Mexico's Labor Market through the Lens of the Beveridge Curve

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August, 2025

Abstract

This paper constructs the first Beveridge Curves for Mexico and its regions using a newly compiled dataset on formal sector job vacancies. Incorporating this novel vacancy dataset helps us define structural macroeconomic shocks and explore business cycle movements both at the national and at the sectoral level. Focusing on the post-COVID-19 period, we document a sharp increase in labor market slack at the onset of the pandemic, followed by a gradual tightening beginning in 2021, with a more rapid recovery in northern regions. By 2023, vacancy rates declined without a corresponding rise in unemployment, suggesting a rebalancing of labor demand. We further introduce a new measure of labor market slack based on the vacancies-to-unemployment (V/U) ratio for Mexico, which is used to explore national and regional Phillips Curves. Finally, we use the data set to estimate a Structural Bayesian VAR model. We show that the dynamics of Beveridge Curve is primarily shaped by labor market shocks rather than those from the goods market. Specifically, we find that unemployment dynamics are mainly driven by labor supply and matching efficiency shocks, while wage bargaining shocks account for most of the variation in vacancies at the national level, with heterogeneity across regions.

Keywords: Beveridge Curve, Phillips Curve, Inflation, Slack.

JEL classification codes: J01, J23, J64,E24,E3

1 Introduction

Understanding labor market dynamics is essential for assessing economic conditions and designing effective policy interventions. A key framework for this analysis is the Beveridge Curve, which illustrates the typically negative relationship between unemployment and job vacancy rates. For example, recent work by Barnichon and Shapiro (2024) and Ahn and Rudd (2025) shows that incorporating data on both vacancies and unemployment can help improve inference not only when it comes to studying the labor market, but also when it comes to studying overall business cycle movements. While extensively used in advanced economies, its application in emerging markets like Mexico has been limited, primarily due to the lack of systematic job vacancy measures.

This paper addresses this gap and represents the first effort to construct Beveridge Curves for Mexico and its regions, using vacancy and conditional formal unemployment data to study the drivers of economic activity at the national and regional level. We compile an unexploited dataset on job vacancy data from the Ministry of Labor and Social Welfare (Secretaría del Trabajo y Previsión Social, STPS; hereafter STPS). Due to the nature of the job posting process, vacancies submitted to the STPS platform originate primarily from firms registered with the Mexican Tax Administration Service, making them more representative of the formal labor market than of the broader economy. Accordingly, the analysis can be understood as offering a lens through which to examine labor market dynamics from the perspective of the formal sector.

When exploring the dynamics of the vacancy and unemployment data, we place particular emphasis on the COVID-19 pandemic, which triggered significant labor market disruptions and provides a unique setting to examine shifts in labor market dynamics. By analyzing stylized facts from Beveridge Curves during the pandemic, we observe that at the onset of the crisis, Mexico experienced a sharp increase in formal labor market slack, followed by gradual tightening beginning in 2021. This tightening was particularly pronounced in northern regions, where labor market conditions recovered more rapidly. Furthermore, mirroring trends observed in the United States, the post-

pandemic decline in job vacancies in 2023 occurred without a corresponding rise in unemployment, suggesting a reduction in labor demand that helped ease labor market imbalances, (see Lubik (2021)).

Additionally, using vacancy data and a comparable measure of the conditional formal unemployment rate used to derive the Beveridge Curves, we construct a labor market slack indicator based on the vacancy-to-unemployment (V/U) ratio. Although the measure is restricted to the formal sector due to data limitations, the resulting estimates closely align with international benchmarks, which typically reflect the overall labor market. Following Crust et al. (2023) and Barnichon and Shapiro (2024), we use the inverse of this ratio (i.e., the unemployment-to-vacancy ratio, (U/V) along with core inflation to construct reduced-form Phillips Curves at both national and regional levels. Results show that during the initial phase of the pandemic, when slack in the formal labor market was high, core inflation remained low. As labor markets tightened in 2021 and 2022, core inflation rose and the Phillips Curve became steeper, particularly at the national level and in northern regions. Starting in 2023, core inflation declined significantly across all regions, even though labor market slack remained broadly unchanged. This pattern suggests that the fall in inflation occurred in a context of easing labor demand, driven by falling vacancies rather than rising unemployment.

To formalize the analysis, we extend the standard representation of Beveridge Curves by identifying structural shocks like demand, technology, and labor market shocks, which include labor supply, wage bargaining, and matching efficiency. We employ a sign-restricted Structural Bayesian Vector Autoregressive (SBVAR) model using quarterly data from 2006:Q2 to 2024:Q3. Our identification strategy builds on previous work in advanced economies (Foroni et al., 2018), and incorporates vacancy data together with employment, wages, unemployment, and prices. The analysis is carried out at both the national and regional levels. The results indicate that labor market shocks—rather than shocks from the goods and services market—are the primary drivers of Beveridge Curve dynamics in Mexico. *Labor supply shocks*, understood as

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changes in the number of people willing or able to work (e.g., due to demographic shifts or health concerns), and *matching efficiency shocks*, which reflect how effectively job seekers are paired with vacancies (e.g., through better job platforms or reallocation mechanisms), explain most of the variation in unemployment. Meanwhile, *wage bargaining shocks*—capturing shifts in workers' negotiating power, such as those caused by minimum wage increases or union agreements—account for the majority of fluctuations in vacancies. These patterns are broadly consistent across regions, although we also find meaningful regional heterogeneity. This regional dimension is crucial given Mexico's pronounced structural asymmetries across states: while some regions, particularly in the north, are highly export-oriented and specialized in manufacturing linked to global value chains, others remain focused on agriculture or domestic services. These differences in production orientation and economic specialization shape the nature and intensity of labor market frictions, making regional-level analysis essential to fully understand national Beveridge Curve dynamics.

The remainder of this paper is structured as follows: Section 2 reviews the literature on Beveridge Curves and their applications. Section 3 presents the job vacancy indicators available for Mexico and describes the data sources used in the construction of the variables required for the Beveridge Curves. Section 4 presents stylized facts and discusses the regional Beveridge and Phillips Curves in the context of the COVID-19 pandemic. Section 5 outlines the empirical framework used to identify labor market shocks, while Section 6 analyzes the effects of these shocks across Mexico and its regions. Section 7 concludes with a discussion of the broader implications of our findings.

2 Beveridge Curve: A Survey of Theoretical and Empirical Insights

The Beveridge Curve has been extensively studied to understand labor market dynamics, particularly in advanced economies such as the United States and European Union countries, where reliable job vacancy data is available. Blanchard and Diamond (1989) pioneered the empirical investigation of the Beveridge Curve in the U.S. labor market

during the postwar period. Using a structural VAR framework, they demonstrated that unemployment fluctuations are primarily driven by cyclical shocks rather than sectoral shifts, challenging the prevailing view of sectoral dynamics. They also documented outward shifts in the Beveridge Curve over time, signaling reduced efficiency in matching unemployed workers to job vacancies. This foundational work highlighted the curve's relevance in analyzing labor market interactions and economic shocks.

Benati and Lubik (2014) extend this analysis, employing a Bayesian time-varying structural VAR model to examine the Beveridge Curve in the U.S. from 1949 to 2011. They documented significant structural shifts during events like the Great Recession and Volcker disinflation, challenging the assumption of a static Beveridge Curve and emphasizing its evolution in response to economic conditions. Further work by Lubik et al. (2016) analyzes the Beveridge Curve dynamics during the Great Recession using a time-varying parameter VAR framework. Their findings highlight the nonlinearity and structural breaks in the U.S. labor market, emphasizing the need for refined models to capture these complexities. Similarly, Lubik (2021) examines the Beveridge Curve during the COVID-19 pandemic, documenting a significant outward shift due to reduced matching efficiency and heightened recruitment challenges.

Foroni et al. (2018) investigate the U.S. labor market, distinguishing between labor supply and wage bargaining shocks using a sign-restricted VAR model. They find that labor supply shocks are particularly important for long-term fluctuations in employment and unemployment, while wage bargaining shocks have more immediate effects. Beyond the U.S., Schiman (2021) examines labor supply shocks in Austria after the 2004 European Union enlargement. Using SVAR models with sign restrictions, he finds these shocks temporarily increased unemployment and vacancies while raising total employment, illustrating the uneven regional impacts of external shocks.

Other work by Crust et al. (2023) links the Beveridge Curve to inflation dynamics through an analysis of the Phillips Curve in the U.S. They demonstrate that when labor market slack is low, the Beveridge Curve steepens, suggesting that even small

increases in slack can significantly reduce inflation, provided inflation expectations remain anchored. Figura and Waller (2024) extend this analysis to the pandemic period, identifying a *soft landing* scenario in the U.S., where vacancies decreased without significant increases in unemployment, a pattern consistent across national and regional markets. Recent work by Ahn and Rudd (2025) finds that different types of reallocation shocks which affect the Beveridge Curve have different effects on inflation depending on whether they are driven by quits or job losses. For the US, the observed Beveridge and Phillips correlations change over time depending on what types of structural shocks predominate in a given period. In contrast to earlier studies, they find that reallocation shocks that accompany job losses were a key source of labor market dynamics and the steepening of the reduced-form Phillips Curve during the Covid-19 pandemic, and were an important driver of the post-pandemic *soft landing.*

While much of the existing evidence has focused on advanced economies, largely due to the availability of detailed vacancy data, extending this research to emerging markets holds the potential to yield important insights. However, this line of research has been constrained by persistent data limitations, particularly the lack of systematic vacancy information, which continues to hamper a comprehensive understanding of labor market frictions in these economies. For Mexico, Arroyo Miranda et al. (2014) analyse the effects of matching frictions on unemployment rates following the 2008 financial crisis. Using a novel dataset from a government job placement service, they estimate a matching function and find a significant decline in matching efficiency, accounting for 70 basis points of the observed 233 basis points increase in unemployment. However, they conclude that matching frictions alone cannot fully explain the rise in unemployment, pointing to other contributing factors. This study not only highlights the importance of addressing data challenges in emerging economies but also broadens the understanding of Beveridge Curve dynamics beyond advanced economies.

In Latin America, the most comparable case to Mexico is Colombia. Álvarez and Hofstetter (2014) construct a historical vacancy series using newspaper advertisements dating back to 1976 and estimate the Beveridge Curve for different periods, identifying a structural shift in the 1980s. As noted by the authors, this was the first such exercise for Latin America, with the primary contribution being the construction of the vacancy series.

Similarly, only a few studies have analyzed Beveridge Curve dynamics in emerging markets. In Eastern Europe, Tanning and Tanning (2012) analyze the case of Estonia. They propose an "augmented Beveridge Curve" that accounts for nonlinearities under high unemployment conditions. Their findings suggest that structural shifts in the curve are related to youth emigration and skill mismatches, highlighting the role of demographic and educational factors in shaping labor market dynamics. In Africa, Gumata and Ndou (2017) document the existence of a Beveridge Curve in South Africa. Using macroeconomic time series, they show that productivity shocks and changes in tax policy can generate outward shifts in the curve. Their analysis connects labor market frictions with inflationary pressures, offering implications for monetary policy in the region.

For Asia, Babangida et al. (2024) estimate the Beveridge Curve for Turkey using annual data from 1951 to 2008 collected by the Turkish Employment Organization. They find a persistent negative relationship between vacancies and unemployment over the long run, but identify structural shifts in the 1970s linked to broader labor market rigidities. A more recent study by Kanik et al. (2013) uses monthly online vacancy and unemployment data from 2005 to 2013, showing that Beveridge Curve movements in Turkey are countercyclical, with shifts largely driven by aggregate demand conditions.

This body of work highlights the importance of the Beveridge Curve in analyzing labor market frictions, structural changes, and macroeconomic dynamics. Building on this foundation, our work contributes to the growing literature on labor market frictions in emerging economies by analyzing Beveridge Curve dynamics in Mexico using newly

available vacancy data. What is more, our analysis explicitly covers the COVID-19 pandemic period, a dimension that, to our knowledge, has not been addressed in existing studies for Latin America or other emerging markets.

3 Job Vacancies and Unemployment Data for Beveridge Curves

3.1 Job Vacancy Indicators in Mexico

Beveridge Curves rely on data for both unemployment and vacancy rates. Vacancies refer to job openings that are currently available or expected to become available in the near future, for which firms are actively seeking candidates. In the case of Mexico, three main sources of vacancy data are available. The first is the Electronic Job Advertisements Index (IAEE), compiled by Banco de México since January 2019. This index captures the number of job vacancies posted online in the classified section of a major national newspaper. It should be noted, however, that its geographical coverage is limited to the Mexico City metropolitan area.

The second source is the recruitment module of the *Monthly Survey of Regional Economic Activity* (EMAER) by Banco de México, which has been collecting data since November 2022. This module gathers information from managers of firms with over 100 employees in the manufacturing and non-manufacturing sectors about the number of job openings for which they were actively recruiting as of the end of the previous month. Managers provide their responses in numerical ranges, which are then used to estimate regional vacancies. EMAER collects data from firms, stratified by their employee count, across the four regions defined by Banco de México.[1] While the survey offers valuable regional insights, its main limitation lies in the short duration of the time series, which restricts its use for longer-term analysis.

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[1] For the number of vacancies captured in EMAER, since November 2022, business managers have been asked the following: "Number of job positions for which your company was actively recruiting personnel as of the end of the month prior to the survey." Managers can respond using the following ranges: 0, 1–5, 6–10, 11–20, 21–40, 41–60, 61–100, >100. The number of vacancies per region is calculated by considering the mean imputed value for each range for each company, as well as the expansion factor associated with each company.

The third source is the job board of the STPS, managed by the National Employment Service Unit.[2] Since January 2001, this job board has provided data on vacancies registered by formal firms, primarily located in urban areas. Registrations can be made in person at one of the 168 National Employment Service offices or online via the agency's portal.[3] In 2023 alone, it recorded over one million job vacancies nationwide, a figure comparable to some of the largest online job boards, such as Online Career Center México, S.A.P.I. de C.V. (commercially known as 'OCC'). However, it is important to note that this source may not fully capture all vacancies in regional formal labor markets, as not all companies use the STPS job board to advertise job openings.

Figure 1a illustrates the trajectory of national vacancy indices constructed using data from the three sources, all normalized to 100 as of November 2022. During the onset of the COVID-19 pandemic, when measures such as the temporary closure of non-essential economic activities and lockdowns were implemented, the vacancy indices based on STPS and IAEE data declined nationwide. Following the reopening of the economy, both indices showed a sustained upward trend until the end of 2022. After this point, the STPS index exhibited a slight decline, while the IAEE index stabilized and has more recently shown signs of recovery. In contrast, the EMAER index has displayed a persistent downward trend since November 2022, broadly aligning with the decline observed in the STPS index.

Given the observed patterns, we rely on the vacancy series from the STPS job board for our empirical analysis. This source offers broader regional coverage than the IAEE, which is limited to the Mexico City metropolitan area, and a longer time span than EMAER, which provides nationwide coverage through survey data. In addition, the STPS series reflects vacancy trends that are broadly consistent with those captured by EMAER, supporting its use as a reliable proxy for formal labor demand.

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[2]The information from this job board is a useful reference for the general dynamics of the Mexican labor market. For more details, see: Arroyo Miranda et al. (2014).

[3]Firms that post vacancies on the STPS job board are required to be registered in the Federal Taxpayer Registry (RFC) maintained by the Tax Administration Service (SAT), which implies that these firms operate within the formal sector of the economy.
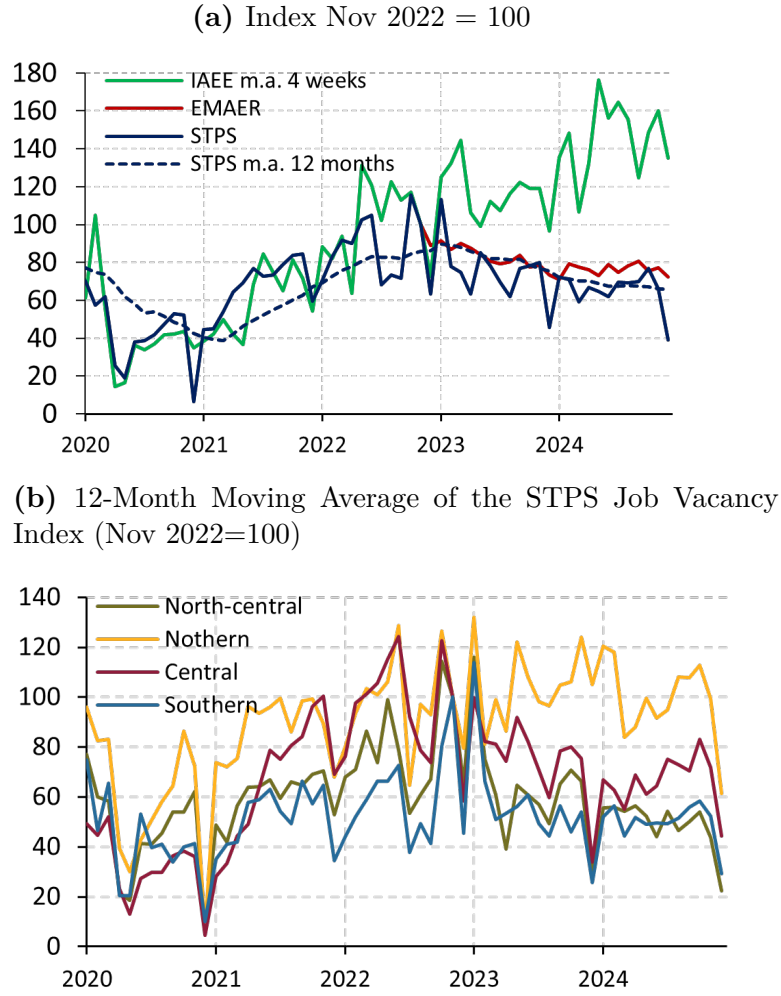
(a) Index Nov 2022 = 100

(b) 12-Month Moving Average of the STPS Job Vacancy Index (Nov 2022=100)

Figure 1: Number of Job Vacancies According to Different Sources
Source: Own estimates based on data from a national newspaper, EMAER, and STPS.
Notes: Monthly Survey of Regional Economic Activity (EMAER); IAEE 4-Week Moving Average: 4-week moving average of the Job Advertisements Index from a newspaper; and the 4-week moving average of the Vacancies from the STPS. The vacancy indices were normalized to November 2022 = 100, as this is the first month for which EMAER information is available.

Furthermore, Figure 1b) shows regional trends in vacancy indices calculated using STPS data. From the first quarter of 2021 to early 2023, these indices exhibited an upward trend across all regions. However, starting in early 2023, the indices began to decline in the north-central and southern regions, while in the northern and central regions they remained more stable, although by late 2024 they also contracted in line with the north-central and southern regions.

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3.2   Construction of the Conditional Formal Unemployment Rate

Since the vacancy data captures job postings in the formal sector, due to the administrative requirements for listing vacancies, our analysis focuses specifically on the formal segment of the labor market. As such, a consistent comparison requires defining unemployment, conditional on prior attachment to the formal sector, a measure we refer to as *conditional formal unemployment rate.*[4] Vacancy rates are calculated using data from the STPS job board, while conditional formal unemployment rates are derived from microdata from the National Employment Survey (*Encuesta Nacional de Ocupación y Empleo*, ENOE, by its Spanish acronym). In both cases, rates are computed using the formal sector's economically active population (EAP) as the denominator, which includes the sum of formal employees and conditional formal unemployed individuals.

The ENOE is the primary source of labor market information in Mexico. It provides monthly and quarterly data on labor force participation, employment, informality, underemployment, and unemployment, among others. It classifies individuals as formally employed only if they report holding a job during the reference quarter, typically understood as coverage by social security. However, individuals who report being unemployed are not assigned a formal or informal status. To impute this status, we implement a three-stage algorithm that takes advantage of the rotating panel structure of the survey[5], as follows:

- **Step 1. Backward Imputation:**

  For each unemployed individual in quarter t, we examine up to four previous quarters ($t-1$ to $t-4$). If the individual was employed in any of those periods, we assign to quarter t the most recent formal status already coded by INEGI.

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[4]Unemployed individuals are defined as persons aged 15 and over who, during the reference week, actively sought employment and were not engaged in any economic activity or remunerated work.

[5]The ENOE follows a rotating panel design. The sample is divided into five panels, each individual remaining in the survey for five consecutive quarters. Every three months, one-fifth of the sample (20%) is replaced with new households of similar characteristics. This design allows for longitudinal analysis over short periods, which we exploit in this work.

- **Step 2. Forward Imputation:**

  When no backward information is available, we look up to four quarters ahead ($t+1$ to $t+4$). If the individual is observed as employed in any of these future periods, we impute to quarter t the formal status recorded in the closest subsequent survey.

- **Step 3. Consolidation:**

  We combine the two imputations, giving priority to the backward result. The forward result is used only when backward imputation is not feasible.

For the construction of the conditional formal unemployment rate, let U_t denote total unemployment and E_t total employment in quarter t and recall the total labor force is defined as $L_t = E_t + U_t$. The conditional formal unemployment rate is thus defined as:

$$\text{Conditional Formal Unemployment Rate}_t = \frac{U_t^{\text{formal}}}{E_t^{\text{formal}} + U_t^{\text{formal}}} \times 100 \qquad (1)$$

The numerator includes unemployed individuals whose status has been imputed as formal using the above procedure considering the weighting factor of each individual in the quarter t. The denominator equals the sum of formal employees and these formally classified unemployed individuals, which is the conditional formal labor force.

4 Regional Beveridge and Phillips Curves in the Pandemic Context

The Beveridge Curve illustrates the typically negative relationship over time between the vacancy rate and the unemployment rate. Its position and changes over time provide insights into distinguishing cyclical variations from changes in the efficiency of the job-matching process in the labor market. Cyclical fluctuations are represented by movements along the curve, driven by periods of economic recession or recovery.[6] For instance, during a recession, production levels decline, leading to reduced employment and fewer job vacancies, causing a movement along the curve downward and to the right. Conversely, during an economic expansion, the unemployment rate falls, and

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[6]For more details on the Beveridge Curves, see: Katz et al. (1989).

the vacancy rate rises, resulting in a movement upward and to the left. Shifts in the Beveridge Curve itself, however, reflect changes in matching efficiency between employers and workers or in labor reallocation. A parallel shift to the left may indicate improved efficiency, where a lower unemployment rate is achieved for the same vacancy rate, while a shift to the right suggests reduced efficiency.[7]

As our primary focus is to analyze the labor market in the context of the COVID-19 pandemic, we construct Beveridge Curves beginning in 2020. Figure 2 presents the Beveridge Curves for the formal sector at both the national and regional levels. Each point on the curve represents the combination of the unemployment rate and the vacancy rate for a given quarter during the analysis period. At the onset of the pandemic (red points), when economic activity contracted, the unemployment rate spiked nationally and across all regions, while the vacancy rate fell. This reflects the labor market weakness observed during that period. However, as economic activity began to recover in late 2020, vacancy rates increased, and unemployment rates declined. This recovery is reflected in movements along the Beveridge Curves, progressing from red points in 2020 to purple points in 2021 and then to green points in 2022.

A key observation is that unemployment rates in the northern and central regions have decreased in a context of relatively higher vacancy rates, suggesting a steeper slope for the Beveridge Curves in these regions compared to the southern region. A steeper slope may indicate greater challenges in filling vacancies.[8] Finally, during 2024 (blue points), vacancy rates declined relative to their 2023 levels (orange points) across all regions, while unemployment rates either remained stable or decreased. This trend may reflect reduced demand for workers, which, nevertheless, has not hindered the labor market from continuing to absorb job seekers.[9]

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[7]Shifts in the Beveridge Curve can be due to changes in inflow into unemployment or changes in outflow out of unemployment or both. Factors affecting inflow into unemployment are the separation rate, which can shift the BC to the right if it increases. Factors affecting the outflow out of unemployment is the job finding rate, which, among many factors, is affected by matching efficiency.

[8]A similar pattern has been observed in the United States. For more information, see Lubik (2021).

[9]The extended Beveridge Curves at the national and regional levels for the full sample, spanning from 2005 to 2024, are presented in Appendix A.

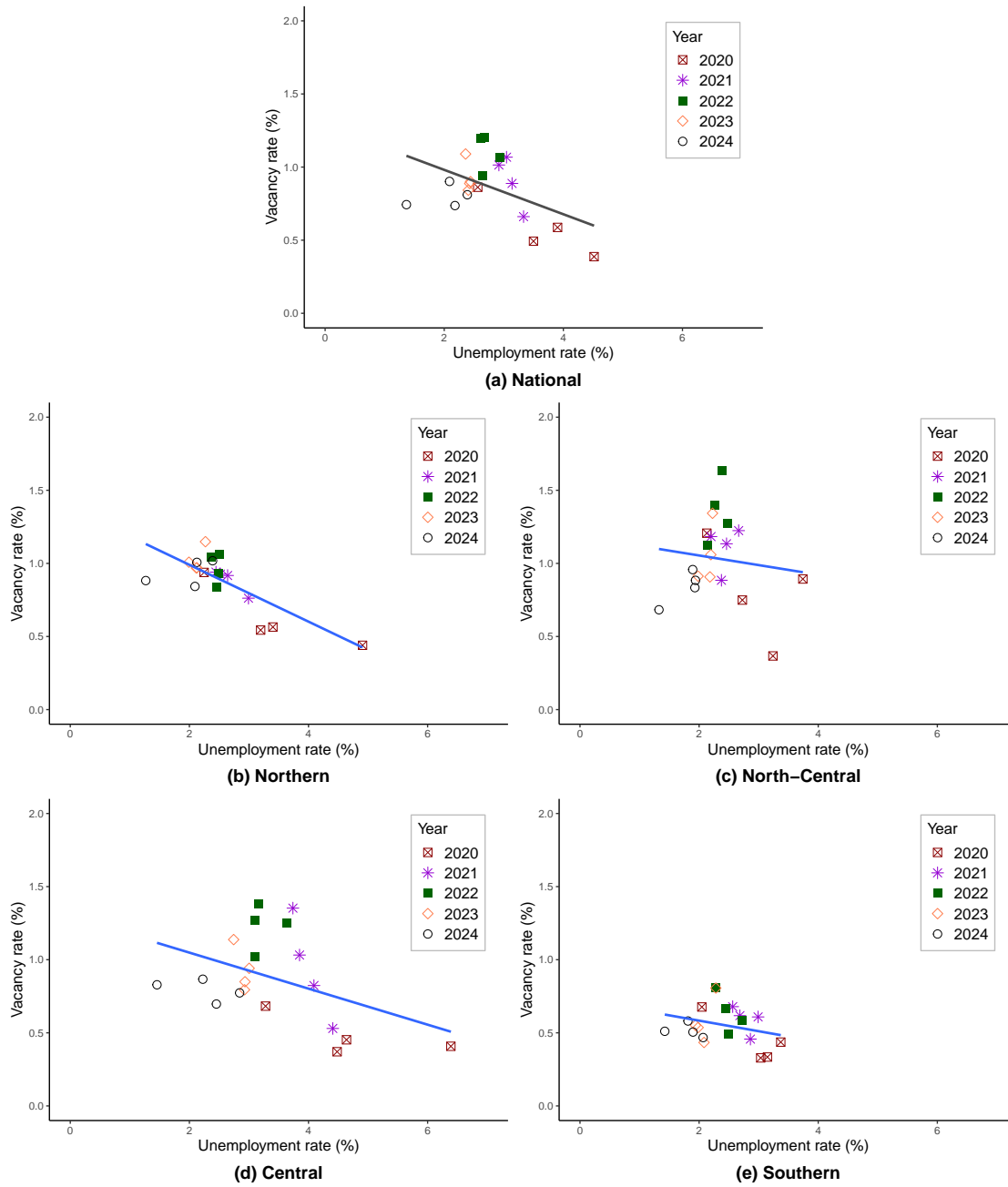**Figure 2: Beveridge Curve in the Context of the COVID-19 Pandemic.**
Source: Own estimates based on data from the National Employment Service Unit of the STPS and INEGI.
Note: The vacancy rate is defined as the number of available job positions listed in the STPS job board expressed as a percentage of the conditional formal labor force. Similarly, the unemployment rate refers to the conditional formal unemployment rate. The dashed line indicates the linear trend of the Beveridge Curve. Each point corresponds to the combination of the unemployment rate and the vacancy rate for a specific quarter within the analysis period.

In addition to the Beveridge Curves, Figure 3 illustrates the V/U ratio as a measure of labor market slack/ tightness in Mexico's regional economies.[10] This ratio represents the number of job vacancies relative to the number of conditional formal unemployed individuals. We believe that the ratio of the job vacancy rate to the unemployment rate is a meaningful measure of labor market slack, as it accounts for both sides of the labor market. While the unemployment rate is the standard measure, representing individuals actively seeking jobs, this ratio also considers the job vacancy rate, which reflects available or soon-to-be-available positions for which firms are actively recruiting. Furthermore, according to Barnichon and Shapiro (2024), at least in the case of the U.S. economy, the vacancy-to-unemployment (V/U) ratio serves as a more effective indicator of labor market conditions compared to traditional slack measures, like the unemployment rate.
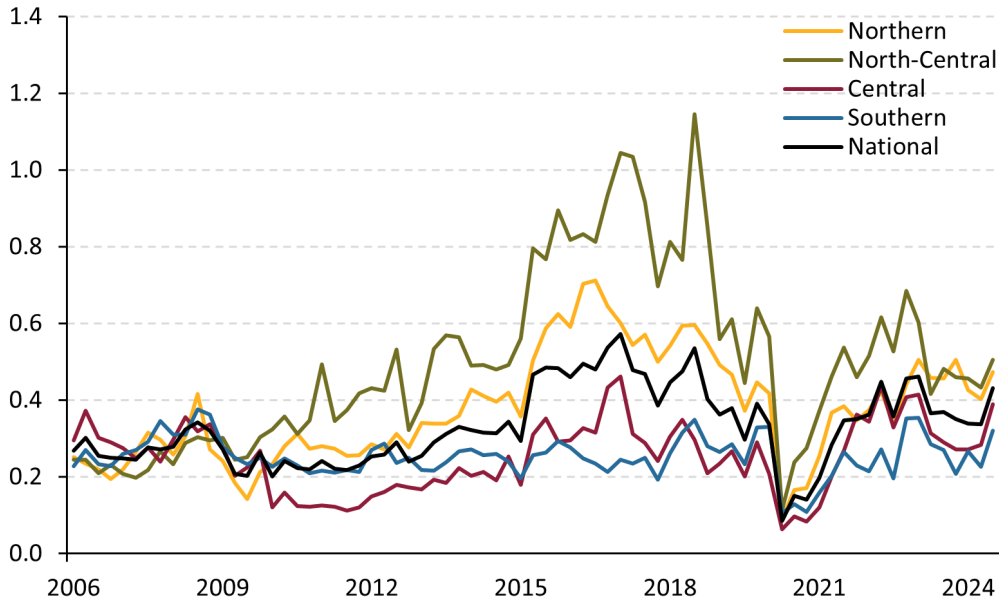

Figure 3: The Vacancies-to-Unemployment Ratio (V/U) as a Measure of Labor Market Slack.
Source: Own estimates based on data from INEGI and STPS.

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[10]Higher values of the V/U ratio indicate a tighter labor market, while higher values of the U/V ratio suggest greater labor market slack.

Figure 3 shows that from 2010 to 2017, the V/U ratio exhibited an upward trend, particularly in the northern and north-central regions, indicating increased formal labor market tightening. However, with the onset of the COVID-19 pandemic, the ratio dropped nationwide and across all regions, reflecting a rise in labor market slack. Beginning in 2021, the ratio rebounded across all regions, signaling tightening conditions—particularly in northern Mexico. By the end of 2023, the ratio had declined in all regions except the north. However, by the end of 2024, the ratio increased across all regions. It is important to note that the southern region is characterized by a high level of informality and a relatively limited presence of the manufacturing sector compared to other regions of the country. To mitigate potential bias arising from this structural feature—and given that the vacancy rate used in the analysis is based exclusively on the formal sector and we use the conditional unemployment rate. This ensures that both variables—vacancies and unemployment—are consistent in terms of sectoral coverage, allowing for a more accurate interpretation of their relationship.

Building on Crust et al. (2023) and Barnichon and Shapiro (2024), we construct Phillips Curves at both national and regional levels using the unemployment-to-vacancy ratio (U/V), the inverse of the vacancy-to-unemployment ratio (V/U), and the core inflation rate. While the (V/U) ratio is used throughout the analysis to assess labor market tightness over time, its inverse (U/V) serves as a measure of labor market slack in the Phillips Curve specification. Figure 4 illustrates these curves, with the horizontal axis representing the unemployment-to-vacancy ratio (U/V) and the vertical axis showing the core inflation rate.

Figure 4 indicates that, at the onset of the pandemic, when formal labor market slack was more pronounced, the core inflation rate remained relatively low at both the national and regional levels (red points). However, by 2021 and 2022 (purple and green points), as labor markets tightened, the core inflation rate rose significantly. This
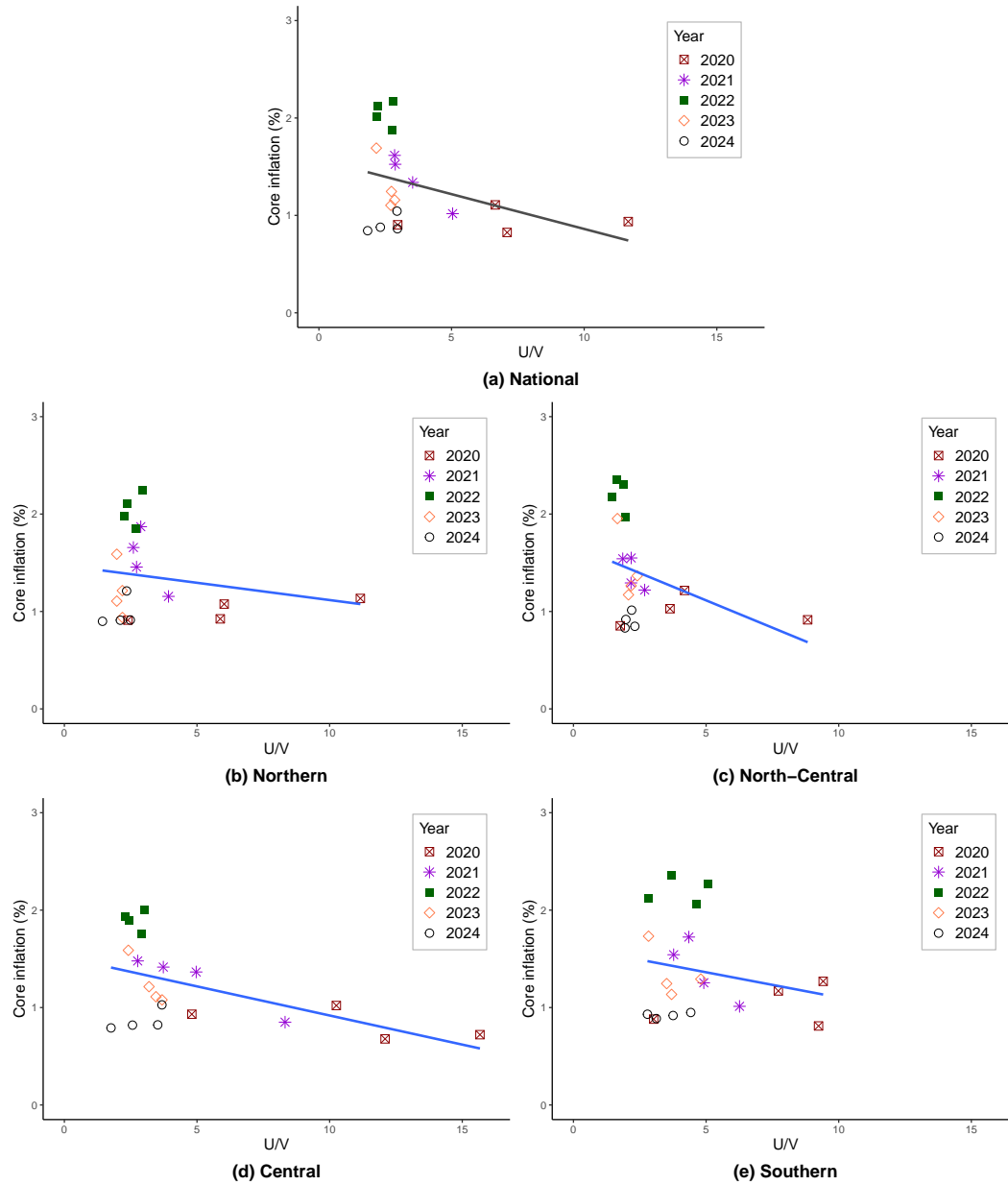
Figure 4: Phillips Curve in the Context of the COVID-19 Pandemic.
Source: Own estimates based on data from the National Employment Service Unit of the STPS and INEGI.
Note: The U/V ratio is defined as the conditional formal unemployment rate divided by the job vacancy rate. The blue line represents the linear trend of the Phillips Curve. Each point corresponds to the combination of the U/V ratio and the year-over-year core inflation rate for a specific quarter within the analysis period.

trend is reflected in a steeper Phillips Curve, particularly at the national level and in the northern and north-central regions. Notably, starting in 2023 (orange points), core inflation declined significantly both at the national level and across regions, even as labor market slack in Mexico remained relatively stable. Thus, the behavior of the Beveridge and Phillips Curves suggests that the decline in core inflation during 2023 and 2024 has taken place in a context of labor market easing—driven by a reduction in job vacancies rather than a rise in unemployment. In fact, not only has unemployment not risen, but it has remained at historically low levels.[11]

Importantly, Figure 5 displays the evolution of the vacancy-to-unemployment ratio (V/U) over time for Mexico and a wide set of OECD countries. The figure shows that trends in Mexico's (V/U) ratio have moved broadly in line with those of other countries. In particular, most countries—including Mexico—experienced a sharp drop in the (V/U) ratio at the onset of the COVID-19 pandemic, followed by a marked labor market tightening (i.e., an increase in (V/U) during the recovery. In more recent quarters, the ratio has begun to decline in several economies, such as the United States. These shared dynamics support the consistency and plausibility of our estimate for Mexico.

To further contextualize the current state of the labor market, we compare Mexico's average (V/U) ratio with international benchmarks. Between 2014Q1 and 2024Q3, the national-level (V/U) ratio for Mexico averaged approximately 0.37. This value is below that of countries such as the United States (0.98), Germany (0.82), Czechia (1.20), and Japan (1.31), but it is comparable to Luxembourg (0.40), Hungary (0.32), and Belgium (0.43), and clearly above that of countries like France (0.15), Portugal (0.09), Spain (0.03), and Greece (0.03). These international comparisons suggest that the tightness of Mexico's labor market, as captured by our measure, falls within a reasonable range observed in other economies.

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[11]The extended Phillips Curves at the national and regional levels for the full sample, spanning from 2005 to 2024, are presented in Appendix A.
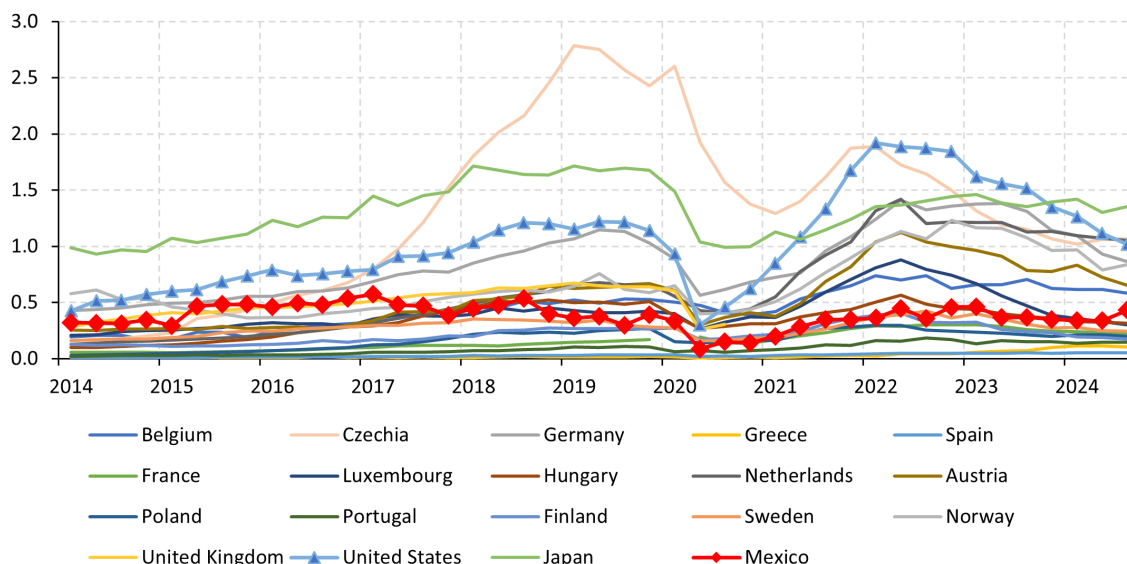
Figure 5: Evolution of the Vacancy-to-Unemployment Ratio (V/U) in Mexico and Selected OECD Countries.
Source: Own estimates based on job vacancy and unemployment data from INEGI and STPS (Mexico), BLS (United States), Eurostat (European countries), and e-Stat (Portal Site of Official Statistics of Japan) for Japan.
Note: The figure presents the evolution of the V/U ratio from 2014Q1 to 2024Q3. The red line with diamond markers corresponds to Mexico, while other countries are shown with lighter lines.

It is important to note that the Mexican (V/U) ratio is calculated exclusively for the *formal sector* given limitations in the vacancy data. Despite this, the fact that our estimate aligns closely with international figures, which generally cover the entire labor market, supports the view that our measurement is consistent and reliable. Unfortunately, we were unable to identify publicly available or methodologically comparable data on vacancy-to-unemployment ratios for countries such as Chile or Colombia, which constrains the potential for regional benchmarking within Latin America.[12]

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[12]For Colombia, Morales et al. (Banco de la República) estimate vacancies using hires data. See: https://repositorio.banrep.gov.co/server/api/core/bitstreams/72aeaee1-aedd-48a8-9777-8cb4ce0f8ab7/content

5 Empirical Framework to Identify Labor Market Shocks

This section begins by presenting the theoretical framework used to analyze shifts and movements along the Beveridge Curve. It then introduces the empirical methodology employed to assess how various structural shocks influence the dynamics of the Beveridge Curve, relying on a Structural Vector Autoregression (SVAR) model. The identification strategy used to recover these shocks is also discussed in detail.

5.1 Deriving the Beveridge Curve in Steady State

To motivate our identification of labor market shocks and interpretation of unemployment–vacancy dynamics, we briefly outline the steps to derive the Beveridge Curve from a steady-state condition under standard assumptions. This serves as a reference for how different structural shocks may shift the curve or generate movement along it.

The Beveridge Curve illustrates a theoretically negative relationship between the unemployment rate and the job vacancy rate under steady-state labor market conditions. This relationship is central to understanding the nature of shocks affecting the labor market—particularly in distinguishing between demand and supply shocks—as emphasized by Elsby et al. (2015) and documented empirically across many countries Michaillat and Saez (2021).

The theoretical derivation begins with the law of motion for unemployment, which describes how the unemployment rate evolves over time. Specifically, unemployment at time t, denoted by u_t, depends on two flows: (1) *inflows into unemployment*, represented by $s(1 - u_{t-1})$, where s is the job separation rate and $1 - u_{t-1}$ is the share of the population employed in the previous period; and (2) *outflows from unemployment*, given by $f_t u_{t-1}$, where f_t is the job finding rate. Thus, the dynamic equation is:

$$u_t = s(1 - u_{t-1}) + u_{t-1}(1 - f_t) \tag{2}$$

We assume a constant labor force (L) and a constant separation rate (s) across time. The variable u represents the unemployment rate normalized by the labor force, while $1 - u$ represents the employment rate.

Subtracting u_{t-1} from both sides of Equation 2 yields the change in unemployment:

$$u_t - u_{t-1} = s(1 - u_{t-1}) - f_t u_{t-1} \tag{3}$$

Under steady-state conditions, $\Delta u = 0$, so inflows into unemployment must equal outflows:

$$s(1 - u) = fu \tag{4}$$

Solving for the steady-state unemployment rate u:

$$u = \frac{s}{s + f} \tag{5}$$

To express f in terms of vacancies, we introduce a Cobb-Douglas matching function with constant returns to scale:

$$H = m(uL)^{1-\alpha}(vL)^{\alpha} \tag{6}$$

Here, H is the number of hires, m is the matching efficiency, α is the elasticity of matches with respect to vacancies, v is the job vacancy rate, and u is the unemployment rate. Dividing both sides by $U = uL$ gives the job finding rate:

$$f = \frac{H}{U} = m\theta^{\alpha} \tag{7}$$

where $\theta = \frac{v}{u}$ is labor market tightness. Substituting this into the steady-state unemployment equation:

$$u = \frac{s}{s + m\theta^\alpha} \quad \Rightarrow \quad \theta = \left(\frac{1-u}{u} \cdot \frac{s}{m} \right)^{1/\alpha}$$

Finally, expressing $\theta = v/u$ and solving for v gives the Beveridge Curve equation:

$$v = \left(\frac{s(1-u)}{mu^{1-\alpha}} \right)^{1/\alpha} \tag{8}$$

This final expression shows the negative relationship between vacancies (v) and unemployment (u): as unemployment falls, filling jobs becomes more difficult, requiring a higher number of vacancies to maintain the same number of matches, and vice versa.

5.2   Model Specification, Data and Identification Strategy

A significant body of literature employs SVAR models with sign restrictions to identify macroeconomic shocks. Following this approach, we estimate a bayesian SVAR model for the Mexican economy to identify demand, technology, and labor market shocks. Furthermore, given that Mexico is a small open economy, its macroeconomic dynamics are largely influenced by external factors, which are assumed to affect the domestic economy without being significantly influenced in return. To reflect this open-economy structure, the model includes two blocks of variables: one capturing external conditions, treated as exogenous, and another representing domestic variables. The domestic block includes: employment, prices, real wages, unemployment, and vacancies, all expressed in annual growth rates to capture the main macroeconomic and labor market conditions relevant to our analysis. As discussed earlier, due to data limitations that restrict vacancy information to the formal sector, all variables are adjusted to reflect dynamics within this part of the economy, with the exception of prices.[13] The data sources for each variable are as follows:

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[13]Due to the lack, to the best of our knowledge, of an official measure of output growth specific to the formal sector, we use the annual growth rate of formal employment as a proxy. This is a reasonable approximation, as the annual growth rates of formal employment and total GDP(which includes both formal and informal sectors) are highly correlated, with a coefficient of roughly 80% over the analysis period.

- ✦ **Employment** is measured by the number of workers registered with the Mexican Social Security Institute (Instituto Mexicano del Seguro Social, IMSS).

- ✦ **Prices** are represented by the Consumer Price Index (CPI), obtained from INEGI.

- ✦ **Real wages** are calculated as the average base contribution salary of IMSS-registered workers, deflated using the National Consumer Price Index (INPC).

- ✦ **Unemployment rate** corresponds to the conditional formal unemployment rate defined in equation (1) computed from microdata obtained through ENOE.

- ✦ **Vacancy data** comes from the Job Board managed by the STPS.

The block of exogenous variables comprises U.S. real GDP, U.S. consumer prices (CPI), the VIX index, and international oil prices. These variables are included to capture, respectively: external demand fluctuations, global cost-push pressures on import prices, global financial market volatility, and commodity price shocks relevant to Mexico's terms of trade. This specification allows us to isolate the influence of external drivers while focusing on the identification of domestic transmission mechanisms.

In addition to accounting for external influences, it is important to control for shocks that may distort model estimates. In the aftermath of the COVID-19 pandemic, it has become necessary to control for pandemic-related effects in VAR models due to the presence of extreme and unprecedented macroeconomic fluctuations that can distort parameter estimates and impulse responses. The pandemic introduced structural breaks and highly volatile observations, such as sharp contractions in output and surges in unemployment, that differ substantially from typical business cycle dynamics. If left unaddressed, these outliers can bias the estimation of model coefficients, inflate uncertainty measures, and undermine the reliability of historical relationships among macroeconomic variables.

Recent studies have pointed out the importance of accounting for the effects of the COVID-19 pandemic when estimating VAR models. Lenza and Primiceri (2022)

explain that the shocks observed at the onset of the COVID-19 pandemic led to a sharp increase in volatility in macroeconomic and financial time series. As a result, they argue that standard VAR estimation becomes unreliable after March 2020. They propose two possible solutions: either treating the pandemic quarters as outliers or adopting models that allow for time-varying volatility. Similarly, Carriero et al. (2022) employ a stochastic volatility model in which the COVID-19 shock is modeled as a random shift in volatility. Schorfheide and Song (2021), using a mixed-frequency VAR framework, suggest a more practical approach that consists of excluding extreme pandemic-period observations in order to preserve the accuracy of forecast results. In turn, Cascaldi-Garcia (2022) propose the inclusion of time dummies with uninformative priors to correct for the atypical observations caused by the pandemic, while preserving the structural relationships among variables. An alternative approach is offered by Ng (2021), who do not treat the pandemic as an outlier or a volatility regime change, but rather as a distinct exogenous shock requiring its own observable channel. Their method involves first regressing each macroeconomic variable on COVID-related indicators, and then estimating the VAR using the residuals. This allows for isolating standard macroeconomic dynamics from pandemic-induced fluctuations.

To account for the exceptional volatility and level shifts induced by the COVID-19 pandemic, we include time-specific dummy variables for the pandemic period as exogenous regressors in the BVAR. This approach, in the spirit of Cascaldi-Garcia (2022), allows us to capture the transitory effects of the pandemic without distorting the underlying macroeconomic relationships. It offers a simple yet effective alternative to more complex methods, such as those that model heteroscedasticity in the error structure, while delivering comparable results.

We also control for outliers from other periods of high volatility. To identify such extreme but transitory observations in our dataset, we detect outlier periods separately for each variable using empirical percentiles. Specifically, we flag observations that fall below the 0.5th percentile or above the 99.5th percentile of each variable's distribution,

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thereby capturing the most extreme 1% of data points.[14] Based on this criterion, we identify the following quarters as outliers: 2009Q2, 2010Q1, 2015Q4, 2020Q2, 2021Q2, 2022Q3, and 2023Q4. We include time dummies for these quarters in the corresponding equations to mitigate their impact on parameter estimates while preserving the dynamics of the remaining sample.

The dataset covers the period from the second quarter of 2006 to the third quarter of 2024. We use quarterly data, as unemployment rates for the formal sector can only be constructed at this frequency. The SBVAR models are estimated at both the national and regional levels. The reduced-form representation of each SBVAR model is outlined below:

$$y_t = C + B_1 y_{t-1} + \cdots + B_p y_{t-p} + DX_t + u_t \tag{9}$$

where y_t is an $N \times 1$ vector of N endogenous variables, C is an $N \times 1$ vector of constants, B is an $N \times N$ matrix of coefficients for lagged endogenous variables, p is the number of lags, and u_t is a vector of residuals for each equation with $u_t \sim N(0, \Sigma)$, where Σ is the $N \times N$ variance-covariance matrix of residuals. X_t denotes an $M \times 1$ vector of M exogenous variables, and D is the corresponding $N \times M$ matrix of coefficients capturing their contemporaneous effect on y_t.[15]

Given the large number of parameters to be estimated, we use Bayesian methods to deal with the dimensionality issue and assume a Gaussian-Wishart prior distribution to derive the posterior distribution of the VAR coefficients.[16]

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[14]These thresholds are broadly consistent with a ± 2.6 standard deviation range under the normal distribution. They allow us to isolate the most extreme 1 percent of observations without imposing parametric assumptions. Compared to alternative cutoffs (e.g., 1st/99th or 2.5th/97.5th percentiles), this choice provides a conservative balance by excluding only the most highly unusual values.

[15]All VAR models are estimated with a lag length of $p = 4$. As a robustness check, we verify that the main results remain qualitatively unchanged when varying the number of lags.

[16]We determine the optimal hyperparameters through a grid search procedure. The selected hyperparameters are used to compute the mean and variance of the prior distribution for the VAR coefficients, based on the combination that maximizes the marginal likelihood. Specifically, for each hyperparameter (λ), we define a range using a minimum, maximum, and step size. The autoregressive coefficient is fixed at 0.9. The overall tightness hyperparameter (λ_1) varies from 0.01 to 0.5 in steps of 0.01, while the lag decay hyperparameter (λ_3) ranges from 1 to 2. These intervals encompass standard values commonly used in the literature (Canova (2011); Dieppe et al. (2016)). The model is estimated

To map the structural shocks of interest from the reduced-form residuals, it is necessary to impose identifying restrictions on the estimated variance–covariance matrix. Under these restrictions, the reduced-form error term u_t can be expressed as a linear combination of structural shocks:

$$u_t = A\epsilon_t \tag{10}$$

with $\epsilon_t \sim N(0, I)$, where I is an $N \times N$ identity matrix and A is a nonsingular parameter matrix. The variance-covariance matrix has the following structure: $\Sigma = AA'$. Therefore, in order to identify A, we impose sign restrictions on impact. Our identification scheme relies on the restrictions imposed on the sign of the endogenous variable's response to each structural shock, following Foroni et al. (2018) and Schiman (2021).

In Equation 9, y_t represents the annual growth rates of the following endogenous variables: formal employment, prices, real wages, unemployment rate, and vacancies. The vector X_t includes exogenous variables capturing external conditions, namely: the U.S. real GDP growth rate, U.S. CPI annual inflation, the VIX index, and the annual growth rate of international oil prices.

For the estimation of the SBVAR models, and in order to identify the labor market shocks, we impose sign restrictions on the response on impact of the endogenous variables. In what follows, we provide a description of the structural shocks' identification, while Table 1 summarizes this identification scheme.[17]

Table 1: Sign Restrictions Identification

	Demand	Technology	Labor Supply	Wage Bargaining	Efficiency
Employment (E)	+	+	+	+	+
Prices (P)	+	-	-	-	-
Real Wages (W)		+	-	-	-
Unemployment (U)	-		+	-	-
Vacancies (V)				+	-

for every combination within this grid, and the marginal likelihood is computed for each specification. The optimal set of hyperparameters corresponds to the combination that yields the highest marginal likelihood. The total number of iterations is 20,000, and the number of burn-in iterations is 19,000.

[17]The shocks are normalized to produce on impact a positive response on formal employment.

✦ **Demand shock:** Following a positive local demand shock, employment (E) and prices (P) rise, while unemployment (U) declines. This shock drives movements along the Beveridge Curve, reflecting the cyclical dynamics of economic activity. For instance, during a recession, output and employment contract, job hiring slows, and unemployment rises. Conversely, in an expansion, output and employment growth is accompanied by increased hiring and lower unemployment. We impose restrictions only on the impact response of employment (E), prices (P), and unemployment (U), while remaining agnostic about the responses of real wages (W) and vacancies (V), allowing the data to speak freely.

✦ **Technology shock:** We assume that following a positive technology shock, there is an increase in productivity, which increases output and employment (E) and reduces the marginal costs for firms and, therefore, pushes prices down (P). The production (Y) expansion creates incentives for increasing hiring resulting in higher real wages (W). Following this technology shock, we remain agnostic about the impact response of vacancies (V) and unemployment (U).

✦ **Matching efficiency shock:** Matching efficiency shocks are exogenous changes in the job-worker matching process that distort the standard matching function and shift the Beveridge Curve. An exogenous improvement in matching efficiency reduces hiring costs, which in turn lowers wages (W) and prices (P), boosts output and employment (E), and reduces unemployment (U). The response of vacancies (V) is likely negative, as suggested by Foroni et al. (2018).

Improvements in matching efficiency (inward shift of the Beveridge Curve) can arise from various factors, such as enhanced labor market reallocation mechanisms, advancements in electronic job advertisements and matching platforms, or refined recruitment strategies by firms, which improve their ability to identify and hire suitable candidates more effectively.

Conversely, a decline in matching efficiency or mismatch (outward shift of the Beveridge Curve) can result from skill mismatches between job seekers and em-

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ployer requirements, geographic barriers that limit worker mobility, or structural shifts in the economy, such as changes in industry demand that leave workers ill-prepared for emerging sectors.

✦ **Wage bargaining shock:** Following a psoitive wage bargaining shock, which assumes that workers have more bargaining power to achieve wage (W) increases. Thus, following a positive shock of this nature, we impose that compensation per employee increases on impact. However, since firms would face higher production costs, they increase their sales prices (P) and reduce their vacancy (V) postings to hire. As a result, we expect production (Y) to decrease and unemployment (U) to increase. In the sign-restriction summary in Table 1, this shock is displayed as a *negative* wage bargaining shock to ensure that all shocks are normalized to imply an increase in employment.

✦ **Labor supply shock:** Following a positive labor supply shock, households experience a reduced disutility of work and become more active in the labor market, leading to an increase in output or employment (E) and a greater number of job seekers. The expansion of labor supply reduces pressure on wages (W) and, consequently, on prices (P). Regarding the job vacancies (V) response, we remain agnostic and allow the data to speak.

While the sign restrictions for the effects of demand, technology, wage bargaining, and efficiency are quite common, it is worth exploring whether the restrictions for the effects of labor market supply shocks are sensible in the context of the Mexican economy.

According to Foroni et al. (2018), an exogenous increase in labor supply may initially lead to a temporary rise in unemployment (U), as some new entrants take time to find a job. However, many of these individuals are expected to secure employment within the following months. To empirically assess whether a similar pattern holds in the Mexican labor market, we construct a quarterly *transition rate* that captures the dynamics of individuals moving from inactivity to employment via unemployment.

We explain the algorithm used to compute this rate, specifically identifying individuals who: (i) were outside the labor force, (ii) entered unemployment, and (iii) subsequently found employment within the following year. The resulting measure—hereafter referred to as the *transition rate*—is expressed as a percentage of total unemployment in each quarter.

Leveraging the rotating panel structure of ENOE microdata, we track each individual's labor market status over time. For every unemployed individual observed in quarter t, we examine their status over the previous four quarters ($t - 1$ to $t - 4$). If the individual was inactive—that is, out of the labor force—in any of those quarters, we then inspect the subsequent four quarters ($t + 1$ to $t + 4$) to determine whether the person eventually becomes employed. If this condition is met, the person is counted as having completed a transition from inactivity to employment via unemployment.

An observation is included in the numerator of the transition rate if all three of the following conditions are satisfied:

1. The individual was inactive in at least one of up to four preceding quarters;

2. The individual is unemployed in the current quarter t;

3. The individual is employed in at least one of up to four subsequent quarters.

Each qualifying individual is counted once, in the quarter when the unemployment status is observed. In all cases, we apply the corresponding survey weighting factor to ensure representativeness. The transition rate from inactivity to unemployment to employment is calculated as:

$$\text{Transition rate}_t = \left(\frac{\text{Transitions}_{t,t\pm k}}{\text{Unemployment}_t} \right) \times 100 \tag{11}$$

This rate answers the following question: *Among all individuals recorded as unemployed in quarter t, what share were inactive up to four quarters earlier and subsequently succeed in finding employment within the next year?* Since the methodology requires observing individuals up to four quarters in both directions, we restrict our analysis to

the period from 2006 to 2023, excluding 2005 and 2024 to avoid artificially lowering the rate due to incomplete observation windows. This ensures each individual has up to four observable periods both before and after the quarter t within the rotating panel.
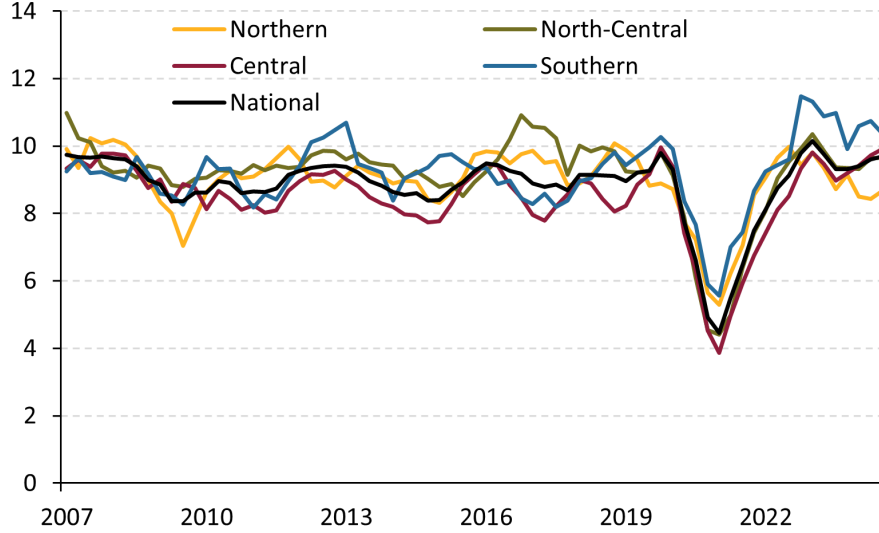

Figure 6: Transition rates at the national and regional level, 4-quarter m.a.
Source: Own estimates based on data from INEGI.
Note: Time in quarters (horizontal axis) and units in percent (vertical axis).

As shown in Figure 6, these transition rates average around 9% and declined sharply during the pandemic. However, they have since recovered and are now close to their pre-pandemic levels. This evidence suggests that a non-negligible share of the previously inactive population enters the labor market via unemployment before securing a job.

6   The Effects of Labor Market and Demand Shocks in Mexico

In this section, Figures 7 to 11 present the impulse response functions (IRFs) for the identified shocks: labor market shocks (labor supply, wage bargaining and matching efficency), demand, and technology shocks, applied to the variables of formal employment, prices, real wages, job vacancies, and unemployment at both the national and regional levels. IRFs are useful for analyzing labor, demand, and technology shocks as they reveal the dynamic response of formal employment, prices, real wages, conditional

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formal unemployment, and job vacancies over time, highlighting the magnitude, direction, and persistence of these shocks on key economic variables. The horizontal axis represents time in quarters (up to 12 quarters or 3 years), while the vertical axis shows the response of the variables as a percentage points. All shocks are normalized to represent one-standard-deviation structural innovations. In Figure 7, we present the impulse responses of the variables of interest to different structural shocks at the national level.

Figure 7: Impulse responses to demand, technology, labor supply, wage bargaining and efficiency shocks at the national level.
Source: Own estimates based on data from INEGI and STPS.
Note: Time in quarters (horizontal axis) and units in percentage points (vertical axis). Shaded area represents 68 percent credibility intervals.

We observe that a positive demand shock leads to an increase in the employment growth rate that lasts for one quarter, while the rise in inflation is more persistent, extending up to eight quarters. The unemployment growth rate falls for approximately two quarters before returning to its pre-shock level. For variables without sign re-

strictions on impact—wage inflation and vacancies growth rate—we do not observe statistically significant responses.

Following a positive technology shock, the increase in employment growth is short-lived, persisting for four quarters, while the decline in inflation growth lasts for up to three quarters. In contrast, real wage growth exhibits a more persistent positive response, extending over five quarters. The growth rates of unemployment and vacancies do not show statistically significant effects.

Similarly, in response to a positive labor supply shock, the employment growth rate rises over ten quarters. The decline in the price growth rate lasts for six quarters, while the drop in real wage growth is highly persistent, lasting for more than twelve quarters. The unemployment growth rate increases for approximately four quarters; however, vacancy growth remains unresponsive.

Moreover, a wage bargaining shock leads to a brief uptick in employment growth and a short-lived decline in inflation, both lasting only one quarter. In contrast, the fall in real wage growth is more persistent, extending over roughly seven quarters. Following the shock, the unemployment growth rate falls for two quarters, while the vacancy growth rate continues to expand for up to seven quarters.[18]

Finally, following a positive matching efficiency shock, the unemployment growth rate declines more persistently than the vacancy growth rate, with effects lasting eight and three quarters, respectively. This improvement in labor market efficiency is accompanied by a rise in the employment growth rate lasting two quarters. After this shock, wage inflation is expected to decline for up to ten quarters.

To assess whether these dynamics hold across different regions, Figures 8 to 11 present the impulse response functions for the northern, north-central, central, and southern regions. Although the regional results are qualitatively similar to those observed at the national level, several important differences emerge.

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[18]This refers to a *negative* wage bargaining shock, i.e., one that increases employment or output through lower negotiated wages.

In the northern region (Figure 8), the response of wage inflation to a positive technology shock is notably more persistent than at the national level. Conversely, the employment growth response to a labor supply shock is shorter-lived. In addition, the decline in unemployment growth following a matching efficiency shock is less persistent in this region compared to the national aggregate.
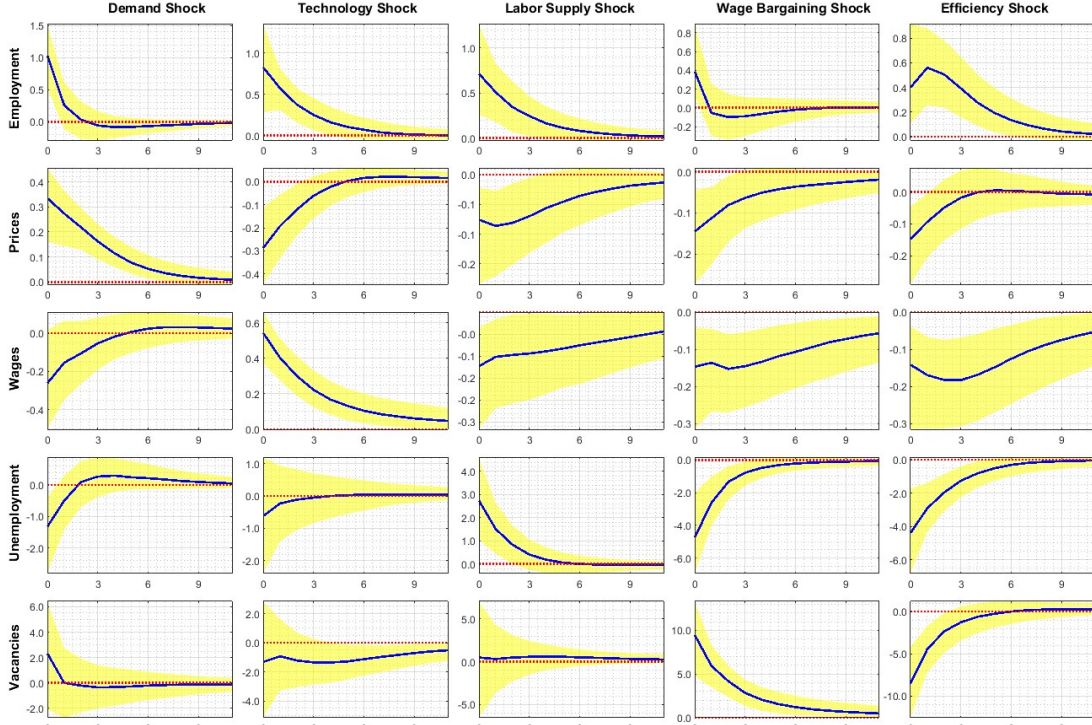

Figure 8: Impulse responses to demand, technology, labor supply, wage bargaining and efficiency shocks for the northern region.
Source: Own estimates based on data from INEGI and STPS.
Note: Time in quarters (horizontal axis) and units in percentage points (vertical axis). Shaded area represents 68 percent credibility intervals.

In the north-central region (Figure 9), wage inflation also exhibits a more persistent response to a technology shock. However, after a labor supply shock, the effects on employment and wage growth are considerably less persistent than those observed nationally. In contrast, the wage bargaining shock leads to a more durable response in both employment growth and wage inflation relative to the national level. Finally,

the decline in unemployment growth following a matching efficiency shock is again less persistent than at the national level.
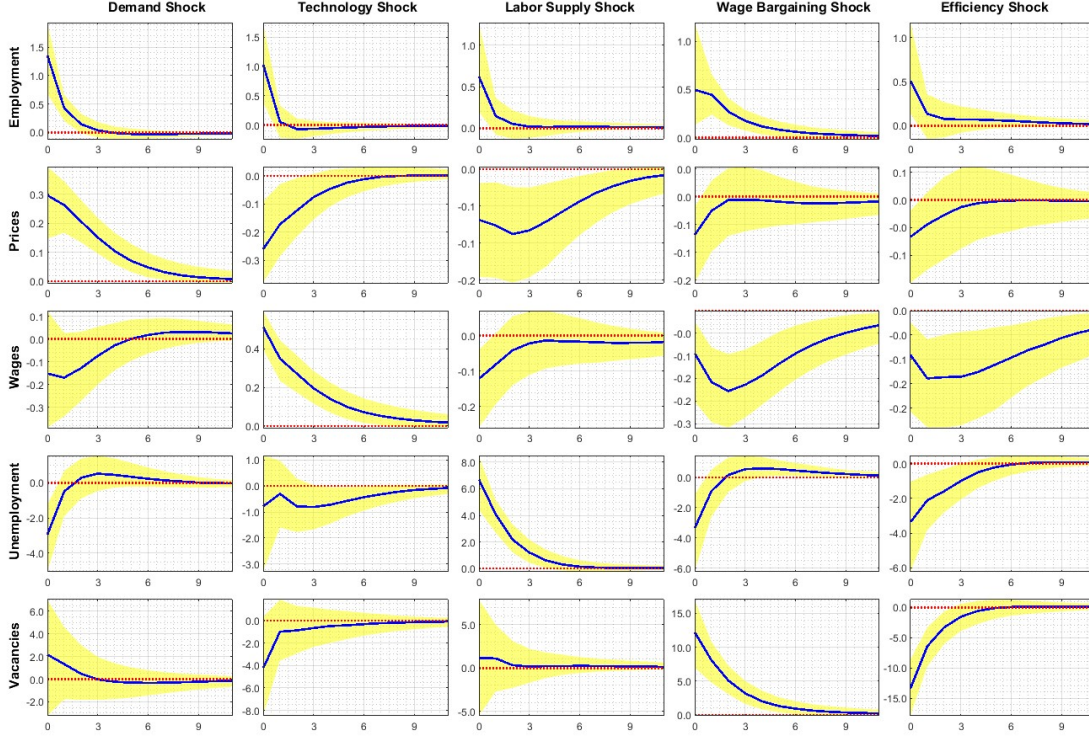

Figure 9: Impulse responses to demand, technology, labor supply, wage bargaining and efficiency shocks for the north-central region.
Source: Own estimates based on data from INEGI and STPS.
Note: Time in quarters (horizontal axis) and units in percentage points (vertical axis). Shaded area represents 68 percent credibility intervals.

In the central region (Figure 10), employment growth and wage inflation display much shorter-lived responses to a labor supply shock. Likewise, the decline in unemployment growth following a matching efficiency shock lasts only four quarters, compared to eight at the national level.
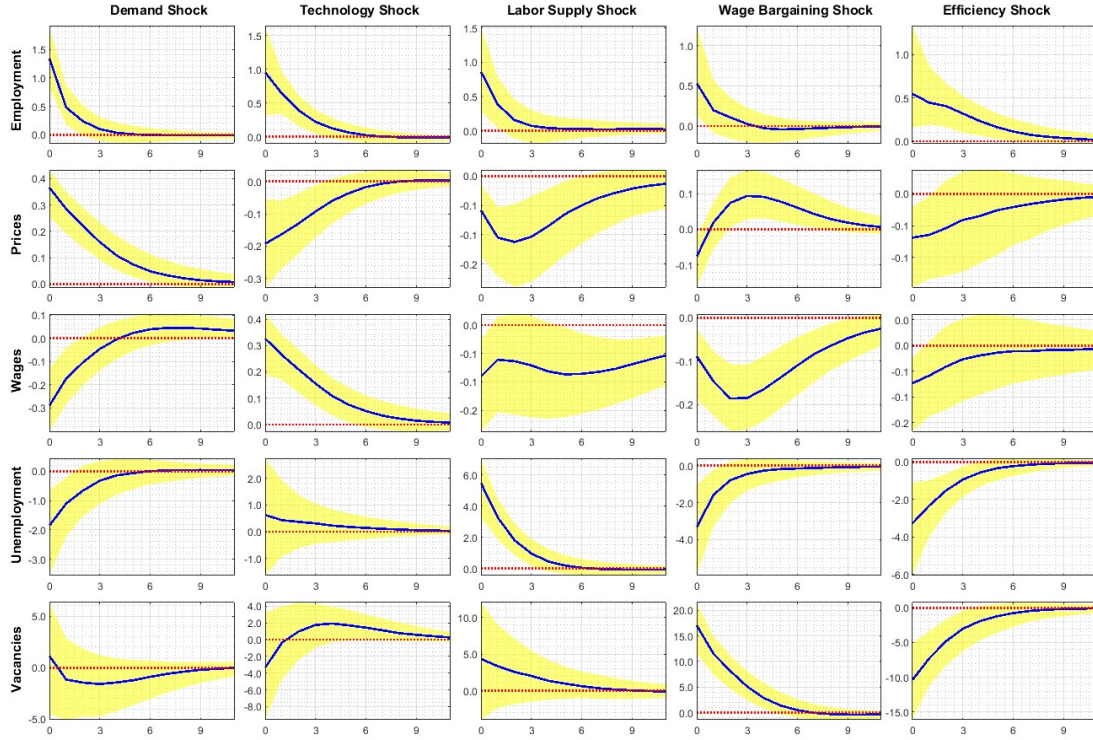
Figure 10: Impulse responses to demand, technology, labor supply, wage bargaining and efficiency shocks for the central region.
Source: Own estimates based on data from INEGI and STPS.
Note: Time in quarters (horizontal axis) and units in percentage points (vertical axis). Shaded area represents 68 percent credibility intervals.

In the southern region (Figure 11), the increase in employment growth following a demand shock is significantly more persistent, while the accompanying rise in inflation is less sustained. A technology shock also produces a notably more persistent increase in wage inflation. Similarly, employment growth following a matching efficiency shock shows a longer-lasting effect than in the national aggregate.
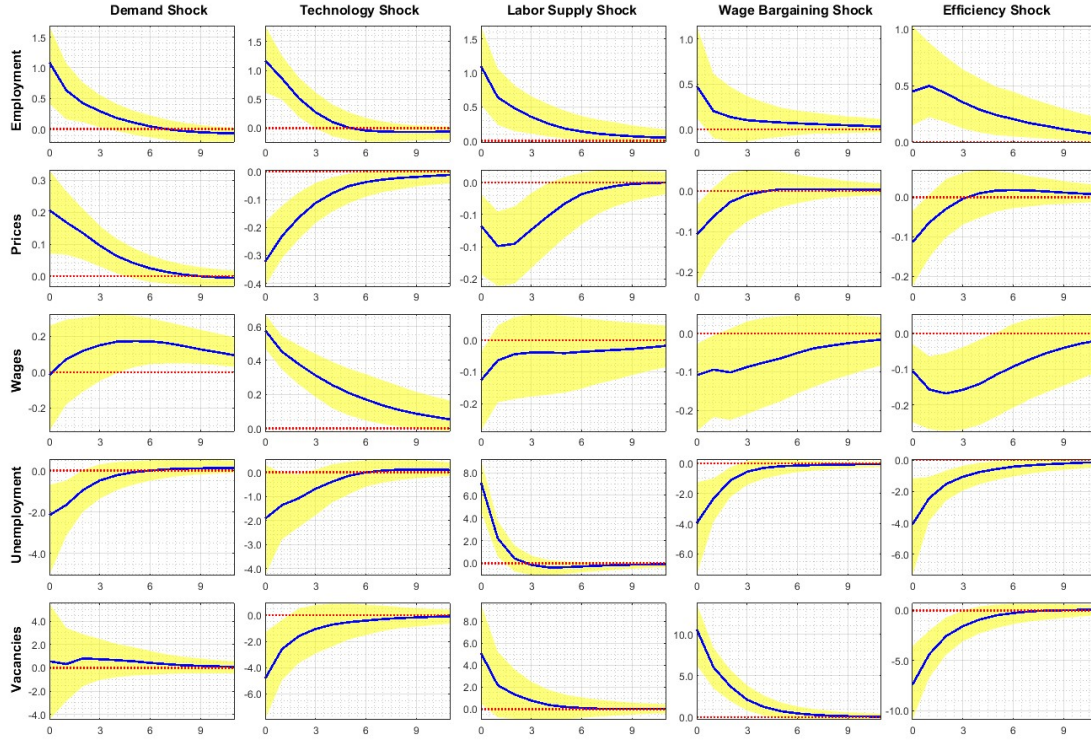
Figure 11: Impulse responses to demand, technology, labor supply, wage bargaining and efficiency shocks for the southern region.
Source: Own estimates based on data from INEGI and STPS.
Note: Time in quarters (horizontal axis) and units in percentage points (vertical axis). Shaded area represents 68 percent credibility intervals.

6.1 *Relative Importance of Demand, Technology, and Labor Market Shocks on Formal Employment, Prices, Real Wages, Conditional Formal Unemployment, and Job Vacancies*

In this section, we assess the relative importance of demand, technology, labor supply, wage bargaining, and matching efficiency shocks in explaining the dynamics of formal employment, prices, real wages, conditional formal unemployment rate, and job vacancies, using the Forecast Error Variance Decomposition (FEVD). This is a standard tool in time series analysis—particularly in SVAR models—that quantifies the contribution of individual structural shocks to the forecast error variance of each variable over time.

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It decomposes the variance of forecast errors into portions attributable to each identified shock, enabling researchers to evaluate how much of a variable's behavior can be explained by each structural innovation at various horizons.

This method is especially valuable for understanding the relative importance of different shocks, as it isolates their individual roles in driving the dynamics of the system. By examining these contributions across short and long-term horizons, FEVD provides insight into both the immediate and persistent effects of each shock. In our context, it allows us to evaluate the extent to which each shock explains the variation in employment growth, inflation, wage inflation, unemployment growth, and vacancies growth.

Figures 12 to 16 present the variance decomposition of formal employment, prices, real wages, unemployment, and vacancies—all expressed in annual growth rates—attributed to demand (red area), technology (green area), labor supply (blue area), wage bargaining (yellow area), and matching efficiency shocks (purple area), both at the national and regional levels. The horizontal axis represents time in quarters, while the vertical axis indicates the percentage of the median contribution explained by each shock over a 12-quarter horizon.

Figure 12 shows that, at the national level, labor supply shocks (blue area) explain 29.0% of the variation in employment growth, making them the dominant driver. Technology shocks (green area) and demand shocks (red area) follow closely, accounting for 26.2% and 23.9%, respectively. In contrast, matching efficiency shocks (purple area, 12.1%) and wage bargaining shocks (yellow area, 8.8%) play a relatively smaller role. While their influence is secondary compared to demand- and supply-side factors, they still contribute meaningfully to labor market dynamics and employment variability.
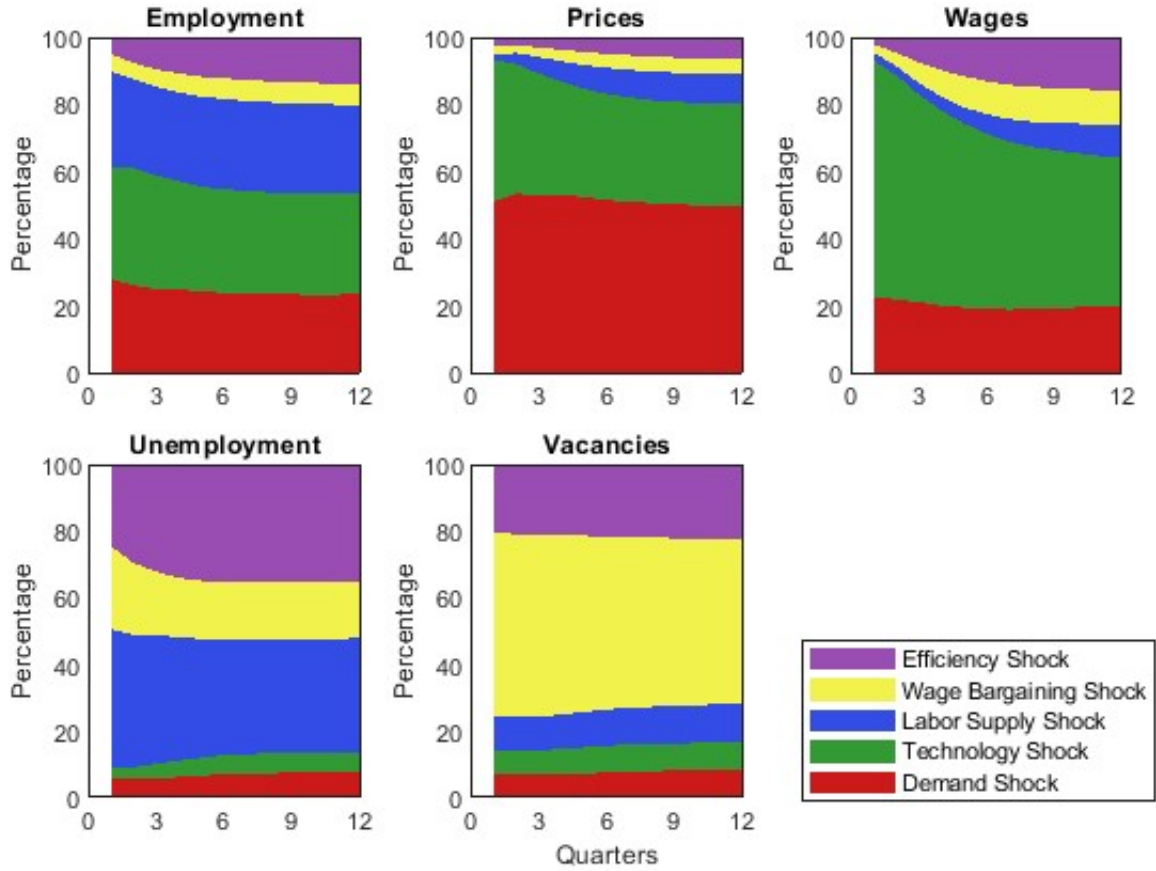
Figure 12: Variance decomposition of formal employment, prices, real wages, unemployment, and vacancy variables driven by demand, technology, labor supply, wage bargaining and efficiency shocks at the national level.
Source: Own estimates based on data from INEGI and STPS.
Note: Time in quarters (horizontal axis) and units in percent (vertical axis).

For inflation, demand shocks (red area) dominate in the short run, contributing 51.3% to price fluctuations, reflecting their strong impact on inflationary pressures via aggregate demand. Over time, their influence wanes, while the contribution of labor supply shocks (blue area) grows, reaching 6.9% of the total variance—suggesting that labor market conditions, such as worker availability, increasingly shape price behavior. Technology shocks (green area) explain 33.2%, highlighting the role of productivity and cost dynamics in long-term price movements. Meanwhile, wage bargaining and match-

ing efficiency shocks (yellow and purple areas, 3.8% and 4.8%, respectively) contribute modestly, yet their effects remain non-negligible.

In the case of wages growth, the decomposition reveals that technology shocks (green area) are the most important factor, accounting for 54.0% of the variation in real wage growth, underscoring the central role of productivity in wage determination. Demand shocks (red area) contribute 19.9%, remaining a consistent driver of wage fluctuations. While matching efficiency shocks (purple area) contribute 11.6%, wage bargaining and labor supply shocks (yellow and blue areas) explain 8.4% and 6.1%, respectively—indicating relatively minor roles in the overall wage dynamic.

Turning to unemployment growth, labor supply shocks (blue area) are the largest contributor, explaining 36.0% of its variation. Matching efficiency shocks (purple area, 33.6%) and wage bargaining shocks (yellow area, 18.3%) also play substantial roles, highlighting how wage-setting behavior and job-matching mechanisms influence unemployment dynamics. Though demand shocks (red area) contribute just 6.8% in the short term, their impact grows over time, suggesting a delayed effect of aggregate demand on unemployment. Technology shocks (green area) play a more limited role, accounting for just 5.3%.

Finally, in the case of the vacancies growth rate, wage bargaining shocks (yellow area) emerge as the dominant force, explaining 52.0% of the variation. This underscores how wage-setting behavior affects firms' hiring decisions and the number of job openings. Matching efficiency and labor supply shocks (purple and blue areas) contribute 21.7% and 10.8%, respectively, pointing to the relevance of search and matching frictions, as well as labor availability. In contrast, technology and demand shocks (green and red areas) explain only 7.9% and 7.6%, reinforcing the idea that vacancy dynamics are primarily driven by supply-side factors rather than productivity or demand conditions.
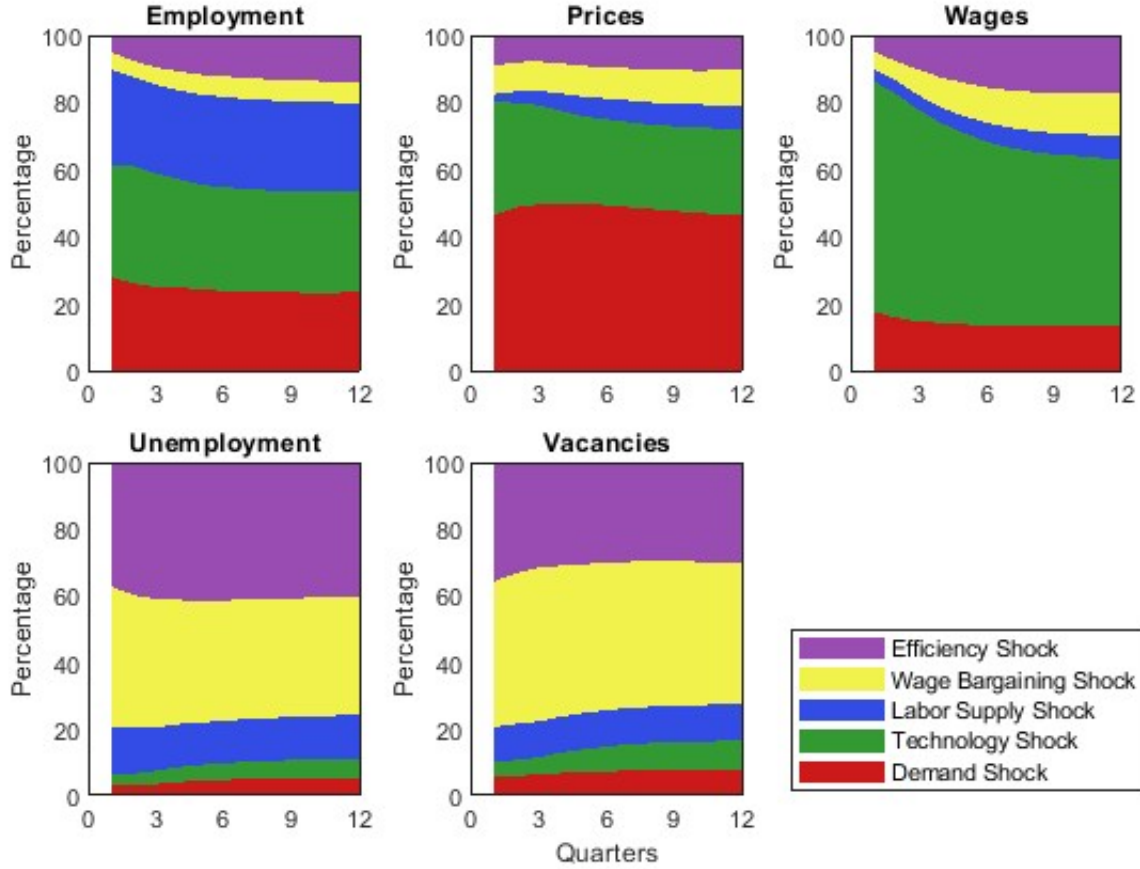
Figure 13: Variance decomposition of formal employment, prices, real wages, unemployment, and vacancy variables driven by demand, technology, labor supply, wage bargaining and efficiency shocks for the northern region.
Source: Own estimates based on data from INEGI and STPS.
Note: Time in quarters (horizontal axis) and units in percent (vertical axis).

We now turn to the regional analysis to evaluate the relative importance of the identified shocks in explaining economic dynamics at the subnational level. The results are presented in Figures 13 to 16. While the median contributions generally mirror national patterns, several notable regional differences emerge.

In the northern region (Figure 13), wage bargaining shocks contribute more prominently to the unemployment decomposition than at the national level, whereas labor supply shocks play a less significant role. In the case of vacancy growth, matching

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efficiency shocks are substantially more influential in this region, while the contribution of wage bargaining shocks is considerably smaller.

In the north-central region (Figure 14), labor supply shocks play a more prominent role in the decomposition of unemployment growth relative to the national level. A similar pattern emerges in the decomposition of vacancies, where matching efficiency shocks remain the dominant driver, while the contribution of wage bargaining shocks is comparatively smaller than at the national level.
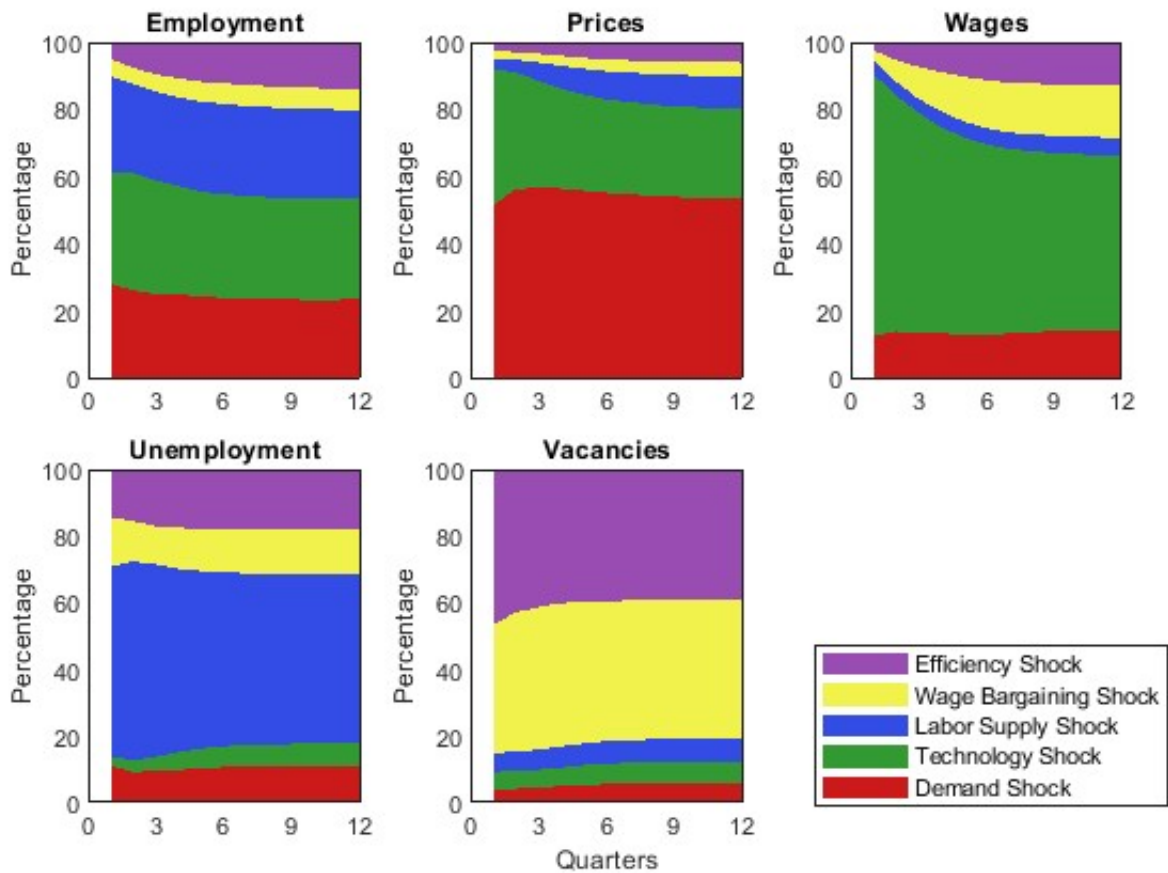

Figure 14: Variance decomposition of formal employment, prices, real wages, unemployment, and vacancy variables driven by demand, technology, labor supply, wage bargaining and efficiency shocks for the north-central region.
Source: Own estimates based on data from INEGI and STPS.
Note: Time in quarters (horizontal axis) and units in percent (vertical axis).

In the central region (Figure 15), labor supply shocks also play a more prominent role in the unemployment decomposition, diverging from national results. In contrast, the influence of matching efficiency shocks is weaker. For vacancy growth, wage bargaining shocks emerge as the most influential factor, with a larger contribution than at the national level.
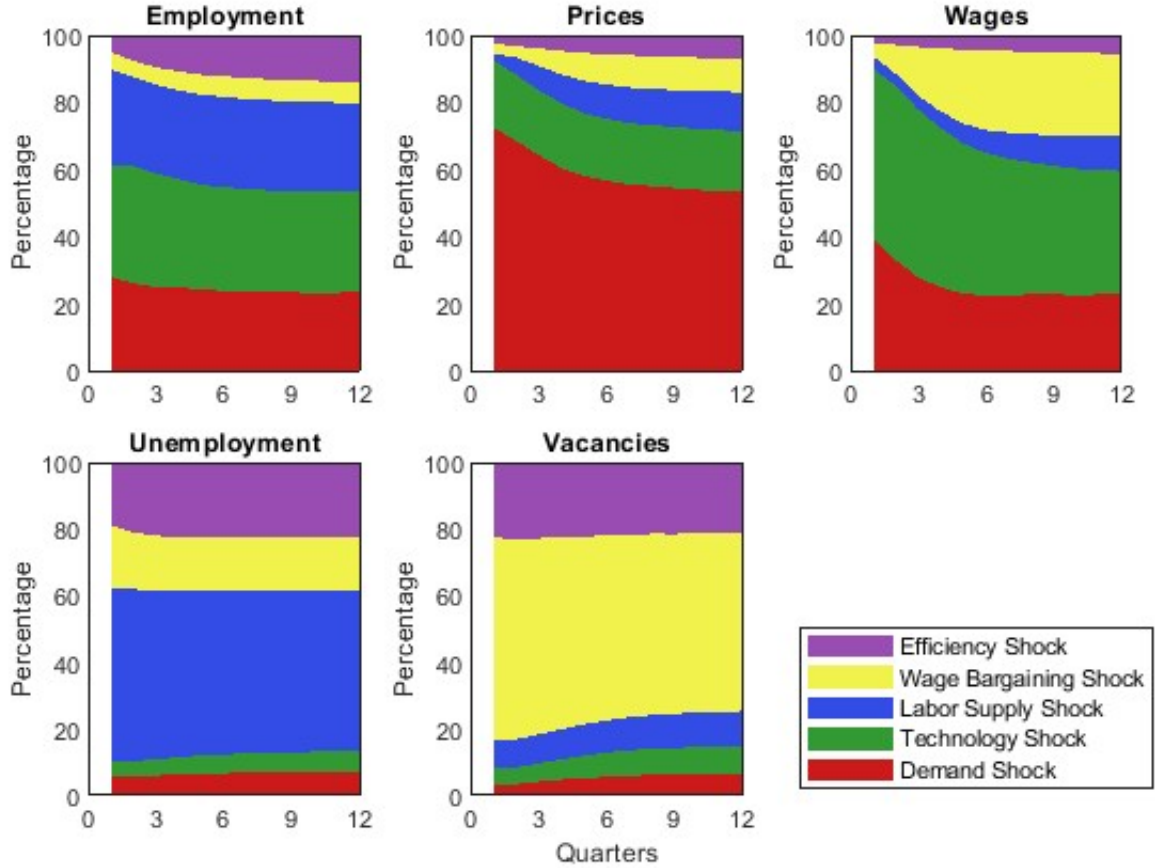

Figure 15: Variance decomposition of formal employment, prices, real wages, unemployment, and vacancy variables driven by demand, technology, labor supply, wage bargaining and efficiency shocks for the central region. Source: Own estimates based on data from INEGI and STPS.
Note: Time in quarters (horizontal axis) and units in percent (vertical axis).

In the southern region (Figure 16), technology shocks play a more substantial role in the wage inflation decomposition than in the national aggregate. With respect to unemployment growth, labor supply shocks become the dominant driver, displaying

a stronger effect than nationally. Similarly, the impact of technology shocks on wage inflation gains further prominence in this region.
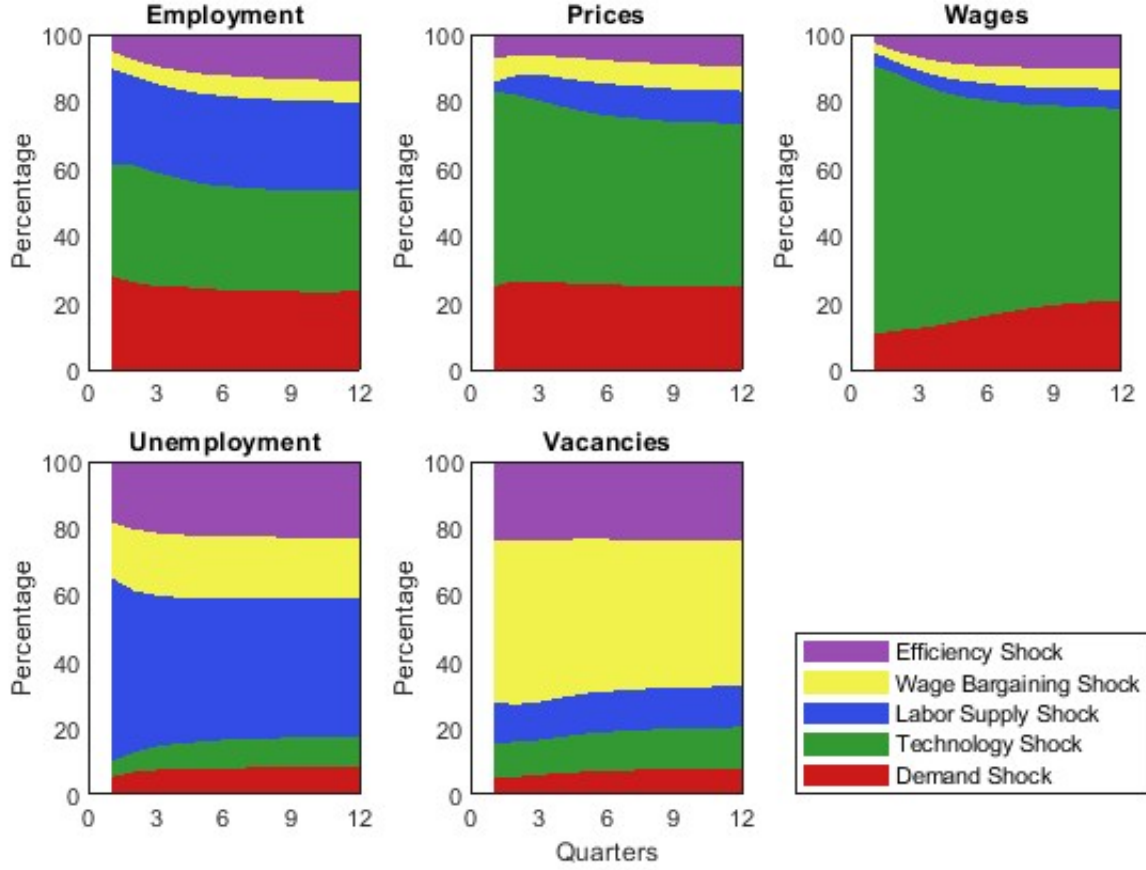

Figure 16: Variance decomposition of formal employment, prices, real wages, unemployment, and vacancy variables driven by demand, technology, labor supply, wage bargaining and efficiency shocks for the southern region.
Source: Own estimates based on data from INEGI and STPS.
Note: Time in quarters (horizontal axis) and units in percent (vertical axis).

We conclude this section by noting that we conducted a battery of robustness checks. Our results remain consistent and qualitatively similar across a range of model variations, including the use of different lag lengths, the inclusion or exclusion of exogenous variables, and the estimation of the models using data in levels rather than growth rates.

7 Concluding Remarks

The analysis of Beveridge Curves provides key insights into the recovery of economic activity in Mexico following the initial shock of the COVID-19 pandemic. Across regions, this recovery was characterized by lower unemployment rates and higher job vacancy rates. However, by 2024, vacancy rates declined below their 2022 levels nationally and across all regions without a corresponding increase in unemployment. This pattern mirrors trends observed in the United States, where a decline in vacancy rates without rising unemployment has been interpreted as a reduction in labor demand, contributing to a post-pandemic rebalancing of labor market conditions. This finding is particularly relevant given that a key prediction of the Beveridge Curve is that a decrease in job vacancies should be accompanied by an increase in unemployment, which did not materialize in Mexico at either the national or regional level in 2024.

Furthermore, the analysis highlights the relationship between labor market conditions and inflation. As labor markets tightened, core inflation rose significantly, particularly in northern and north-central Mexico. However, starting in 2023, core inflation declined substantially, suggesting the possibility of a *soft landing* in 2023 and 2024, where labor market easing occurred through a reduction in the vacancy rate rather than an increase in the unemployment rate.

Our empirical findings confirm that labor market shocks are the primary drivers of Beveridge Curve dynamics, rather than shocks originating in the goods and services market. At the national level, labor supply and matching efficiency shocks are the main contributors to unemployment growth, while wage bargaining shocks primarily explain vacancy growth.

These patterns generally hold across regions, but the results also reveal important regional heterogeneity. For example, labor supply shocks play a more dominant role in driving unemployment fluctuations in the north-central region, whereas wage bargaining shocks are more relevant in the northern region. Regarding vacancy growth, while

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national-level patterns broadly apply, in the north-central region matching efficiency shocks are just as important as wage bargaining shocks.

Overall, these results underscore the importance of labor market frictions in explaining unemployment and vacancy dynamics in Mexico, while highlighting regional differences in the mechanisms driving labor market adjustments.

Given that our findings suggest that the relationship between vacancy rates and unemployment rates evolves over time, future research will aim to identify structural shocks by incorporating time-varying coefficients, allowing for a deeper understanding of the dynamic nature of labor market fluctuations.

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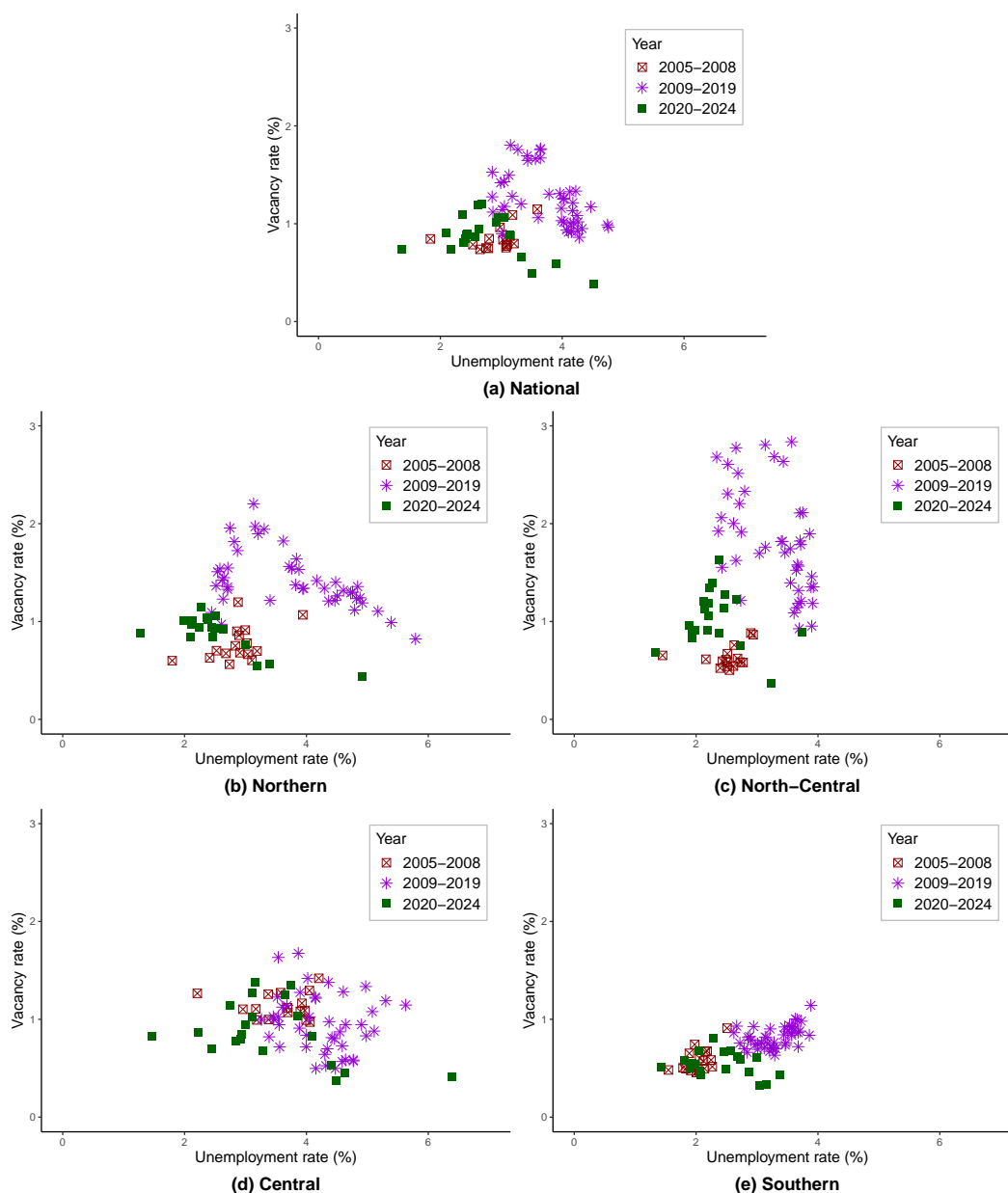**Appendix A:** *Beveridge Curves and Phillips Curves for the Full Sample: 2Q-2005 to 3Q-2024*

(a) National

(b) Northern

(c) North–Central

(d) Central

(e) Southern

Figure A1: Beveridge Curve.
Source: Own estimates based on data from the National Employment Service Unit of the STPS and INEGI.
Note: The vacancy rate is defined as the number of available job positions listed in the STPS job board expressed as a percentage of the conditional formal labor force. Similarly, the unemployment rate refers to the conditional formal unemployment rate. Each point corresponds to the combination of the unemployment rate and the vacancy rate for a specific quarter within the analysis period.
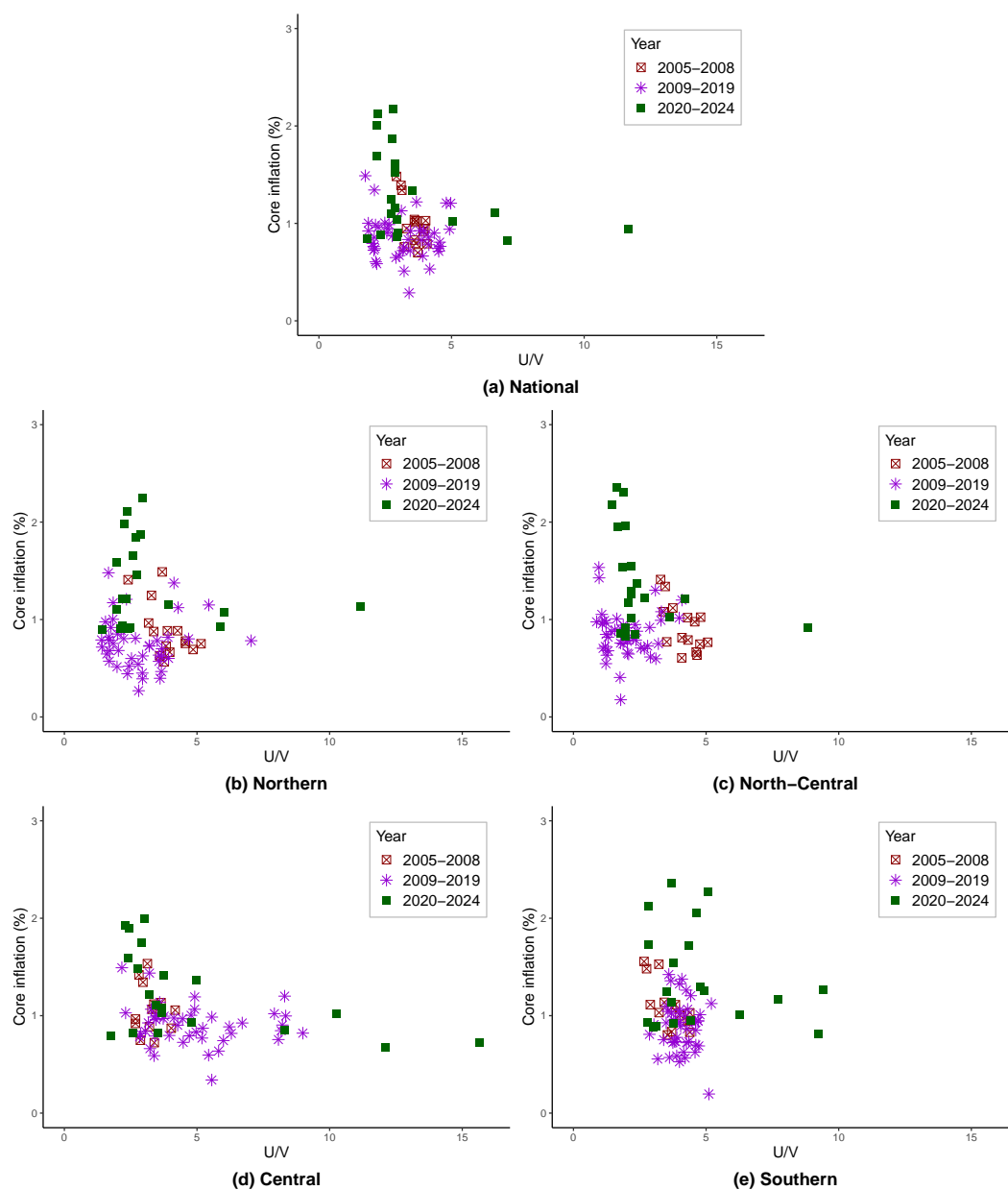
Figure A2: Phillips Curve.
Source: Own estimates based on data from the National Employment Service Unit of the STPS and INEGI.
Note: The U/V ratio is defined as the conditional formal unemployment rate divided by the job vacancy rate. Each point corresponds to the combination of the U/V ratio and the year-over-year core inflation rate for a specific quarter within the analysis period.