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Lorenzo Aldeco Leo
Banco de México

Horacio Reyes Rocha
Banco de México

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An estimation of the Phillips curve in Mexico using city-level data*

Lorenzo Aldeco Leo†
Banco de México

Horacio Reyes Rocha‡
Banco de México

Abstract: We estimate the slope of the Phillips curve in Mexico between 2005 and 2020 using city level data. We overcome the endogeneity of unemployment and core inflation through a panel instrumental variable strategy. Time-period fixed effects account for aggregate supply, demand, and expectation variables, while possible endogeneity between unemployment and core inflation at the city-quarter level is addressed with local labor demand shock instruments. We find a statistically significant Phillips curve linking local unemployment to local core inflation in Mexico, but this relationship is relatively weak: an increase of 1 percentage point in city-level unemployment lowers year-on-year core inflation by approximately 0.18 percentage points. We analyze city-level characteristics that relate to steeper Phillips curves, and find that informality rates, cash transfers, and some demographic characteristics in cities strengthen the relationship between unemployment and inflation.
Keywords: Phillips Curve, Core Inflation, Unemployment, Instrumental Variables, Panel Data, Labor Market
JEL Classification: J23, C23, C26, E31, O54

Resumen: En este trabajo se estima la pendiente de la curva de Phillips en México entre 2005 y 2020 utilizando datos a nivel ciudad. Para superar la endogeneidad del desempleo y la inflación subyacente se usa una estrategia de variables instrumentales con datos panel. Los efectos fijos de tiempo capturan variables agregadas de oferta, demanda y expectativas, mientras que la posible endogeneidad entre el desempleo y la inflación subyacente a nivel ciudad-trimestre se atiende utilizando como instrumento choques de demanda laboral local. Los resultados muestran una curva de Phillips estadísticamente significativa que vincula el desempleo con la inflación subyacente a nivel local, aunque esta relación es relativamente débil: un aumento de 1 punto porcentual en el desempleo a nivel ciudad reduce la inflación subyacente anual en aproximadamente 0.18 puntos porcentuales. Se analizan características a nivel ciudad que pueden influir sobre la pendiente de la curva de Phillips, y se encuentra que las tasas de informalidad, las transferencias y algunas características demográficas fortalecen la relación entre el desempleo y la inflación.
Palabras Clave: Curva de Phillips, Inflación Subyacente, Desempleo, Variables Instrumentales, Datos Panel, Mercado Laboral

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† Dirección General de Investigación Económica. Email: lorenzo.aldeco@banxico.org.mx
‡ Dirección General de Investigación Económica. Email: horacio.reyes@banxico.org.mx

1 Introduction

The Phillips curve relates current inflation to measures of economic slack, supply shocks, and inflation expectations. Recent work has proposed techniques to estimate the slope of the Phillips curve (with respect to unemployment, a common measure of slack) using panel data strategies, which address some important identification challenges; namely, that supply, expectations, or monetary policy shocks to the economy can confound the estimation by simultaneously affecting unemployment and inflation. Research implementing these techniques has shown that in the U.S. the Phillips curve is relatively flat (Hazell et al., 2022) but that its slope varies with macroeconomic conditions (Cerrato and Gitti, 2022), raising the question of how the Phillips curve slope differs across economic contexts and especially as labor market fundamentals vary.[1]

In this paper, we explore the heterogeneity of Phillips curve slopes across economic settings in two ways. First, we implement a panel instrumental variables strategy to estimate the Phillips curve slope with city-level data for the pre-pandemic period in Mexico. Mexico is a middle income country where labor is relatively abundant, and that displays some characteristics that are common and important in other developing country labor markets: for instance in the existence of a large informal sector and cash transfer programs. We find that a Phillips curve exists in the Mexican macroeconomic environment, but that the relationship between unemployment and inflation is relatively weak: an additional 1 percentage point (pp) of unemployment translates to a decrease of 0.18pp in core inflation. Our results point to a Mexican Phillips curve less steep than that found in the U.S., consistent with a hypothesis that the labor-abundant Mexican labor market is capable of accomodating demand shocks without generating strong inflationary pressures.[2] Consistent with the finding for the U.S., our estimates suggest that variations in unemployment over the 2005-2020 period contributed in a limited way to core inflation, relative to other factors, in a sample of Mexican cities. Despite the existence of other margins of adjustment in the labor market, such as informality or underemployment (Leyva and Urrutia, 2020, Faberman et al., 2020), our results point to the unemployment rate as the main measure of slack that influences core inflation.

Given that the Phillips curve slope likely varies with labor market institutions, in the second part of the paper we study how some features of local labor markets contribute to a steeper

[1] The slope of the Phillips curve is determined, in a family of models, by features of the labor market. See Section 6.

[2] In the United States using these methods to estimate the slope results in estimates of around -0.34 before the pandemic (Hazell et al., 2022).

or flatter curve. We focus on factors suggested by the literature and the context (Aoyama et al., 2022; Lombardi, Riggi, and Viviano, 2023; Alberola and Urrutia, 2020) including informality, cash transfers, measures of labor supply, and the degree of labor market power. In sub-national units where cash transfers are more widespread (either in the form of government transfers or remittances) the Phillips curve tends to be steeper, as well as where families have more children. This suggests that shifts in unemployment tend to translate more strongly to inflation where households' income and time use are less closely linked to the labor market. We also find that informality tends to steepen the curve, as first suggested by Gomez Ospina (2023), and that labor market power tends to flatten it, as predicted by the model of Lombardi, Riggi, and Viviano (2023).

Our finding that local labor market characteristics influence the slope of the Phillips curve runs counter to the assumption common to models of regional Phillips curves by which the curve has a homogeneous slope across locations. In this light, we revisit the model of regional Phillips curves from Hazell et al. (2022) and find that this heterogeneity in slopes is only a threat to the estimation if the slopes are correlated with unemployment, under a simple logic of omitted variable bias. Following M. H. Pesaran (2006), we implement a mean-group estimator for the Phillips curve slope, which is robust to this heterogeneity, and compare it to our baseline estimate. A Hausman test does not reject both estimators are consistent, lending credence to our baseline estimation strategy even in the presence of slope heterogeneity.

The rest of the paper is organized as follows. Section 2 reviews the existing literature and highlights our contributions. Sections 3 and 4 detail our data and estimation procedure, respectively. Section 5 shows our main result. Section 7 evaluates systematic variation in the case of slope heterogeneity across cities, while Section 6 discusses how features of local labor markets influence the slope of the Phillips curve. Finally, Section 8 concludes.

2 Literature Review

Our work contributes to a large body of research that estimates the Phillips curve and examines the determinants of its slope. Since the original work of Phillips (1958), which documented a statistical relationship between wage inflation and unemployment, an extensive literature has modelled inflation determinants, including the labor market. From the introduction of adaptive expectations (Friedman, 1968; Phelps, 1968) and cost-push shocks (Gordon, 1982) to the microeconomic foundations of the New Keynesian Phillips curve, which emphasizes forward-looking behavior (Galí and Gertler, 1999; Galí, Gertler, and López-Salido,

2001) and sticky prices (Calvo, 1983), significant theoretical advancements have guided empirical strategies in the estimation of the structural relationship between inflation and cyclical economic activity.

However, until a decade ago, most empirical work relied on aggregate macroeconomic time series to estimate the slope of the Phillips curve. These strategies have limitations concerning shifts in monetary policy or forward-looking expectations if both variables covary with measures of slack. For example, agents may adjust short-term inflation expectations over the business cycle, potentially overestimating the effect of the unemployment gap on contemporaneous inflation. Under the rational expectations assumption, some studies have included future inflation or survey forecasts, and employed Generalized Method of Moments (GMM) to control for potential biases. Nonetheless, on one hand, Mavroeidis, Plagborg-Møller, and Stock (2014) and Fidrmuc and Danišková (2020) find that these estimates can be highly sensitive to specification choices; on the other hand, Mavroeidis, Plagborg-Møller, and Stock (2014) argue that there is insufficient variation in aggregate data, leading to weak-instrument identification issues.

An additional identification problem may arise under an optimal monetary policy framework, as the central bank would respond to demand shocks, potentially offsetting the effect of the unemployment gap on contemporaneous inflation. This misspecification might explain the findings related to the flattening of the Phillips curve and the increasing importance of anchored expectations (Ball and Mazumder, 2011; International Monetary Fund, 2013; Blanchard, Cerutti, and Summers, 2015). To address this concern, McLeay and Tenreyro (2020) and Fitzgerald et al. (2024) use cross-sectional regional variation in unemployment to estimate inflation, by assuming that monetary policy respond to (average) national-level indicators rather than local demand shocks.

Although previous studies have exploited sub-national data to estimate the Phillips curve (Kiley, 2015; Babb and Detmeister, 2017; Bharadwaj and Dvorkin, 2020; Eser et al., 2020), Hazell et al. (2022) and Cerrato and Gitti (2022) are the first to formally derive the equivalence between the regional and the national Phillips curves, offering a theoretical foundation for empirical estimations based on regional variation. Using a benchmark multiregion model of a monetary union, Hazell et al. (2022) demonstrate that the slopes of the regional Phillips curve for non-tradable goods and the aggregate Phillips curve for all items are the same, providing support for the use of regional Phillips curve slopes to inform the aggregate slopes.[3]

[3] They show that the regional slope is equal to the aggregate slope scaled by the share of non-tradable con-

In the same vein, Cerrato and Gitti (2022) conclude that the slopes of both all-items Phillips curves are equal. The difference arises from the assumptions behind the production structure of the economy. The former authors assume a two-type aggregated consumption bundle of tradable and non-tradable final goods, whereas the latter propose a vertically-linked production structure in which tradable goods are inputs for non-tradable final goods. In our work, we focus on estimating the regional Phillips curve, and rely on these existing results to argue that our estimates reflect relationships that hold in the aggregate. In both works, the authors provide a solution to the problem of endogenous monetary policy and shifting values of the long-term inflation expectations by using a fixed-effect panel specification. Under this strategy, Hazell et al. (2022) estimate a flat slope of the Phillips curve even during Volcker disinflation period in the early 1980s, which underscores the importance of shifts in expectations and rejects the hypothesis of a flattening process.

Our research also relates to the growing literature that accounts for heterogeneity in the Phillips Curve slope across regions (Schuffels et al., 2024; El-Shagi and Tochkov, 2024), and more broadly to the literature that employs the mean group (MG) estimator as an alternative approach to address systematic variation in coefficients (M. Pesaran and Smith, 1995; M. H. Pesaran, 2006; Breitung and Salish, 2021). This strand of research concludes that when the slope coefficients are correlated with the regressors, fixed effects estimators become inconsistent, potentially leading to biased inference.

We also contribute to the literature studying the Phillips curve in developing countries and comparing it to other settings (Behera, Wahi, and Kapur, 2018). In the Mexican context, this line of research includes Bailliu et al. (2003), who estimate a relationship between the output gap and the inflation rate of 0.4 using a traditional Phillips curve framework with adaptive expectations and a standard OLS method for the period 1983-2001. Ramos-Francia and Torres (2008) apply the New Keynesian Phillips curve framework to assess the relationship between real marginal costs and inflation. By including backward and forward-looking expectations in a GMM estimation, the authors find a small Phillips curve slope between 0.006 and 0.012 for the period 1992-2007. They also find that both types of expectations are important in explaining inflation dynamics, although the former plays a decreasing role. This near-zero estimate might be a consequence of endogenous monetary policy, which could offset the effect of demand shocks on the inflation rate. Some studies use a reduced-form Phillips curve

sumption. The intuition is that prices of tradable goods are determined at the national level and do not respond to local labor market conditions. Consequently, estimating the Phillips Curve for all items using regional data would lead to an upward bias in the estimated aggregate slope.

approach with adaptive expectations to estimate the non-accelerating inflation rate of unemployment (NAIRU). Rodríguez, Ludlow, and Peredo (2004) estimate a negative relationship between the unemployment gap and inflation of 0.462 for the period 1987-2004. Aguilar et al. (2022) obtain a negative coefficient between 0.06 and 0.09 for the period 2005-2016 under a recursive estimation and for different state-space specifications. Finally, Loría, Valdez, and Tirado (2019) estimate an accelerating Phillips curve of -0.191 using a GMM method for the period 2002-2018. Our estimates fall in the middle of the range of results found in the literature, with unemployment relating in a statistically significant but modest magnitude to core inflation. The studies on the Phillips curve in Mexico use aggregate time series, which are exposed to the identification issues previously mentioned. To our knowledge, this work represents the first effort to estimate the relationship between unemployment and inflation for Mexico using methods from the recent regional Phillips curve literature.

Lastly, our heterogeneity exercises contribute to the existing literature that aims to know how different labor market factors influence the Phillips curve slope. In particular, our evidence speaks directly to the works of Lombardi, Riggi, and Viviano (2023), Alberola and Urrutia (2020), Gomez Ospina (2023), and Aoyama et al. (2022), who have modelled the role of informality, labor market power, and labor supply for the determination of the Phillips curve slope.

3 Data

Our empirical strategy is based on observing price index variation and the unemployment rate at the city level. We use two main sources of information. The first is the Mexican Consumer Price Index (INPC) published by the Mexican Statistical Agency (INEGI). Prices in Mexico are collected bi-monthly from a sample of establishments in 55 geographical areas. These areas include 49 metropolitan areas, 32 state capitals, and other municipalities, which in total account for 73.6% of the population as of 2010. We refer to these geographical areas as cities. In July of 2018, INEGI added 9 cities to the previously sampled 46 (see Appendix C).

For our empirical strategy, we also need tradable-intermediate good prices. The Mexican Producer Price Index (INPP), published by INEGI, collects prices at which producers buy and sell intermediate or final goods—*i.e.*, excluding any margins or profits from wholesale and retail sales. The Producer Price Index for intermediate-input goods does not distinguish between tradable and non-tradable. Therefore, we choose those industries that are highly export-oriented as an approximation of tradable-intermediate good prices.

The second source of information is the National Survey of Occupation and Employment (ENOE), a household survey that is collected quarterly with a rotating panel structure, published by INEGI. ENOE gathers information on respondents' employment status, including whether they are searching for employment, as well as some job characteristics. In terms of the sample, each quarter, INEGI drops one-fifth of the sample in a rolling order, which implies that we observe a specific household for five consecutive quarters. The survey is representative for a set of 39 cities—at least one for each state—, and is conducted since the first quarter of 2005. These cities include 38 metropolitan areas, 31 state capitals, and municipalities where 45.7% of the population resides. Until the fourth quarter of 2018, the set of cities numbered 32, with other seven included in the sample over the following period (see Appendix C). We use these data to construct unemployment rates at the city level, as well as expanded measures of labor market slack commonly reported by INEGI.[4] At the start onset of the COVID-19 pandemic, ENOE moved from in-person to phone interviews and adjusted the questionnaire and sampling frame. As a consequence, our study period ends in the first quarter of 2020.

We plot our raw inflation and unemployment data in Figure 1. Core inflation and the unemployment rate vary widely in our sample, across the whole sample and within regions.[5]

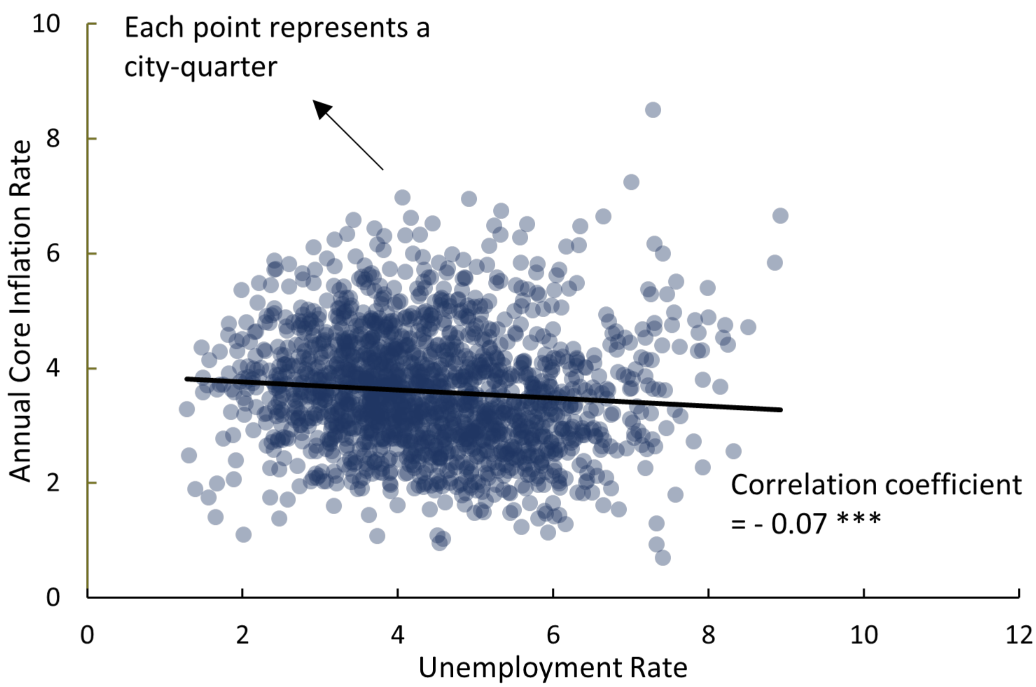
We also use the ENOE to construct our shift-share instrument. This data enables us to identify the economic industry of each employer, allowing us to aggregate employment by industry at the national level and calculate industry-specific employment shares for each city.

Finally, to construct the variables that allow us to assess heterogeneity in the Phillips curve slope across cities, we rely again on data from the ENOE, particularly the sociodemographic sections. For conciseness, we focus on three supply-related factors. First, we include the share of the working-age population and the proportion of households receiving cash transfers, where we group together remittances and government transfers. A household is considered to receive economic support if at least one member benefits from such transfers. Second, we incorporate the average number of children per household. Third, we include the informality rate at the city level.

[4]In particular, we expand the set of individuals available to work in several dimensions and calculate the corresponding measures of slack: 1. UE: the sum of unemployed and underemployed relative to the labor force; 2. Amp: the sum of unemployed, underemployed, and those who whould take a job if offered even if not actively searching, relative to the labor force and 4. the sum of unemployed and informal workers relative to the labor force.

[5]While the national unemployment rate in Mexico is generally low and stable, at the city-year level variation is substantial. Appendix Figure 4 shows time series of national and city-level unemployment in our sample.

FIGURE 1: CITY-LEVEL ANNUAL CORE INFLATION AND UNEMPLOYMENT RATE



Note: The figure shows the city-level annual core inflation rates and unemployment rates at quarterly frequency that compose our main sample. The black line shows an unweighted linear fit.

Additionally, we incorporate the quit rate elasticity in the formal labor market using administrative records from the Instituto Mexicano del Seguro Social (IMSS). By law, all private firms in Mexico must register their employees with IMSS, the largest social security institution in the country. These records offer a reliable approximation of the formal workforce and provide monthly municipality-level data on firm size, geographic location, and economic activity, as well as workers' characteristics such as wages, gender, and age. The quit rate elasticity measures the likelihood that an employee will move to another formal-sector firm in response to a wage change, serving as a proxy for employers' labor market power. We estimate this elasticity using data from 2018–2019. In Appendix A, we provide detailed information on how we estimate this parameter following the method in Bassier, Dube, and Naidu (2022), including details about the largest connected set of workers used to calculate the firm and worker components of wages.

We merge our two datasets at the city level. Our analysis spans from the first quarter of 2005 to the first quarter of 2020, just before the onset of the COVID-19 pandemic. For this period, our dataset includes 37 cities, of which 27 have information for all quarters.

4 Estimation

The New Keynesian Phillips curve is a structural relationship (ψ) between the labor market tightness ($\hat{u}_t$) and variation in prices (π_t) conditional to forward-looking inflation expectations ($\mathbb{E}_t\pi_{t+1}$) and cost-push shocks (ν_t).

$$\pi_t = \beta\mathbb{E}_t\pi_{t+1} + \psi\hat{u}_t + \nu_t \tag{1}$$

where $\hat{u}_t = u_t - u_t^n$ is the deviation of the unemployment rate from its natural level, and $\beta > 0$ is the household's discount factor. If we solve Equation 1 forward, defining the unemployment level as the result of a transitory and a permanent components $u_t = \tilde{u}_t + \mathbb{E}_t u_{t+\infty}$, we obtain

$$\pi_t = -\psi\mathbb{E}_t\sum_{j=0}^{\infty}\beta^j\tilde{u}_{t+j} - \frac{\psi}{1-\beta}\mathbb{E}_t u_{t+\infty} + \omega_t \tag{2}$$

where $\omega_t = \mathbb{E}_t\sum_{j=0}^{\infty}\beta^j(\psi u_{t+j}^n + \nu_{t+j})$. If we assume that natural unemployment u_t^n and cost-push ν_t shocks are transitory, then in the long-run $\mathbb{E}_t\pi_{t+\infty} = -\frac{\psi}{1-\beta}\mathbb{E}_t u_{t+\infty}$. Also, let us assume that $\tilde{u}_t$ follows a AR(1) with an autoregressive coefficient ρ_u. Considering these assumptions, we derive the following equation.

$$\pi_t = \mathbb{E}_t\pi_{t+\infty} - \kappa\tilde{u}_t + \omega_t \tag{3}$$

where $\kappa = \frac{\psi}{1-\rho_u\beta}$. In this sense, κ is proportional to ψ and strictly larger if the coefficient $\rho_u > 0$.

Our empirical goal is to identify the effect of labor market tightness on inflation (κ). To achieve this, we need to isolate demand-side variation in local unemployment rates from cost-push and expectation shocks. Based on the works of Hazell et al. (2022) and Cerrato and Gitti (2022), we implement a two-instrumental variable strategy in a panel of sub-national units to estimate the slope of the Phillips curve. Both cited works use a theoretical model to derived their empirical specifications, although they differ in some important caveats. Since our concern is entirely empirical, we present a reduced-form specification and use the theoretical implications in both works to guide us. Our estimation equation is then the following:

$$\pi_{it} = \alpha_i + \gamma_t + \kappa u_{it} + \beta^{'} X_{it} + \varepsilon_{it} \tag{4}$$

where π_{it} is the core annual inflation rate in city i in quarter t; α_i and γ_t represent city and quarter-year fixed effects, respectively; u_{it} is the unemployment rate in city i in quarter t; and X_{it} is a vector of variables controlling for idiosyncratic cost-push and productivity shocks.

City fixed effects control for time-invariant heterogeneity across cities, while time fixed effects absorb aggregate supply and demand shocks. Since the central bank sets monetary policy at the national level, it, along with variations in long-run inflation expectations—which we assume are also set at the national level—would be captured by the time fixed effects. This is the main reason why we aim to estimate κ in Equation 3 rather than ψ in Equation 1: short-term inflation expectations may differ across cities. Even if long-term expectations differ across cities, this heterogeneity would be absorbed by the city fixed effects if these differences are constant.

However, a two-way fixed effect strategy does not address endogeneity coming from time-variant heterogeneity across cities—*e.g.*, city-level labor supply or productivity shocks that affect both inflation rate and unemployment rate. To to that, we need to identify demand-driven variation in the local unemployment rate. We achieve this by using a shift-share instrument as framed by Borusyak, Hull, and Jaravel (2021). The shift-share instrument is

$$z^x_{it} = \sum_{j=1}^{N^x} s_{ij} \times g_{jt}$$

where N^x is the set of tradable industries, which includes primary industries, mining, manufacturing, wholesale trade, transport, mail and storage, and financial services; s_{ij} denotes the employment share of city i for industry j at the beginning of the period; and g_{jt} is the national employment growth in industry j, excluding city i.

The intuition behind the shift-share instrument is that the response of local unemployment rates to aggregate industry-level shocks might depend on each city's exposure to these shocks, which is measured by its employment industry shares. We expect cities with a larger employment share in a tradable industry to respond more significantly to a national shock in that specific industry. Therefore, under this strategy, it is plausible that our instrument will isolate demand-side variation in local unemployment rates from local labor supply shocks.

There are two plausible cost-push channels through which our instrument may violate the exclusion restriction assumption, following the reasoning from Cerrato and Gitti (2022). First, demand-side variation in unemployment might come from local productivity shocks that simultaneously affect the inflation rate. For example, a negative productivity shock to tradable goods might boost the unemployment rate in cities with a large employment share in those industries, and also affect final goods inflation if those tradable goods are used as inputs in non-tradable industries. To address this concern, we include in our specification a shift-share control variable using the national Producer Price Index (PPI) for intermediate goods,

$$p^x_{it} = \sum_{j=1}^{N^p} s_{ij} \times g_{jt}$$

where N^p is the set of intermediate industries, which includes primary industries, non-petroleum minning, manufacturing, and transportation, mail and storage; s_{ij} denotes the employment share of city i for industry j at the beginning of the period; and g_{jt} is the national employment growth in industry j, excluding city i. This variable allows us to control for productivity shocks to tradable industries that impact cities differently. By incorporating this control, we account for productivity shocks to tradable inputs, including commodities, ensuring that our instrument captures demand-side variations in unemployment without being confounded by productivity-related inflationary effects.

Second, if tradable goods are used as inputs in non-tradable industries, then productivity shocks to the latter might affect both the inflation rate and the unemployment rate. A negative productivy shock to non-tradable industries would diminish demand for tradable goods used as inputs, and simultaneously affect final goods inflation through an increase in marginal costs. To avoid this, we add a shift-share control variable with the same structure as our instrument but for non-tradable goods.

$$z_{it}^{y} = \sum_{j=1}^{N^y} s_{ij} \times g_{jt}$$

where N^y is the set of non-tradable industries, which includes construction, retail, business, personal and professional services, hospitality and tourism, healthcare services, and education; s_{ij} denotes the employment share of city i for industry j at the beginning of the period; and g_{jt} is the national employment growth in industry j, excluding city i.

We overidentify our model by adding the city-level unemployment rate lagged four quarters as a second instrument. The identifying assumption for this instrument is that, under rational expectations, inflation does not depend on lagged inflation (see Hazell et al., 2022). On the other hand, unemployment tends to be quite persistent. Therefore, contemporaneous annual inflation would be affected by lagged unemployment only through contemporaneous unemployment.

5 Results

Table 1 shows our main results. All specifications include quarter-year-level fixed effects, to account for time-varying aggregate factors (such as long term expectations, monetary policy, and aggregate demand and supply shocks), as well as city-level fixed effects to control for cross-sectional confounders. Columns 2-5 show IV estimates of the effect of the unemployment rate on (annual) core inflation, at a quarterly frequency. An additional 1 percentage point (pp) of unemployment at the city level translates to between 0.17pp and 0.18pp lower inflation at the city-quarter level, robust to the inclusion of controls. The same estimator applied to the U.S. setting results in a more pronounced Phillips curve: the comparable estimate for the U.S. yields a slope about twice as steep (-0.34 pp inflation change per 1 pp unemployment from Hazell et al., 2022). First, Mexico's economy possesses a relatively abundant supply of labor with respect to the U.S. (Amoroso et al., 2008), suggesting that demand shocks can be accomodated through adjustments in employment, as opposed to wages that pressure firms' costs.

While both OLS and IV specifications account for aggregate variation in monetary policy, expectations, demand, and supply through the time fixed effects, these two estimators deliver markedly different point estimates. This implies that some local-level shocks are meaningful confounders. In particular, that OLS estimates are smaller in absolute value than IV ones suggest that unobserved supply shocks that induce unemployment and inflation to co-move are likely to be correlated with demand shocks, contributing to bias OLS estimates towards zero. Conversely, that the estimates don't change when including the controls suggested by Cerrato and Gitti (2022) indicates that the non-tradeable productivity shocks they raise as potential confounders, z_{it}^{y} are likely not playing a substantial role in this setting.

One implication of the small magnitude of our estimated effects is that the Phillips curve plays a limited role in explaining the variation in core inflation over time in the cities in our sample. To illustrate this, we calculate a quarterly time series of predicted average core inflation in our sample, conditional only on quarterly city-level unemployment rates. Our aim is to quantify the variation in core inflation over time coming from variation in unemployment, and we construct it as follows. For each city i, we recover the estimated $\hat{\alpha}_i$, $\hat{\kappa}$, and $\hat{\beta}$ from the IV model with controls. Then, we average the value of the time-varying controls in each city over the study period, and call the result $\bar{X}_i$. Then, we calculate the core inflation in each city without the time variation coming from fixed effects or the time-varying controls as:

$$\hat{\pi}_{it} = \hat{\alpha}_i + \hat{\kappa} u_{it} + \hat{\beta}' \bar{X}_i \tag{5}$$

TABLE 1: PHILLIPS CURVE SLOPE ESTIMATES

	Dep. Var.: Annual Core Inflation Rate				
	(1)	(2)	(3)	(4)	(5)
	OLS	IV	IV	IV	IV
Unemployment Rate	-0.057**	-0.173**	-0.181**	-0.172**	-0.181**
	(0.0208)	(0.0555)	(0.0521)	(0.0550)	(0.0514)
F-stat		64.71	61.09	65.30	61.58
F-stat p-value		< 0.001	< 0.001	< 0.001	< 0.001
Control p_{it}^{x}	Yes	No	Yes	No	Yes
Control z_{it}^{y}	Yes	No	No	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Quarter-Year FE	Yes	Yes	Yes	Yes	Yes
N	1,562	1,562	1,562	1,562	1,562

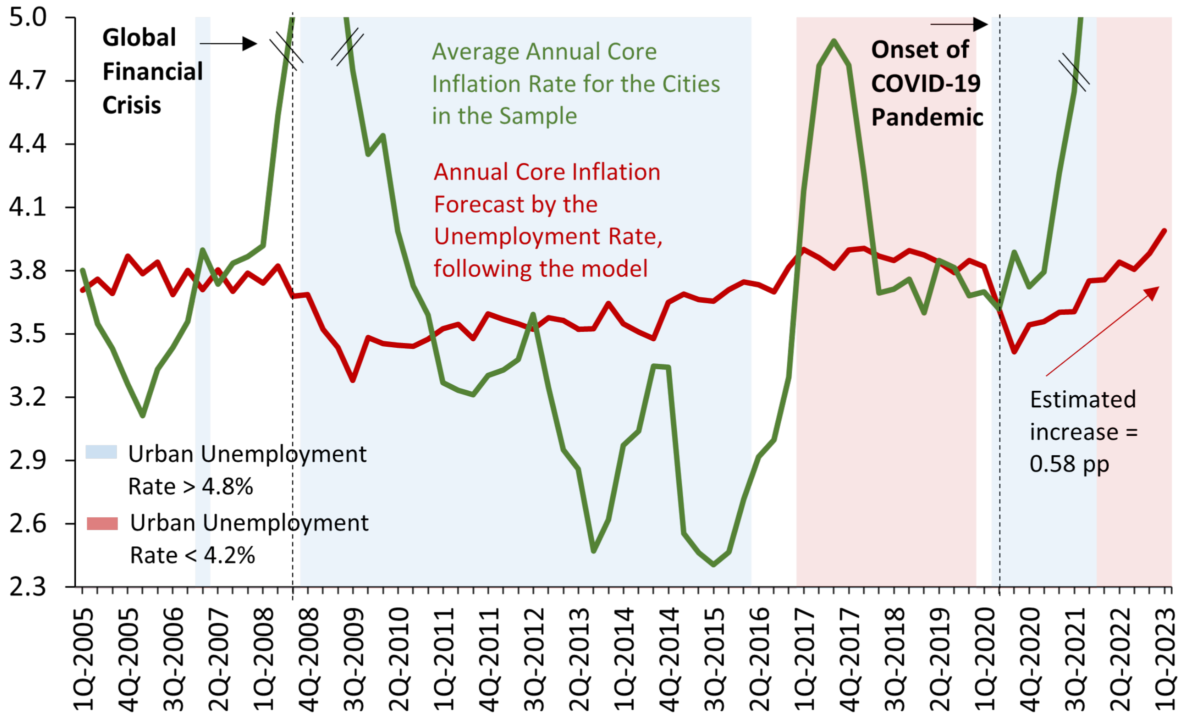
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table shows point estimates for the effect of city-level unemployment on annual core inflation, both at quarterly frequency. p_{it}^{x} and z_{it}^{y} are shift-share controls for intermediate good prices and non-tradable productivity shocks, respectively. Standard errors in parentheses, clustered at the city level.

We then average these to the quarter level using city-level population aged 15 and above as weights.

Figure 2 shows the resulting time series. Core inflation in our sample of cities registered substantial variation over the study period, with spikes after the global financial crisis and the onset of the COVID-19 pandemic. However, variation in unemployment predicts, through our estimated model, only modest shifts in core inflation over time.

FIGURE 2: CORE INFLATION IN SAMPLE CITIES: OBSERVED AND PREDICTED BY UNEMPLOYMENT



Note: This figure shows, in red, the population-weighted average inflation in our sample of cities that is predicted by variation in city-level unemployment, as detailed in Equation 5. The green line shows the observed average core inflation (also population weighted) in the same set of cities. Quarters where national unemployment was above or below the shown tresholds are highlighted to illustrate unemployment levels throughout the period. Vertical lines mark periods where core inflation rose sharply: the global financial crisis and the COVID-19 pandemic.

This suggests that other factors, in particular aggregate supply and expectations, are likely to have been stronger determinants of inflation than the labor market over our study period. This finding is consistent with Ha et al (2018), who report using aggregate data that expectations and supply shocks are the main drivers of inflation in emerging economies. To our knowledge our result constitutes the first microeconomic evidence of this important fact. While it is possible that the slope of the Phillips curve shifted in the aftermath of the COVID-19 pandemic as in other settings (Cerrato and Gitti, 2022), our estimates along with the low levels of unemployment observed in Mexico suggest that the labor market may have contributed to core inflation only in the order of half a percentage point in our sample of cities.

5.1 Alternative slack measures

An important literature has pointed out that alternative measures of labor market slack can capture some specific margins of labor availability in the economy better than the unemployment rate. The unemployment rate assumes that available labor in the economy takes the form of workers who are not employed and searching for work, but it is possible that employed workers would prefer to supply more labor and that individuals who stop searching would still be available to work (Faberman et al., 2020). Among the employed, workers may take jobs where they work less hours than they could, or, as is common in middle income countries, take relatively unproductive jobs in the informal sector. In Mexico, the informality rate (meaning the share of workers who are informal) is countercyclical, suggesting that more informality is a signal of larger economic slack (Leyva and Urrutia, 2020, Fernández and Meza, 2015). The hidden unemployed (those who would accept a job even if not actively searching) represent an additional group of individuals available to work, as pointed out by Blanchflower and Levin (2015).[6] While all these alternative measures represent labor that is available to the economy, which margins relate more strongly to firms' costs, and therefore to inflation, is an empirical question. We now leverage our empirical strategy to study the relationship between core inflation and these alternative measures of slack.

Table 2 reports IV estimates of the effects of several measures of labor market slack on core inflation. We consider four alternative measures other than the unemployment rate, which we present again in column 1. Column 2 corresponds to an expanded definition of unemployment that also includes the underemployed, meaning part-time workers who would work full time. In column 3, this measure is further broadened to include hidden unemployment i.e. those out of the labor force who would accept a job if offered. These three measures are calculated as a proportion of the labor force. Column 4 shows the informality rate (i.e. informal employment as a share of employment), which as mentioned above has been shown to be an important margin of adjustment in the labor market in response to shocks in the Mexican

[6] In the U.S., these measures have represented a significant proportion of the slack in the labor market, especially after the Great Recession (Blanchflower and Levin, 2015).

setting (Fernández and Meza, 2015, Leyva and Urrutia, 2020). Last, column 5 shows the rate of critical labor conditions (RCLC) as reported by INEGI. This measure reflects the share of those employed who face low labor demand, in particular by working less than full time because of market reasons, or whose earning are low relative to their work hours.[7]

Unemployment shows the largest marginal effect on core inflation, providing evidence in favor of its use as an measure of labor market tightness in the Phillips curve, even in the presence of alternative measures. In the context of the U.S., other work has pointed out that some of these alternative measures perform better in explaining inflation dynamics relative to the unemployment rate (Faberman et al., 2020), given that they vary more in the context of a relatively stable unemployment rate. These expanded definitions capture a wider group of workers whose labor is available for production, and in our sample do indeed vary more relative to unemployment, as seen in their larger standard deviations. However, our results suggest that the unemployment rate more closely reflects the marginal cost of labor that matters for firms' costs in the empirical Phillips curve.[8] In particular, notwithstanding the countercyclicality of the informality rate, we do not find strong evidence that it influences core inflation.

[7]In particular, the rate of critical labor conditions includes workers who (i) work less than 35 hours a week because of market reasons, (ii) work more than 35 hours but earn less than minimum wage, (iii) work more than 48 hours and earn more than one but less than two minimum wages.

[8]We find strong first stages in all IV estimations with alternative slack measures, indicating that the null results are evidence of weaker economic effects of these alternative measures.

TABLE 2: ESTIMATES OF THE PHILLIPS CURVE SLOPE USING ALTERNATIVE SLACK MEASURES

	Dep. Var.: Annual Core Inflation Rate				
	(1)	(2)	(3)	(4)	(5)
	UR	UE	Broad	Inf rate	RCLC
Slack Measures	-0.181**	-0.031	-0.0315	-0.050	-0.017
	(0.0514)	(0.0188)	(0.0200)	(0.0263)	(0.0493)
Average	4.28	11.06	12.41	45.06	8.20
Std. Dev.	1.37	4.69	4.23	8.93	4.43
F-stat	61.58	90.58	87.13	63.43	66.75
F-stat p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
N	1,562	1,562	1,562	1,562	1,562

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table presents city-level point estimates of the effect of different slack measures on annual core inflation, with both variables measured at a quarterly frequency: (1) the unemployment rate; (2) the sum of the unemployment and underemployment rates; (3) the sum of the unemployed, underemployed, and available population as a percentage of the working-age population; (4) the informality rate; and (5) the rate of critical labor conditions. The available population or hidden unemployment is defined as individuals who are not employed or actively seeking employment but would accept a job if offered. RCLC is defined as the percentage of the employed population who: (i) work fewer than 35 hours per week due to market-related reasons; (ii) work more than 35 hours per week but earn less than the monthly minimum wage; or (iii) work more than 48 hours per week while earning more than one and up to two minimum wages. All thresholds are expressed in equivalent minimum wages, adjusted to 1Q2005 constant pesos. As our baseline model, we introduce shift-share controls for intermediate goods prices (p^x_{it}) and non-tradable productivity shocks (z^y_{it}). Standard errors clustered at the city level are shown in parentheses.

6 City-level characteristics and the Phillips curve

Our data and empirical strategy allow us to examine how the Phillips curve slope depends on city-level characteristics that are likely to be important in our setting. First we focus on factors related to the labor supply. The labor supply elasticity is a core structural parameter that determines how demand shocks transmit to prices through the labor market (see the literature ranging from Galí, 2011, to the recent treatment in Hazell et al., 2022). While the labor supply elasticity is not immediately observable at the local level, we incorporate it into the analysis through city-level aggregates of demographic and socioeconomic characteristics of households that are likely to affect it. In particular, we consider measures of the penetration of government and other transfers of non-labor income in the location, and variables related to the availability of labor (such as family composition).[9] We also study the effect of informality, which is a core feature of developing country labor markets and whose influence on the role of the Phillips curve is contested in the literature (see Alberola and Urrutia, 2020; Gomez Ospina, 2023). Finally, in recent work, Lombardi, Riggi, and Viviano (2023) suggest that the Phillips curve is affected by labor market power, which is likely to vary across locations. We test this channel by first estimating a city-level measure of the labor market power of employers (the quit rate elasticity) following Bassier, Dube, and Naidu (2022) and data from Mexico's largest social security agency, *Instituto Mexicano del Seguro Social*. We detail how we construct this city-level measure of labor market power in Appendix A. In their analyisis of factors that underlie the slope of the Phillips curve, Aoyama et al. (2022) suggest that the bargaining power of workers, the elasticity of labor supply, non-standard work arrangements, and household characteristics are the main factors that can tilt the Phillips curve. These are all captured to some degree in our analysis.[10]

For each of these city-level variables H_i, we estimate the effect of the interaction between H_i and the city-level unemployment rate on inflation. In particular, we estimate the equation below. We aim to estimate the difference in Phillips curve slopes between locations with different levels of characteristic H_i, so we no longer include a standalone unemployment rate term u_{it} in the model.

$$\pi_{it} = \alpha_i + \gamma_t + \kappa_H u_{it} \times H_i + X_{it} + \nu_{it}. \tag{6}$$

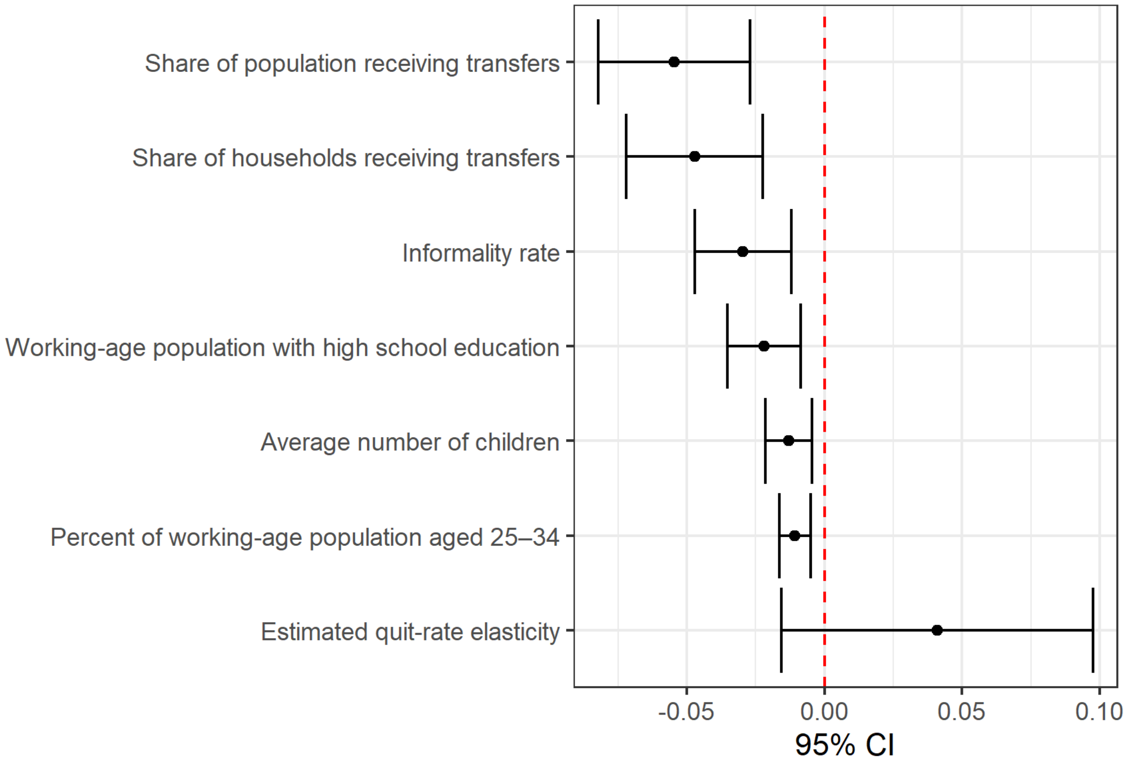
Given that $u_{it} \times H_i$ is likely to be endogenous to inflation by way of the ommited variables that relate u_{it} and π_{it}, we instrument $u_{it} \times H_i$ with $Z_{it} \times H_i$, where Z_i is again our set of instruments from Section 4 above. All variables H_i are expressed in standard deviations in the city-level distribution. As a consequence, the resulting coefficient corresponds to the difference in the Phillips curve slope between two cities one standard deviation of H_i apart. Figure 3 shows the point estimates and 95% confidence intervals of each of the interactions κ_H, in increasing order sorted by the point estimate value.[11] A negative effect means that a marginal increase in that city-level characteristic implies a steepening of the Phillips curve - i.e. a more negative slope.

[9]The relationship between government transfers and labor supply has been the object of many studies. See Banerjee et al. (2017) for a review and meta-analysis.

[10]In our setting these differences are manifested in steeper or flatter Phillips curves across cities, but the exercise is informative of the influence of these factors in the aggregate as well.

[11]Descriptive statistics of these city-level characteristics in our sample are shown in Appendix Table 7.

FIGURE 3: CITY-LEVEL FACTORS AND THE SLOPE OF THE PHILLIPS CURVE



Note: This figure shows estimates of κ_H in Equation 6. All variables are expressed in standard deviations in the city-level distribution. Confidence intervals are shown at 95%, constructed from standard errors clustered at the city level.

TABLE 3: HETEROGENEITY IN THE SLOPE OF THE PHILLIPS CURVE ACROSS CITY-LEVEL FACTORS

City-Level Factor	Slope Bounds (2 SD)
Share of population receiving transfers	[–0.285, –0.077]
Share of households receiving transfers	[–0.270, –0.092]
Informality rate	[–0.245, –0.117]
Average number of children	[–0.207, –0.155]
Estimated quit-rate elasticity	[–0.318, –0.044]

This table reports the estimated range of the Phillips Curve slope (κ_H) between cities that differ by two standard deviations from the average level of each factor. All variables are expressed in standard deviation units relative to their city-level distribution.

Labor supply To frame the interpretation of the following results, it is useful to analyze the following expression for the slope of the Phillips curve (the specific equation is from Galí

(2011) due to its simplicity).[12] In it, φ is the inverse elasticity of labor supply, and $(1-\theta_w)$ is the share of workers whose nominal wages can change in a given period (i.e. the degree of flexibility of wage setting in the labor market). [13]

$$\kappa = -\frac{(1-\theta_w)(1-\beta\theta_w)}{\theta_w(\frac{1}{\varphi}+\epsilon_w)} \tag{7}$$

The equation makes clear that the smaller is φ, meaning the more elastic is labor supply, the lower κ will be in absolute value, i.e. that the Phillips curve will be flatter. This is an intuitive relationship: if labor supply is more elastic, then shifts in demand will tend to manifest to a greater degree through changes in employment rather than wages, and price pressures will be softer (relative to a case with an inelastic labor supply). This theory suggests then that factors that tend to make labor supply less responsive to wages will also manifest as a steeper Phillips curve.[14]

Our first finding in Figure 3 is that as the share of households and individuals in a city that receives transfers increases, the slope of the Phillips curve is steeper. This is consistent with that transfers may make the quantity of labor supply less responsive to demand changes, i.e. more inelastic. Our results suggest this effect is substantial. If unemployment drops by 1pp in two cities one standard deviation apart in the distribution of transfers, the one with more transfers will register an inflation hike 0.05pp larger relative to the other city - between one third and one quarter of the average slope (which we estimated at around 0.18pp of core inflation per 1pp of unemployment change).

This result is related but distinct to a large literature that studies the relationship between transfers and labor supply. While there are many works studying the relationship between transfers and the quantity of labor supplied, our result is consistent with that transfers may not only shift labor supply but change its elasticity.[15] Our finding also speaks to recent work that studies the heterogeneous effects of monetary policy across regions and particularly to Herreño and Pedemonte (2022). That work finds that the transmission of monetary policy is

[12] This is the New Keynesian Wage Phillips curve slope expression from equation 13.

[13] The parameter ϵ_w is the labor demand elasticity and is less relevant than the other parameters in our application.

[14] In the Galí (2011) model we use to frame our argument the elasticity of labor supply is assumed to be the same for the whole economy. However, as Bargain and Peichl (2016) show, estimates of the labor supply elasticy are very heterogeneous across space and time. In our setting, this implies that labor supply elasticities may vary substantially across cities.

[15] This is expected if transfers shift people to be inframarginal in their decisions to work or not.

stronger in locations where incomes are lower. To the extent that larger shares of population tend to receive transfers in poorer locations, our finding is consistent with theirs.

Family composition and especially the need to care for children is a main determinant of labor supply.[16] Given this fact, we include the average number of children in a household as an observable proxy of the capacity of households to provide labor to the market. We find evidence that the Phillips curve tends to be steeper in cities where households have more children on average. This is consistent with the finding from the literature that as childcare needs increase, households tend to supply less labor (Berlinski et al., 2024). Our findings suggest then that in a location with more child care demands, a shock to the labor market has less space to be accomodated along the employment margin, meaning the Phillips curve tends to be steeper.

Informality is a central feature of labor markets in many developing countries, and can influence the transmission of labor market tightness to inflation. However, the sign of the effect depends on the relative strength of the different channels it can operate through. As the model in Gomez Ospina (2023) shows, informality can have two opposing effects. First, it increases the flexibility of wages: informal labor arrangements are usually not bound to the legal or institutional restrictions that limit nominal wage changes. If this were the only channel, it would imply that as informality increases, shifts in the labor market would translate more weakly into inflation (as in the model in Alberola and Urrutia, 2020) However, informality can also amplify the effect of a given shock. As modelled by Gomez Ospina (2023), informality serves as an outside option to formal workers, but its value is procyclical. In that model, when a productivity shock arrives in an environment with informality, it affects both the formal labor market and the outside option of workers, so its effect on wages is larger relative to a case without an informal sector. This channel is present in the baseline Galí (2011) model as well – in Equation 7, the slope of the Phillips curve is increasing in absolute value as the share of workers whose wages are fully flexible increases. Our results suggest that this last channel tends to dominate: in locations where informality is larger, we estimate the Phillips curve is steeper. While not explicitly included in other models, we speculate that other features of informal labor can induce a stronger relationship between labor market tightness and inflation. For example, a more extensive informal sector does not necessarily imply a larger pool of workers available for formal firms, which could make the Phillips curve

[16] A large body of work studies the relationship between family structure, childcare and labor supply. Berlinski et al. (2024) provides a recent overview of this literature and a comprehensive joint model of the labor market and households' child care decision.

flatter. On the contrary, due to the more rigid labor regulations faced by formal firms, which might translate into higher entry costs (see Arias et al., 2018), informal workers may be less responsive to changes in formal wages.

Along with the results shown earlier, these findings imply that unemployment and inflation may be traded off to different degrees in different locations, and that in locations where workers are more vulnerable in some dimensions (i.e. given they receive transfers or work informally), shifts in labor demand may translate to inflation to a greater degree (consistent with the finding from Herreño and Pedemonte, 2022).

Finally, while it is common for models of the Phillips curve to assume that the labor market is competitive, a large literature has shown that employers exercise substantial market power. The model and empirical results from Lombardi, Riggi, and Viviano (2023) find that worker's market power is inversely related to the slope of the Phillips curve. Our data allow us to test this hypothesis in our setting. To do so, we first calculate the quit rate elasticity for each city in our sample, which serves as a measure of labor market power at the city level. The quit rate elasticity is the change in the rate at which workers move away from a firm when the wage component attributable to the firm increases.[17] We leverage administrative records from Mexico's largest social security instituion (*Instituto Mexicano del Seguro Social*), which registers the employer and wage of most formally employed workers in the country. Using this data and the methodology from Bassier, Dube, and Naidu (2022), we compute quit rate elasticities for each city in our sample. Our measure of labor market power provides us with less power than the other variables we test for, but the results are consistent with the results from Lombardi, Riggi, and Viviano (2023) (at 90% confidence). Their model suggests that where firms have more labor market power, they can more easily accomodate demand shocks by adjusting employment as opposed to wages. This implies that a given change in unemployment at the local level will translate more weakly to price increases.

Our findings provide evidence for the heterogeneity in Phillips curve slopes within countries, and highlights that local labor market characteristics mediate the relationship between labor market slack and inflation. This fact raises an important question, in that monetary policy may have effects that vary to some extent across locations depending on these local characteristics. While we estimate a flat Phillips curve in general, our results highlight that if demographics,

[17]In a more competitive environment, employers that decrease their wage policies would lose more workers to other firms, relative to a case where they exercise more market power. The quit rate elasticity then is closely related to the labor supply elasticity faced by the firm, which increases as employers compete more for workers and is a measure of the degree of labor market power. See Manning (2003).

non-labor income, or labor market features such as market power or informality shift in the aggregate, it is plausible to expect changes in the tradeoff between economic slack and core inflation.

7 Slope heterogeneity across regions

As in Hazell et al. (2022) and Cerrato and Gitti (2022), our empirical strategy implicitly assumes a homogeneous Phillips curve slope. However, there may be heterogeneity in the intensity with which market conditions transmit to price dynamics. If such heterogeneity exists, then additional assumptions are needed to properly interpret the aggregated Phillips curve slope. To illustrate this point, consider the regional Phillips curve:

$$\pi_{it} = \mathbb{E}_t \pi_{t+\infty} - \kappa_i \tilde{u}_{it} + \omega_{it} \tag{8}$$

where $\kappa_i = \kappa + \eta_i$ is the regional slope, and η_i is the region-specific deviation from the average slope κ, such that $\eta_i \sim \mathcal{N}(0, \sigma_\eta^2)$. Let us assume there is a finite set of regions. Aggregating across regions yields

$$\pi_t = \mathbb{E}_t \pi_{t+\infty} - \kappa \tilde{u}_t + \text{cov}(\kappa_i, \tilde{u}_{it}) + \omega_t \tag{9}$$

As shown in Equation 9, if $\text{cov}(\kappa_i, \tilde{u}_{it}) \neq 0$, estimating the Phillips curve without accounting for slope heterogeneity results in a biased estimate of κ, due to the systematic variation in regional coefficients (Breitung and Salish, 2021). For example, if regions with steeper slopes also tend to experience larger unemployment gaps, the estimated average slope will be inconsistent. Schuffels et al. (2024) provides both simulation and empirical evidence from the European Monetary Union (EMU) showing substantial heterogeneity in Phillips curve slopes, and demonstrates that ignoring this heterogeneity can lead to underestimation of the true aggregate slope.

This bias can also arise from endogeneity induced by centralized monetary policy. Consider a scenario in which all regions are hit by a uniform demand shock, but regions with steeper Phillips curves carry more weight in the national aggregate. A central bank targeting the national outcome will respond more aggressively to economic conditions in these heavily weighted, high-slope regions. This policy response may inadvertently depress labor market activity in lower-slope regions, thereby distorting the aggregate relationship between inflation and the unemployment gap. Since time fixed effects may not fully absorb the effects of monetary policy, the estimated Phillips curve slope will be biased downward.

To avoid this issue, one possible assumption is that slope heterogeneity is uncorrelated with regional unemployment gaps. This does not rule out heterogeneity per se; rather, it assumes that regional slope coefficients are orthogonal to the variation in labor market conditions. In this case, κ would be just the weighted average of κ_i. However, this assumption may not hold in practice, and in such cases, the resulting estimator would be inconsistent.

A more robust approach is to apply a mean-group estimator, as proposed by M. Pesaran and Smith (1995) and Breitung and Salish (2021), which allows for slope heterogeneity by estimating separate regressions for each region and averaging the estimated coefficients. To formally assess the presence of slope heterogeneity, we conduct a Hausman test comparing the mean-group and fixed effects estimators. Under slope homogeneity or no correlation between the regressor and the coefficients, both estimators are consistent, but the fixed effects estimator is efficient. However, if there is systematic variation in regional coefficients, the fixed effects estimator becomes inconsistent, and the mean-group estimator is preferred.

Table 4 presents estimates of the Phillips Curve slope using both estimators. Column 1 reports results from our baseline fixed effects specification. Column 2 reports estimates from the mean-group estimator, which includes cross-sectional weighted averages of both the dependent variables and the region-specific regressors to control for unobserved common factors, following M. H. Pesaran (2006).[18] Incorporating common correlated effects (CCE) allows us to control for national shocks—such as monetary, supply, and demand shocks—that affect all cities, but to different degrees. To compute the MG estimate, we first estimate city-specific regressions and then average the resulting slope coefficients across cities. For inference, we use a bootstrap procedure to approximate the sampling distribution of the average slope and construct robust standard errors.

In Column 3, we report the Hausman test statistic, where the null hypothesis is that both estimators are consistent, but the fixed effects estimator is efficient. The alternative hypothesis is that the fixed effects estimator is inconsistent, while the mean-group estimator provides consistent estimates of the average slope (M. Pesaran and Smith, 1995). As expected, the fixed ef-

[18] We use different weights depending on the variable of interest: for the unemployment rate, we weight by the active population; for the inflation rate, we use the population aged 15 and above. The National Statistical Institute (INEGI) weights inflation by the share of expenditure across cities. While this reflects consumption preferences, it also implicitly depends on the number of consumers.

TABLE 4: HAUSMAN TEST FOR SLOPE HETEROGENEITY IN THE PHILLIPS CURVE

	FE	MG	Hausman
Phillips Curve Slope (κ)	-0.180**	-0.228**	0.384
	(0.0517)	(0.0793)	(0.536)
City FE	Yes	-	
Quarter-Year FE	Yes	CCE	
N	1,539	1,539	

This table reports estimates of the Phillips Curve slope using two methods: (i) a Fixed Effects (FE) estimator, as in our baseline specification; and (ii) a Mean Group (MG) estimator, which involves estimating separate regressions for each city and then averaging the resulting city-specific slope coefficients. To account for common correlated effects, we include cross-sectional weighted averages of inflation and unemployment rates, following M. H. Pesaran (2006). Both specifications employ our two-instrument strategy and control for city-level exposure to intermediate goods prices (p_{it}^x) and non-tradable productivity shocks (z_{it}^y) using shift-share instruments. The sample is restricted to cities observed in all time periods. We report standard errors for both estimators and the p-value of the Hausman test in parentheses. Standard errors are clustered at the city level for the FE estimator, while for the MG estimator, we compute bootstrap standard errors by iteratively excluding one city and recalculating the common correlated effects in each iteration. We apply this same strategy to compute the variance of the Hausman statistic.

fects estimate is smaller, consistent with a scenario where aggregate shocks—possibly driven by monetary policy—have a stronger influence in cities with steeper Phillips Curves. Nevertheless, we find no evidence to reject the null hypothesis, indicating that $\text{cov}(\kappa_i, \tilde{u}_{it}) = 0$. Note that this does not rule out slope heterogeneity, but only rejects the presence of systematic correlation between regional slopes and unemployment gaps.

8 Conclusion

We show evidence, based on panel-data causal inference techniques, that a Phillips curve exists in Mexico but that this relationship between city-level unemployment and core inflation is relatively weak. Our estimates suggest that labor market tightness explains a small share of the observed variation in core inflation in our sample of cities over our study period. Further, our results point to a Phillips curve in Mexico that is flatter than that found with similar estimation techniques for the U.S. context. We apply instrumental variable techniques to estimate how the Phillips curve varies with local labor market characteristics, and find that economic and demographic features of cities, including informality and the prevalence of cash transfers among households, influence the slope of local Phillips curves. Our work then highlighs that the characteristics of labor markets, both national and regional, matter for the determination of inflation.

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A Estimation of city-level labor market power measure

The estimation approach comprises two stages, as outlined by Bassier, Dube, and Naidu (2022). First, using an additive fixed-effects model, we estimate the firm-specific component of individual wages. Next, we estimate the separation rate elasticity by exploiting variation in this firm-specific component of wages. To address potential estimation error in the firm fixed effects, we apply an instrumental variable method. By isolating demand-driven wage variation that is exogenous to market conditions, we can identify supply-side responses in employment.

In a simple static monopsonistic labor market setting with idiosyncratic preferences over firms, the real wage that agent i earns in firm $j \epsilon J$ is given by

$$w_{ij} = \underbrace{g^{'}(S_j(W))\rho_i \, \psi_j}_{MRPL_{ij}} \underbrace{\frac{\varepsilon_j}{1+\varepsilon_j}}_{\text{markdown}} \tag{10}$$

where $g(.)$ is the production function, such that $g(.) > 0$; ρ_i is an individual-specific component such as skills, ψ_j is a firm-specific component; $S_i(W)$ is the labor supply faced by firm j, dependent on the wages of all firms (W); and ε is the labor supply elasticity. This equation indicates that wages are a markdown of the marginal revenue product of labor. As the labor supply elasticity increases, wages converge to the marginal productivity.

Applying log function to Equation 10, and assuming a linear production function, we find that log real wages are equal to the sum of worker-specific and firm-specific components, such that $log(w_{ij}) = \alpha_i + \Phi_j$, where $\alpha_i \equiv log(\rho_i)$ represents the worker-specific labor productivity and $\Phi_j \equiv log(\psi_j \beta_j)$ represents the firm-specific component of wages, which includes a firm-specific labor productivity ψ_j and a labor supply component $\beta_j \equiv \frac{\varepsilon_j}{1+\varepsilon_j}$. We could also interpret ψ_j as firms' wage policy, such as rent-sharing or efficiency wage premia, that boosts labor productivity. As the subscript indicates, this wage policy applies to every employee in firm j. With this in mind, we propose the following reduced-form empirical model.

$$w_{ijt} = \alpha_i + \gamma_t + \sum_J \Phi_j f_{ijt} + \varepsilon_{it}$$

where w_{ijt} is the log real wage of worker i in firm j at time t; α_i, Φ_j, and γ_t are individual, firm and time fixed effects, respectively; f_{ijt} is an indicator variable equal to one if agent i works for firm j at time t; and ε_{ijt} is the error term. Firm fixed effects capture variation in wage policies across firms, so identical workers may receive different wages for the same type of job. This is important because a firm's wage policy is an arbitrary decision, regardless of market conditions.

As in Card, Heining, and Kline (2013) and Bassier, Dube, and Naidu (2022), we impose some restrictions on the assignment function. First, we assume that the probability of working in firm j (f_{ijt}) is orthogonal to the error term, and solely depends on firm and worker fixed effects.

$$f_{ijt} = \mathbb{E}(J_{it} = j) = \mathbb{E}(J_{it} = j|\varepsilon) = G_{jt}(\Phi_1, \Phi_2, \dots \Phi_J; \alpha_i)$$

This assumption does not rule out sorting or assortative matching; *e.g.*, more productive workers may have a higher probability of matching with more productive firms ($\text{Cov}(\alpha_i, \Phi_j) > 0$). This is because pure sorting depends on the overall productivity distribution of workers and firms. However, specific worker-firm matching patterns may violate orthogonality conditions; there may be some unobserved heterogeneity correlated with the probability of working in firm j (f_{ijt}). For example, some workers may employ more effective job search or bargaining strategies that are not solely worker-specific but depend on the type of firm they target. This may allow them to extract higher rents from a successful match, leading to heterogeneous wage premiums among workers hired by the same firm.

Even though pure sorting does not violate the assumptions behind the AKM model, it may violate those required for estimating separation rates using firm-specific wage variation. For instance, more productive workers may sort into more productive firms and simultaneously have a lower probability of moving. For that reason, following Bassier, Dube, and Naidu (2022), we assume that f_{ijt} is monotonic and increasing in a firm's own wage policy, regardless of worker characteristics or other firms' wage policies. This allows us to decompose the assignment function into a labor supply component and a residual component, which may include sorting. The assignment function that enables identification of the causal effect of firm-specific wages on the probability of moving to another firm is:

$$G_{jt}(\Phi_1, \Phi_2, \dots \Phi_J; \alpha_i) = s(\Phi_j, \{\Phi_{j'}\}_{j' \neq j}) + h(\alpha_i, \{\Phi_{j'}\}_{j' \neq j})$$

Note that the assignment function depends on the firm's own wage policy only through the labor supply component $s(\cdot)$, and on worker characteristics only through the residual component $h(\cdot)$. We do not allow $h(\cdot)$ to depend on the firm's own wage policy, as this would imply that separations respond to firm-specific wages through, perhaps, sorting. Similarly, we do not allow $s(\cdot)$ to depend on worker characteristics, thereby excluding worker–firm-specific sorting in the labor supply channel. Nonetheless, this restriction does not rule out heterogeneity in the assignment function conditional on worker type and the distribution of other firms' wages. Thus, $G(\cdot)$ captures the labor supply channel as the sole mechanism through which firm-specific wages affect separations.

To avoid collinearity, for the period of analysis, we need to identify a set of firms connected by workers. AKM model does not allow for isolated firms, *i.e.*, firms with workers who never move to another firm. In such cases, worker fixed effects would be a linear combination of the firm fixed effects. We estimate the largest "connected set" using the algorithm from Card, Heining, and Kline (2013). Movers among firms from the connected set allow the AKM model to decompose wage variation into worker-specific and firm-specific components.

TABLE 5: DESCRIPTIVE STATISTICS FOR THE LARGEST CONNECTED SET OF FIRMS

	Firms	Workers	$\overline{W}$	SD(W)
Largest Connected Set	77,964	8,073,736	286.82	204.50
Full Sample	862,917	11,994,662	272.92	213.14
% of Full Sample	9.03	67.3		

This table presents descriptive statistics for the largest connected set of firms, identified using the methodology of Card, Heining, and Kline (2013), along with their corresponding percentages relative to the full sample defined above. The reported statistics include: (1) the number of firms; (2) the average monthly number of workers; (3) the daily average real wage; and (4) the standard deviation of the daily average real wage. The full sample is estimated on a monthly basis for the period 2018–2019, filtering for employees who move to another firm at least once.

As in Bassier, Dube, and Naidu (2022), we propose an empirical model to estimate the separation rate elasticity using the firm-specific component of wages from the AKM model.

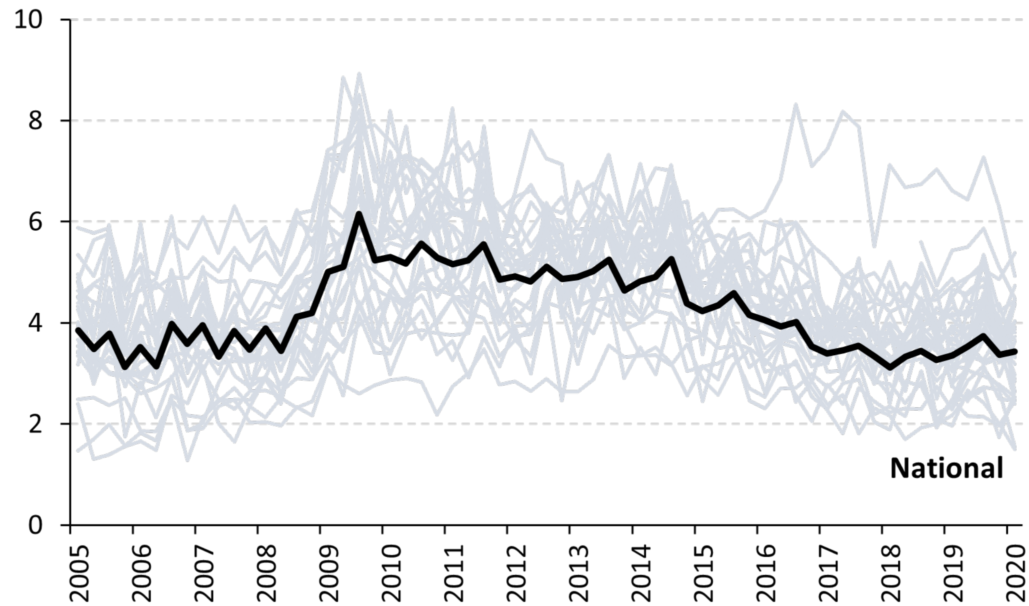
$$s_{ijt} = \eta \sum_{j} \hat{\Phi}_j f_{ijt} + \gamma_t + \upsilon_{ijt}$$

where s_{ijt} is an indicator variable that takes one if the worker i in firm j moves in period t; $\sum_j \hat{\Phi}_j f_{ijt}$ is firm fixed effects vector estimated with the AKM model; γ_t represents time fixed effects; and υ_{ijt} is the error term. Our goal is to recover the causal effect of the firm-specific component of wages (η) on the separation rate.

Given that Φ_j is an estimated regressor, there may be issues related to measurement error. Additonally, there may be a mechanic correlation between the separation rate (s_{ijt}) and our regressor: firm wage component (Φ_j) depends directly on movements across firms. Therefore, we apply a sample splitting approach, stratified by movers. We estimate two firm fixed effects vectors, Φ_j^A and Φ_j^B, and regress s_{ijt} in sample A on Φ_j^A, instrumenting it with Φ_j^B. Workers' movements in sample B might only affect the separation rates of workers in sample A through the firm-specific wage variation.

B Additional Figures

FIGURE 4: NATIONAL AND CITY-LEVEL UNEMPLOYMENT RATE



Note: The figure shows national and city-level unemployment rates, not seasonally adjusted, at a quarterly frequency.

TABLE 6: PHILLIPS CURVE SLOPE ESTIMATE. ROBUSTNESS TEST

	Dep. Var.: Annual Core Inflation Rate	
	(1)	(2)
Unemployment Rate	-0.181**	-0.190**
	(0.0514)	(0.0619)
RCLC		0.017
		(0.0366)
F-stat	61.58	57.22
F-stat p-value	< 0.001	< 0.001
N	1,562	1,562

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

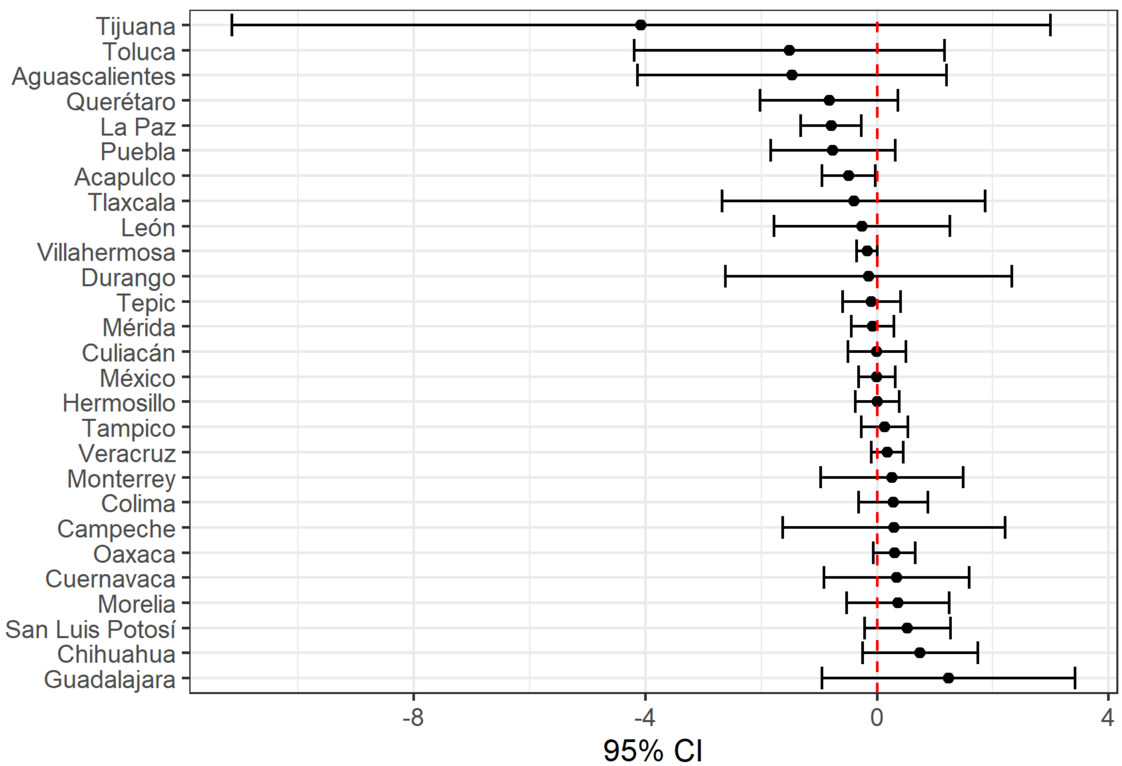
This table shows point estimates for the effect of city-level unemployment on annual core inflation, both at quarterly frequency, including as control the rate of critical labor conditions (RCLC). RCLC is defined as the percentage of the employed population who: (i) work fewer than 35 hours per week due to market-related reasons; (ii) work more than 35 hours per week but earn less than the monthly minimum wage; or (iii) work more than 48 hours per week while earning more than one and up to two minimum wages. All thresholds are expressed in equivalent minimum wages, adjusted to 1Q2005 constant pesos. As our baseline model, we introduce shift-share controls for intermediate goods prices (p^x_{it}) and non-tradable productivity shocks (z^y_{it}). Standard errors are shown in parentheses and clustered at the city level.

TABLE 7: DESCRIPTIVE STATISTICS FOR CITY-LEVEL FACTORS INFLUENCING THE PHILLIPS CURVE SLOPE

	Mean	Std. Dev.
Share of population that receives transfers	8.60	2.54
Share of households that receives transfer	19.50	4.70
Informality rate	46.69	7.91
Number of children (average)	2.38	0.18
Estimated quit rate elasticity	-0.05	0.09

This table presents descriptive statistics for the variables shown in Figure 3 corresponding to the baseline period.

FIGURE 5: PHILLIPS CURVE SLOPES AT THE CITY LEVEL



Note: This figure presents city-level estimates of the Phillips Curve slope, obtained by estimating the slope independently for each city. The sample includes only cities with complete observations across all periods. Ninety-five percent confidence intervals, based on robust standard errors, are displayed for each estimate.

C List of cities

A checkmark (✓) indicates availability of data in the National Survey of Occupation and Employment (ENOE) and the National Consumer Price Index (INPC). In the last column, a checkmark denotes cities with complete data coverage for the entire period of analysis (Q1 2005 to Q1 2020).

City Name	ENOE	INPC	Complete Sample Status
Acapulco, Gro.	✓	✓	✓
Cd. Acuña, Coah.	×	✓	
Aguascalientes, Ags.	✓	✓	✓
Atlacomulco, Mex.	×	✓	
Campeche, Camp.	✓	✓	✓
Cancún, Qroo.	✓	✓	×
Chetumal, Qroo.	×	✓	
Chihuahua, Chih.	✓	✓	✓
Ciudad de México, CDMX.	✓	✓	✓
Coatzacoalcos, Ver.	✓	✓	×
Córdoba, Ver.	×	✓	
Cortazar, Gto.	×	✓	
Colima, Col.	✓	✓	✓
Cuernavaca, Mor.	✓	✓	✓
Culiacán, Sin.	✓	✓	✓
Durango, Dgo.	✓	✓	✓
Esperanza, Son.	×	✓	
Fresnillo, Zac.	×	✓	
Guadalajara, Jal.	✓	✓	✓
Hermosillo, Son.	✓	✓	✓
Huatabampo, Son.	×	✓	
Iguala, Gro.	×	✓	
Izúcar de Matamoros, Pue.	×	✓	
Jacona, Mich.	×	✓	
Jiménez, Chih.	×	✓	
Cd. Juárez, Chih.	✓	✓	×
La Paz, BCS.	✓	✓	✓

City Name	ENOE	INPC	Complete Sample Status
León, Gto.	✓	✓	✓
Mérida, Yuc.	✓	✓	✓
Mexicali, BC.	✓	✓	×
Matamoros, Tamps.	×	✓	
Monclova, Coah.	×	✓	
Monterrey, NL.	✓	✓	✓
Morelia, Mich.	✓	✓	✓
Oaxaca, Oax.	✓	✓	✓
Pachuca, Hgo.	✓	✓	×
Puebla, Pue.	✓	✓	✓
Querétaro, Qro.	✓	✓	✓
Saltillo, Coah.	✓	✓	×
San Andrés Tuxtla, Ver.	×	✓	
San Luis Potosí, SLP.	✓	✓	✓
Tampico, Tamp.	✓	✓	✓
Tapachula, Chis.	✓	✓	×
Tehuantepec, Oax.	×	✓	
Tepatitlán, Jal.	×	✓	
Tepic, Nay.	✓	✓	✓
Tijuana, BC.	✓	✓	✓
Tlaxcala, Tlax.	✓	✓	✓
Toluca, Mex.	✓	✓	✓
Torreón, Coah.	✓	✓	×
Tulancingo, Hgo.	×	✓	
Tuxtla Gutiérrez, Chis.	✓	✓	×
Veracruz, Ver.	✓	✓	✓
Villahermosa, Tab.	✓	✓	✓
Zacatecas, Zac.	✓	✓	×