a baseline set of bivariate VARs, then extend the analysis to multivariate specifications that control for pandemic-related shocks and include additional macroeconomic variables. Throughout, we assess robustness across different detrending approaches and alternative uncertainty proxies. Our basic identification assumptions are that higher uncertainty leads to (i) higher withing-forecaster dispersion - FEDISP - and (ii) higher cross-forecaster disagreement - FDISP.

3.3.1 Baseline VAR Specification

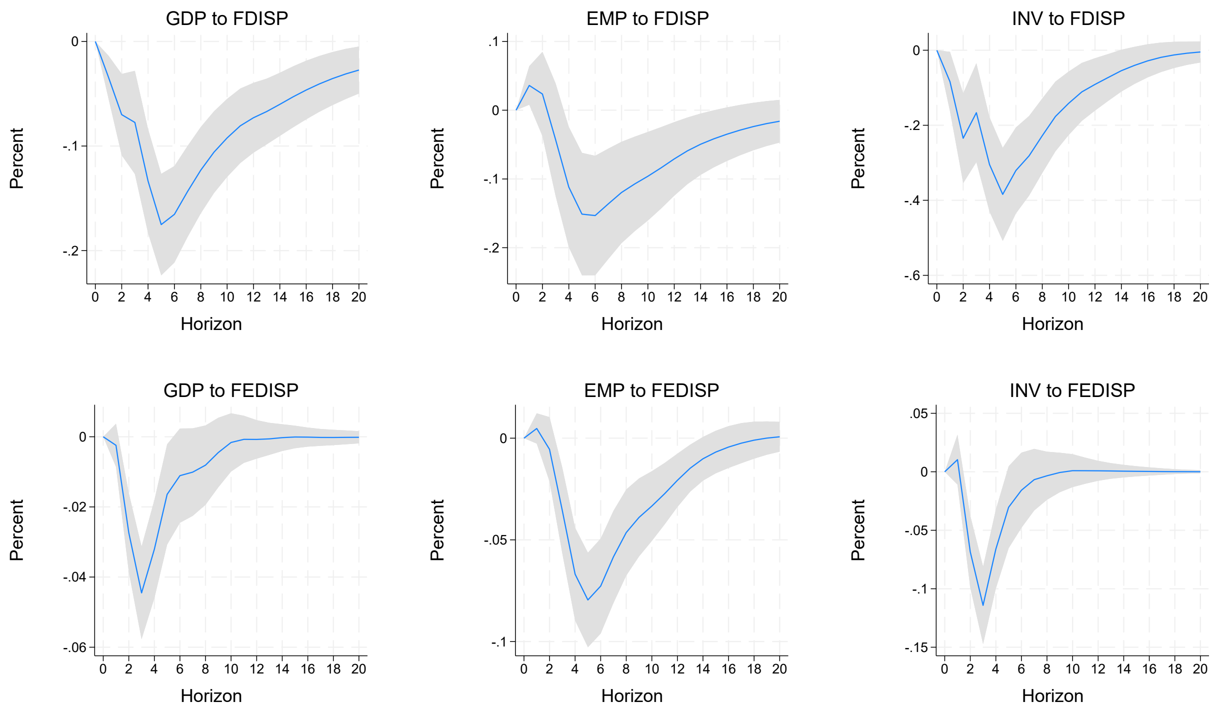
Our baseline empirical framework estimates a set of bivariate VAR models, each including one of the survey-based uncertainty measures - either ex-ante ($FDISP$) or ex-post ($FEDISP$) - and a macroeconomic variable of interest: real GDP, private investment, or employment. All variables are monthly, seasonally adjusted, and expressed in logarithmic levels. The sample spans February 2015 to December 2024.

Lag selection is based on the Akaike Information Criterion (AIC), which consistently favors four lags across specifications. Structural shocks are identified using a Cholesky decomposition, with uncertainty ordered first. This recursive ordering assumes that uncertainty contemporaneously affects macroeconomic aggregates, but not vice versa - a standard identifying assumption in the uncertainty literature (Bloom, 2009; Baker *et al.*, 2016; Alessandri and Mumtaz, 2019). All VARs turn out to be stable, namely, all eigenvalues are inside the unit circle.

Impulse response functions (IRFs) from these models, depicted in Figure 2, reveal that uncertainty shocks are contractionary. A one-standard-deviation innovation in $FDISP$ leads to a statistically significant decline in GDP, which reaches its trough approximately six months after the shock. The magnitude of the contraction is moderate, on the order of 0.2 percent. Investment responds more strongly and more rapidly, declining by nearly twice as much on impact. This pattern is consistent with real options channel, where firms postpone investment in response to greater uncertainty (Bloom, 2009; Bloom *et al.*, 2018; Fernández-Villaverde and Guerrón-Quintana, 2020).

Employment exhibits a delayed response, declining gradually over the second - to six-month horizon. The lag in labor adjustment is consistent with models incorporating hir-

Figure 2: IRFs to uncertainty



Note. The top (bottom) row plots the impulse responses to FDISP (FEDISP). The IRFs were obtained from separately estimating bivariate VARs with 4 lags. The uncertainty measure was ordered first. All data in logs times 100. Shaded regions represent the 68% boostrapped confidence bands.

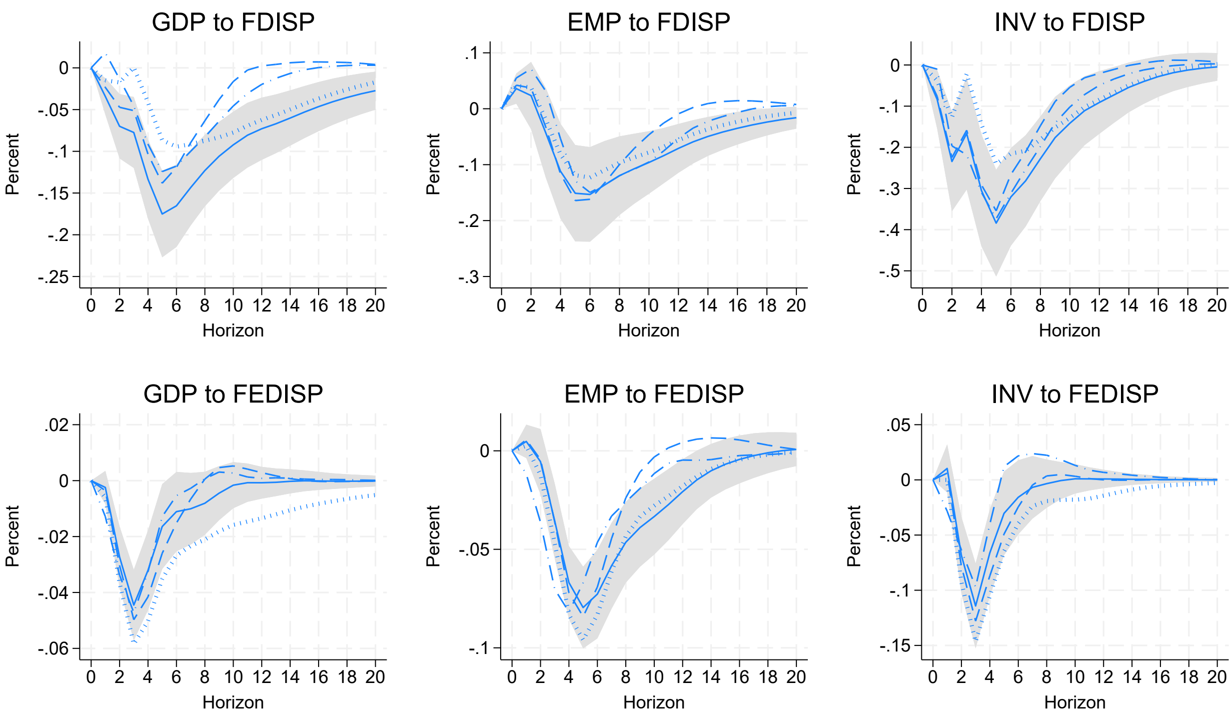
ing/firing frictions, adjustment costs, or institutional rigidities in the labor market (Choi *et al.*, 2024). These dynamics are broadly consistent across the ex-ante and ex-post measures, although the magnitude of the responses is relatively muted for $FEDISP$, potentially reflecting greater measurement noise or differences in information timing.

3.3.2 Robustness to Detrending

To ensure that the results are not driven by low-frequency trends or non-stationarity in the data, we re-estimate the VARs using detrended macroeconomic series. We apply three common detrending methods: (i) a linear-quadratic trend, (ii) the Hodrick-Prescott (HP) filter with a smoothing parameter of 14400 (monthly data), and (iii) 12-month log differences.

The qualitative results are robust across all detrending methods. As shown in Figure 3, the IRFs retain their overall shape: uncertainty shocks reduce output, investment, and employment. Notably, in the detrended specifications, the variables do not return to their pre-shock trends, suggesting that uncertainty shocks may cause persistent losses in economic activity. The latter echoes the findings of Cerra and Saxena (2008) regarding non-V-shaped

Figure 3: IRFs to uncertainty



Note. The top (bottom) row plots the impulse responses to FDISP (FEDISP). The IRFs were obtained from separately estimating bivariate VARs with 4 lags. The solid lines are the IFRs from the VARs estimated with log data. In the other specifications, the (log of) GDP, employment and investment are detrended. The dashed lines corresponds to HP-filtered data. The dotted lines corresponds to linear-quadratic detrended data. The dotted-dashed lines corresponds to 12-month differenced data. Shaded regions represent the 68% boostrapped confidence bands from the VARs estimated with log data.

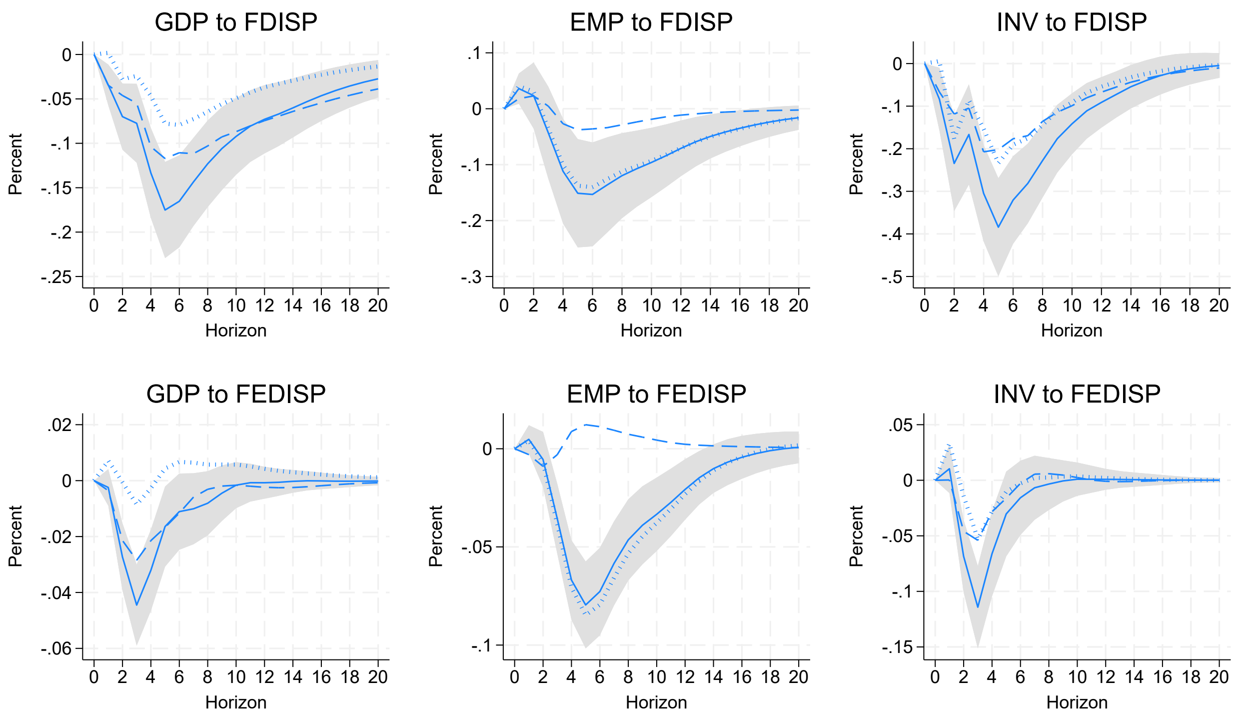
recoveries after major downturns and suggests that uncertainty shocks interact with financial frictions (Alessandri and Mumtaz, 2019; Llosa *et al.*, 2025).

3.3.3 Controlling for COVID-19 Effects

The COVID-19 pandemic presents a unique identification challenge. The simultaneous collapse in economic activity and spike in uncertainty complicates inference about causality, as both may be driven by a third factor - the emergence of the SARS-CoV-2 virus and the associated containment policies (Baker *et al.*, 2020).

To address this, we estimate augmented VARs that include exogenous controls for pandemic-related shocks. Specifically, we incorporate: (i) a dummy variable equal to one in March 2020 and zero otherwise, and (ii) the Oxford COVID-19 Stringency Index (Hale *et al.*, 2021), which captures the intensity of government-imposed mobility and activity restrictions.

Figure 4: IRFs to uncertainty

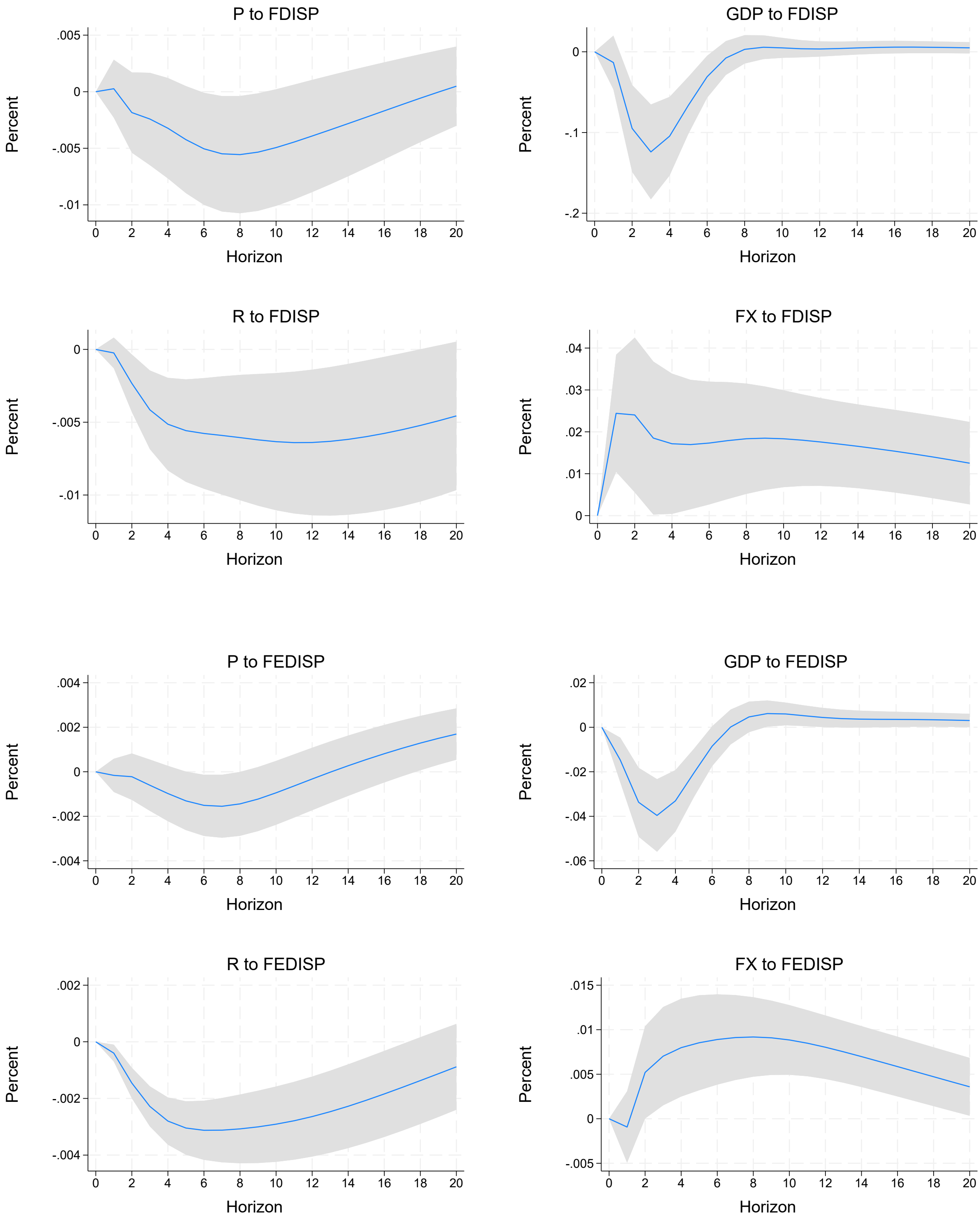


Note. The top (bottom) row plots the impulse responses to FDISP (FEDISP). The IRFs were obtained from separately estimating bivariate VARs with 4 lags. The solid lines are the IRFs from the VARs, estimated with log data without exogenous variables. The dashed lines are the IRFs from the VARs with the first 4 lags of the Stringency Index as exogenous variables. The dotted lines are the IRFs from the VARs with a March 2020 dummy variable. Shaded regions represent the 68% confidence bands from the VARs without exogenous variables.

As shown in Figure 4, accounting for COVID-19 reduces — but does not eliminate —the estimated macroeconomic effects of uncertainty shocks. For instance, the contraction in investment and output is smaller in magnitude when COVID-19 controls are included. However, the qualitative pattern of responses remains: uncertainty shocks are recessionary, with the most pronounced effects concentrated in investment. These results suggest that although pandemic-specific factors contributed to both uncertainty and output fluctuations, our uncertainty measures retain independent explanatory power even when controlling for the direct effects of the pandemic.

This robustness is particularly important given that the COVID-19 outbreak represents both a macroeconomic shock and a surge in uncertainty - making it difficult to cleanly separate cause and effect. Our approach, while imperfect, provides evidence that the macroeconomic role of uncertainty extends beyond its correlation with pandemic-related disruptions.

Figure 5: IRFs to uncertainty



Note. The IRFs were obtained from separately estimating VARs with 2 lags. The solid lines are the IFRs from the VARs, estimated with 12-month log differenced macroeconomic data. The shaded regions represent the bootstrapped 68% confidence bands.

3.3.4 A Multivariate VAR

To examine broader transmission mechanisms, we estimate a larger VAR model that includes five variables: uncertainty, the consumer price index (inflation), real GDP, the short-term domestic interest rate, and the nominal exchange rate (PEN/USD). This specification allows us to assess how uncertainty shocks propagate through nominal and financial variables, in addition to real activity.

Given data limitations and the short sample, we include two lags and transform GDP, prices, and the exchange rate into 12-month log differences to ensure stationarity. The identifying assumption remains recursive, with uncertainty ordered first.

The IRFs from this specification, shown in Figure 5, reaffirm the contractionary effects of uncertainty. A one-standard-deviation shock to either $FDISP$ or $FEDISP$ leads to a decline in GDP, as in the bivariate models. The domestic currency depreciates persistently against the U.S. dollar, while the short-term interest rate falls — a pattern consistent with monetary policy accommodation in response to weakening demand. The response of inflation is relatively muted and barely statistically significant, likely reflecting the interplay of demand-driven disinflation and cost-push inflation from imported goods.

These results suggest that uncertainty shocks in Peru primarily act through demand-side channels, reducing output and interest rates while exerting depreciatory pressure on the exchange rate. The weak response of inflation may reflect offsetting forces, as stressed by Alessandri and Mumtaz (2019), or differences in the origin or nature of the uncertainty shock (e.g., domestic vs. external).

4 Concluding remarks

This paper provides new evidence on the macroeconomic effects of uncertainty in an emerging market economy by constructing and analyzing survey-based measures of firm-level uncertainty in Peru. Using responses from the Central Bank's Survey of Macroeconomic Expectations, we build ex-ante and ex-post proxies grounded in cross-sectional forecast dispersion and realized forecast errors, following the approach of Bachmann *et al.* (2013). These measures respond strongly to major domestic and global shocks — including political crises, El Niño episodes, and the COVID-19 pandemic — capturing firm-level uncertainty not visible in conventional financial or news-based indicators.

We estimate the dynamic effects of uncertainty shocks using structural VAR models.

Across specifications, uncertainty shocks are contractionary: output, investment, and employment all decline, with investment exhibiting the strongest and most immediate response. Employment reacts with a lag, consistent with labor market frictions. In an extended model, we document that uncertainty also induces exchange rate depreciation and lower domestic interest rates. These findings are robust to alternative detrending approaches and to the inclusion of exogenous controls for pandemic-related restrictions.

The framework developed here opens several avenues for future research. Understanding heterogeneity in firms' responses to uncertainty, and how such heterogeneity aggregates to economy-wide outcomes, remains a key empirical challenge. Further, exploring the interaction of uncertainty with financial conditions, policy credibility, or external volatility would enrich our understanding of business cycle transmission in developing economies. Our results support the broader case for integrating firm-level expectations into the toolkit for macroeconomic monitoring and policy analysis.

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A Data

The uncertainty indicators are calculated directly from the microdata of the Survey of Macroeconomic Expectations conducted by the Central Bank of Peru. This data is not public. The monthly macroeconomic data for Peru are sourced from the Central Reserve Bank of Peru. GDP is the seasonally-adjusted gross domestic product, investment is the seasonally-adjusted gross domestic capital formation, and employment is the seasonally-adjusted employed working-aged population. Consumer prices are measured by the consumer price index for *Lima Metropolitana*, the interest rate in the domestic currency is measured by the short-term interbank interest rate in soles, and the exchange rate is measured by the foreign exchange rate (soles per US dollar) in the interbank market. All series, except investment, are public. An updated series for the macroeconomic uncertainty indicator of Llosa *et al.* (2025) was obtained directly from the authors. The monthly averages of the VIX index and the Economic Policy Uncertainty (EPU) index are sourced from the FREDFED website.