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Abstract: The non-accelerating inflation rate of unemployment (NAIRU) is not directly observable and the presence of informal workers imposes an additional challenge in its estimation. Countries with large informal sectors, traditional measures might not depict labor slack properly, as it has the wage flexibility needed to incorporate formal workers that cannot find a formal job. In this paper, we present an estimation of the traditional NAIRU for Mexico and an alternative measure that includes informality as an indicator of labor underutilization. We find that both measures of NAIRU and the associated labor market slack indicators follow similar patterns over time. However, the slack estimated with the indicator that includes informality seems to predict inflationary pressures more accurately when the unemployment gap is close to zero.

Keywords: Unemployment, Informality, NAIRU, Business cycle
JEL Classification: E26, E32, E52

Resumen: La tasa de desempleo no aceleradora de la inflación (NAIRU) no es directamente observable y la presencia de trabajadores informales impone un desafío adicional en su estimación. En países con un sector informal importante, las medidas tradicionales de desempleo podrían no reflejar la holgura de la mano de obra adecuadamente, ya que el sector informal tiene la flexibilidad salarial necesaria para incorporar trabajadores formales que no pueden encontrar un trabajo formal. En este artículo, presentamos una estimación de la NAIRU tradicional para México y una medida alternativa que incluye la informalidad como un indicador de subutilización laboral. Encontramos que ambas medidas de NAIRU y sus indicadores de holgura del mercado laboral siguen patrones similares a lo largo del tiempo. La holgura estimada con el indicador que incluye la informalidad parece predecir las presiones inflacionarias con mayor precisión cuando la brecha de desempleo es cercana a cero.

Palabras Clave: Desempleo, Informalidad, NAIRU, Ciclo económico

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1. Introduction

The reading of the economic cycle is essential to the formulation and implementation of monetary policy. Economic indicators such as the gross domestic product, credit indicators, interest rates, and unemployment can help to assess the current stage of the business cycle and thus the appropriate policy stance. The analysis is even more sensitive when there is a transition from an expansionary stage of the economy to a contractionary one, or vice versa. An important topic in monetary policy focuses on whether employment is approaching its potential: the rate of unemployment at which inflation remains constant in the absence of supply shocks. This rate is called the non-accelerating inflation rate of unemployment (NAIRU). However, the estimation of the NAIRU is complicated, because it is not directly observable. In Mexico and other Latin American countries, the presence of a sizeable number of informal workers imposes an additional challenge. The existence of unions, the degree of centralization in the bargaining process, distortions caused by labor legislation, the existence of monopolies, and other factors could limit labor market flexibility in the formal sector. However, the lack of labor regulation in the informal sector official promotes a competitive equilibrium and greater wage adjustment in that market.

Given that Mexico does not have unemployment insurance, workers who become unemployed immediately face the pressure to find a new job. The wage flexibility of the informal sector allows it to absorb most of the people who cannot find a job in the formal labor market; and workers who would otherwise be unemployed can find a job there. As a result, the unemployment rate in Mexico is low: it includes only frictional unemployment and a fraction of the cyclical unemployment that is absorbed by the informal sector.

Given these particular characteristics of the Mexican labor market, it is possible that the unemployment rate does not fully reflect the labor market slack. We thus estimate measures of labor market slack, first using the traditional unemployment rate, and then complementing this analysis with a new indicator of labor market underutilization that includes a measure of informality by including both unemployed workers and informal wage earners. Using standard methodologies, we estimate the NAIRU over time using both the traditional unemployment rate (NAIRU-trad) and the modified unemployment rate that takes informality into account (NAIRU-inf).

Allowing the NAIRU to vary over time is important because changes in this rate could be related to changes in structural labor market conditions such as flexibility, competitiveness, productivity, and demographic changes that alter the composition of the economically active population, as well as other institutional or policy issues.[1] In general terms, the NAIRU may present variations due to structural changes in the fundamental factors affecting labor supply and demand.

We find that the NAIRU and labor market slack follow similar patterns over time using either indicator of labor market underutilization. However, according to an endogenous threshold model, the indicator including informal wage earners seems to predict inflationary pressures better when the unemployment gap is close to zero; as a result, it appears to anticipate the inflationary pressures observed in 2007–2008 more clearly than the traditional slack indicator. In addition, both estimates show labor market slack decreasing throughout 2016 and approaching zero. The indicator taking informality into account shows relatively more slack, which is consistent with the absence of significant wage pressures observed during this period. Given these results, we conclude that it is important to assess the level of labor market slack in the economy using measures like the NAIRU as estimated in this paper, and that analysis of the economic cycle can be effectively complemented by considering informal employment. This method could be a convenient tool for monetary policy, particularly in countries like Mexico and other emerging economies with significant informal labor.

The rest of this paper is organized as follows. In Section 2, we explain how informal employment relates to labor market slack. In Section 3, we present the data sources and the methodology to estimate both measures of the NAIRU. Section 4 describes our results. Section 5 provides additional information about the Mexican labor market throughout the economic cycle, and Section 6 offers some conclusions.

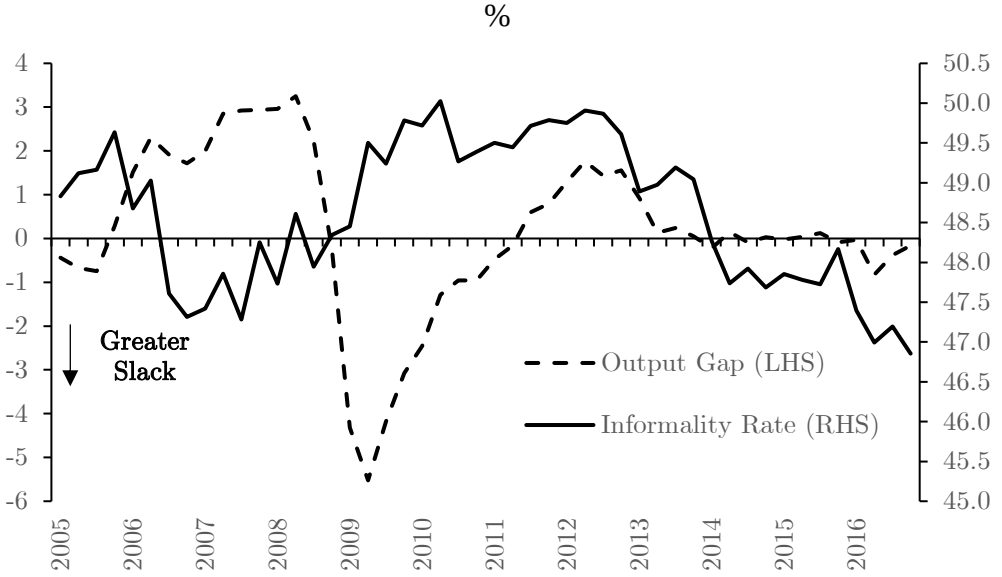
2. Informal Employment and Labor Market Slack

One of the key features behind the presence of informality in some economies is the low flexibility of their labor markets. Different degrees of flexibility in formal and informal

[1] Additional issues could include changes in female labor force participation, migration flows, or the educational level of the working-age population, as well as tax structure, minimum wage, and trade unions.

labor have implications for the cyclical adjustment of labor markets. During recessions, for example, wage flexibility in the informal sector allows the market to absorb individuals who do not find formal employment: workers who would otherwise be unemployed. This dynamic would imply that the informality rate is countercyclical—a stylized fact amply documented in the literature (see, for example, Chiquiar and Ramos Francia 1999, Alcaraz 2009, Gasparini and Tornarolli 2009, Fiess, Fugazza, and Maloney 2010, Perry et al. 2007, and Peterson 2014).[2] Figure 1 shows the evolution of the informality rate and the output gap in Mexico, which indeed suggests that the informality rate in the Mexican economy follows a countercyclical trajectory.[3]

Figure 1. Informality Rate and Output Gap



Note: The output gap is shown as a percentage of potential GDP. We calculate informality in urban areas with a population larger than 15,000.
Source: Authors' calculations using data from ENOE and INEGI.

[2] The fact that informality rate is countercyclical does not implies that the level of informal workers is countercyclical. The level of informal workers could be procyclical, countercyclical or acyclical. For example, during a contraction in de GDP the level of informal work could increase, remain stable but could also decrease due the slowdown of the economic activity. In this case, the relevant for us is that the informality rate (the evolution of informal workers in relative terms to the formal workers) increases. The elasticity of informal labor and formal labor to changes in GDP is relevant but is beyond the scope of this study.

[3] The countercyclical behavior of the informal rate is robust to alternative measurements of informality, e.g., defining the informal sector in terms of the size of the firm in which the worker is employed or using only wage earners. In Figure 1, we employ the most widely used definition of informality that includes wage earners and the self-employed, following the criteria of the International Labor Organization (ILO 2003).

With these considerations in mind and given the characteristics of the Mexican labor market, Mexico's unemployment rate is low, as it tends to include only part of cyclical unemployment. Chiquiar and Ramos Francia (1999) were the first to note that for this reason, the unemployment rate in Mexico may not adequately reflect labor slack. However, they did not use informal labor to measure labor market slack or estimate an NAIRU that includes informal labor. To our knowledge, the present study is the first time data for informal labor has been used to obtain additional information about the economic cycle and labor market slack.

The lack of regulation of the informal sector is the most obvious explanation of its flexibility. In Mexico, the Federal Labor Law (*Ley Federal del Trabajo*, LFT) aims to promote safe working conditions for wage earners by defining minimum wages and benefits and regulating union activity and labor contracts. For instance, Article 23 requires that those who have worked for an employer for more than a year are entitled to a severance payment equal to three months' wages if laid off or fired. The complete absence of labor regulation in the informal sector simplifies the hiring and firing of workers. There is no need to comply with the costly bureaucratic requirements typically found in the formal sector, such as enrolling workers in social security and registering them with the tax authorities. The absence of union activity in the informal sector is also an important determinant of its flexibility. The process of hiring a worker is usually even more difficult if a firm has a unionized workforce because unions impose substantial restrictions on hiring and firing workers, and act as a strong source of pressure in the negotiation of wages.

There are ways to explain the differences in wage flexibility between the formal and informal labor markets which do not assume that regulations affect each sector differently. Esfahani and Salehi-Isfahani (1989) link effort observability with informality in a theoretical model, using efficiency wage theory; they argue that the main characteristics of the informal sector (small firm size, low-skill workers, and low technological level) are associated with higher levels of effort observability and more competitive wages, which imply greater flexibility and no involuntary unemployment. In the formal sector, however, with lower levels of effort observability, wages are usually above the reservation wage level, which promotes lesser flexibility and involuntary unemployment. More recent studies have proposed integrated labor markets with frequent transitions between informal and formal

jobs. For example, Maloney (1999) argues that in Mexico there is no segmentation, and that informality exists because some workers want to take advantage of the dynamic and unregulated informal labor market. Meghir et al. (2015) propose an equilibrium wage-posting model with heterogeneous firms that decide to locate in the formal or informal sector and workers who search randomly on and off the job. However, some authors have also argued the possibility of a heterogeneous labor market where part of the informal sector is voluntary, while the other includes workers who would like to obtain a formal job but cannot get it because of the barriers created by regulation (see, for example, Fields 1990 and Perry et al. 2007). Therefore, even if part of informal labor is voluntary and integrated with the rest of the economy, we might still observe a countercyclical informality rate.

2.1 Labor and Economic Activity Indicators of Slack

A standard national accounts statistical procedure is to update the base year to estimate the GDP series. This process includes an important effort by the Mexican National Institute of Statistics and Geography (INEGI) to update the value of the different goods produced in the economy. The GDP series is thus more accurate and the historic GDP series changes, both in terms of level and growth rates. This change may affect the measurement of economic activity and, as a result, the estimation of economic activity slack in real time.[4] However, labor market slack is not subject to this problem, because the variables used to compute this indicator are generally based on the number of employed or unemployed workers and is not subject to periodic revisions. These considerations highlight the importance of taking labor market information into account to evaluate slack in the economy in real time.

2.2 Informal Labor Definition and Identification

According to international criteria proposed by the International Labour Organization (ILO 2003), informal workers include self-employed persons and wage earners not registered in social security. Some informal workers, particularly the unregistered self-employed, may earn relatively high incomes and may work voluntarily in the informal sector, that is, they

[4] We recognize that the calculation of the output gap is affected by other issues, such as the econometric methodology used (for example, the HP filter problem towards the end of the sample), and the revision to which the GDP data are subjected. These issues affect the measure of the output gap in real time. However, our main point is to emphasize the problem of the change of the base year for the GDP series.

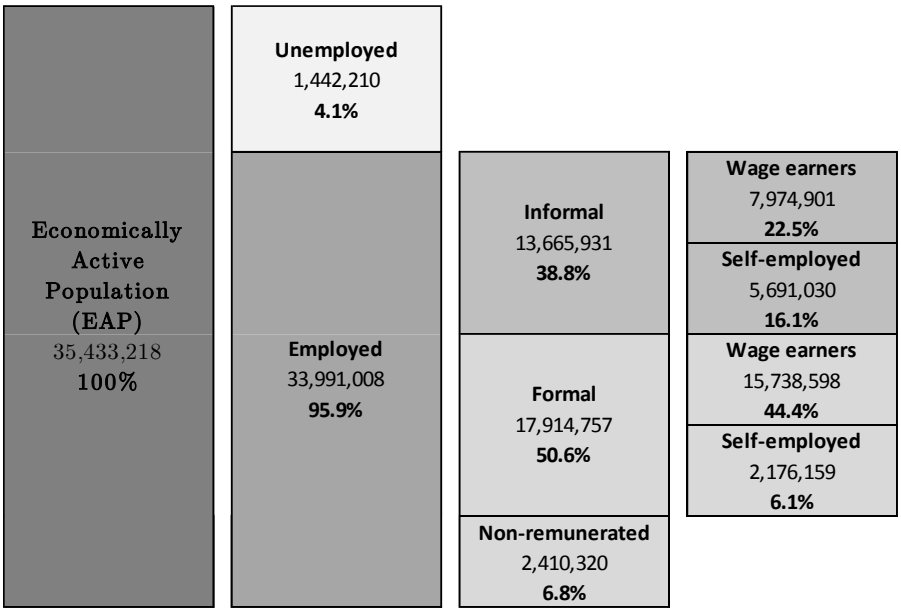
remain informal even if they have an opportunity to enter the formal sector. In contrast, involuntary informal workers—those who would rather have formal employment but cannot obtain it—tend to concentrate in the group of informal wage earners (see Alcaraz et al. 2015, and Fajnzylber and Maloney 2007). The World Bank flagship report "Informality Exit and Exclusion" (Perry et al. 2007) finds that informal wage workers are more disadvantaged than their informal self-employed counterparts in several Latin American countries. Alcaraz et al. (2015) use a model of self-selection with entry barriers into the formal sector to detect endogenously involuntary informal workers, and find a higher proportion of involuntary informal workers among wage workers. Informal wage earners may thus best represent disadvantaged workers and, consequently, behave similarly to unemployed workers. We therefore combine informal wage earners and unemployed workers to construct our extended indicator of slack in the Mexican labor market, defined as the extended indicator of the level of unemployment consistent with an environment of stable inflation. We use this indicator to analyze the evolution of slack in the Mexican labor market from 2005 to 2016. To evaluate the advantages of using this variable as an alternative to traditional measures, we also estimate the NAIRU using only the unemployment rate (NAIRU-trad) and compare the slack estimated with both indicators (*slack-inf* and *slack-trad*). By comparing these indicators through different stages of the economic cycle, we can evaluate their ability to indicate inflationary pressures.

In order to assess the participation of our proposed new indicator of labor slack *slack-inf* within the Economically Active Population (EAP), we calculate the EAP composition from ENOE data, using expansion factors to obtain population-representative data, as shown in Figure 2.[5] The data correspond to the survey of the fourth quarter of 2016. Among the population aged 15 years and older, just over 35 million are economically active, and of these, 4.1 percent were unemployed. There were just under 34 million who were employed, almost 13.7 million of them were informal. In turn, informal wage earners (informal employees) represented 14.8 percent of the AEP in the fourth quarter of 2016. Our alternative rate of unemployment, taking informal labor into account, was 26.6 percent (the traditional

[5] Almost all rural workers are informal because they are not required to register, so the division between formal and informal workers is relevant only for urban areas. In this study we thus use data for urban workers, and the figures we present consider only urban areas. Appendix A, however, shows the same figure including both urban and non-urban areas.

unemployment rate of 4.1 percent plus the informal wage earners' rate of 22.5 percent). It is important to notice that non-remunerated workers (workers that receive no wage) represented 6.8 percent of the EAP. These workers earn some kind of non-monetary income but is not observable. Furthermore, in general, these workers have a particular type of labor relationship associated with family activity. In line with other empirical labor market studies, we exclude these workers from our analysis.

Figure 2. Labor Market Composition, Urban Areas, ENOE (Q4-2016)
Percentage of Total Economically Active Population (EAP), 15 Years and Older.



Note: Survey weights were used to obtain the population-representative figures.
Source: Authors' calculations with data from ENOE, INEGI.

2.3 Exogenous Policy Changes That Could Trigger Changes in Incentives Between Formal and Informal Labor

One potential problem with our alternative measure of slack is the possibility of legal or administrative actions aimed at reducing informal employment in the economy. If these measures are successful, such a reduction could take place regardless of the economic cycle, resulting in an erroneous attribution of the decline to the slack in the economy. We argue that this problem is not severe enough to offset the usefulness of our alternative indicator. Unfortunately, we can only provide circumstantial evidence for some cases, but for the rest, we have administrative data that allows us to quantify the effect of these measures on the number of formal workers. Since our empirical strategy allows for changes in the NAIRU

over time, we do not expect that gradual changes in the informality rate caused by these measures will bias our results. In order to assess the magnitude of this problem, we list in Table 1 all the actions taken during the study period that encouraged worker registration, and we link them to the informality rate over time (see Figure 1). Mexico's primary social security institution, the Mexican Social Security Institute (IMSS), regularly sponsors campaigns to encourage formalization of employment. However, none of these campaigns seem to have resulted in a significant decrease in informal employment. The government also promoted a series of "first job" programs encouraging young workers to register in 2007 and 2010. According to administrative data, these programs registered 25,000 workers per year. If we consider that approximately 700,000 new workers register at IMSS every year, it is clear that these programs did not meaningfully increase formality during the time span of our analysis. In 2012, the Congress approved a labor law reform, which may have encouraged the registration of wage earners (see Banco de México 2012). However, according to the Banco de México, the increase in the number of formal workers due to this reform would be gradual, over a few years. Given that our methodology allows for changes over time in the NAIRU, we do not believe this reform is a serious source of bias in our analysis. In 2014, the government launched the program *Crezcamos Juntos* ("Let's Grow Together") to encourage the registration of small firms. This program might have led to an increase in the number of registered workers and thus a reduction in informal employment, but the increase was negligible. Finally, in the same year, IMSS and the tax authorities agreed to share information about registered workers. It is advantageous for employers to register workers and wages with the tax authorities because they receive tax deductions, but there is also an incentive not to register workers with IMSS, as the employer pays part of the cost of social security. It was expected that as a result of the sharing agreement, employers with more workers registered with the tax authorities than with IMSS would increase IMSS registration, so the numbers would match. This measure could thus have induced the formalization of workers. However, the effect of this measure might be limited by the fact that employers may assume that both institutions shared information with no need of agreement, and as a consequence, they regularly matched the workers' registration in both institutions independently of the celebration of any agreement.

Table 1. Policy Measures Possibly Affecting Informal Employment in Mexico, 2000-2014

Period	Policy/Program	Effects on formal employment
2000-2014	The Mexican Social Security Institute (IMSS) implemented various measures to increase formal employment registration.	No information available.
2007	First Job Program (*Programa de Primer Empleo*)	From 2007 to 2011, these programs increased the number of young formal workers by approximately 25,000 per year, on average.
2010, relaunched in 2011	First Job Promotion Program (*Programa de Fomento al Primer Empleo*)	
2012	Federal Labor Law reform	Banco de México (2012) predicts a gradual increase in informality, mainly among young and part-time workers, including women, students, and the elderly.
2013	Employment Formalization Program	No information available.
2014	Agreement between IMSS and the tax authorities to share information about registered workers.	This measure may have had an impact on the formalization of employees.
2014	*Crezcamos Juntos* Program	The number of new formal workers registered in the tax system has increased since the start of the program, but there has been an insignificant increase in the number of workers registered for social security (IMSS).

Source: IMSS, Federal Labor Law, *Secretaría del Trabajo y Previsión Social*, *Servicio de Administración Tributaria*

Figure 1 shows an important variation of informality over time, but we observe no relationship with any of the policy measures explained in this section. Even though there have been some changes in regulations that could bias our results, we conclude that the magnitude of this problem is not significant enough to affect them.

3. Modeling Inflation Dynamics and the NAIRU in Mexico

3.1 Econometric Methodology

There are different methodological approaches in the literature to estimate the NAIRU and thus to calculate the corresponding unemployment gap. In this paper, we focus on the estimation of the NAIRU from equations that model inflation dynamics based on the Phillips curve. The consensus in the literature is that the most suitable conceptual framework for studying the NAIRU is a reduced-form Phillips curve approach. We use this approach to

compute the NAIRU as the unemployment rate consistent with stable inflation, subject to an expectations-augmented Phillips curve. This relationship broadly establishes a negative link between inflation and the unemployment gap—the difference between the observed unemployment rate and the NAIRU—in the short run, such as the following:

$$\pi_t = \pi_t^e + \beta(u_t - \bar{u}) + \delta X_t$$

where:

π_t is the annual inflation rate and π_t^e is the expected inflation rate;

$(u_t - \bar{u})$ is the unemployment gap, defined as the difference between the observed unemployment rate (u_t) and the NAIRU ($\bar{u}$); and

X_t represents a vector of variables controlling for the presence of supply shocks (e.g., fluctuations in the real exchange rate, telecommunication and commodity prices, and external sector variables).

In order to better approximate the dynamics of the inflationary process, we generalize this relationship and, following Staiger, Stock, and Watson (1997a and 1997b), we use the following empirical model to estimate inflation dynamics:

$$\Delta\pi_t = \beta(L)(u_t - \bar{u}) + \gamma(L)\Delta\pi_{t-1} + \delta(L)X_t + \varepsilon_t \quad (1)$$

where:

$\Delta = 1-L$, and L is the lag operator;

$\beta(L)$, $\gamma(L)$, and $\delta(L)$ are lag polynomials; and

ε_t is an error term.

The literature on the estimation of the NAIRU includes different interpretations of these ways of modeling inflation. Gordon (1997) deliberately omitted inflation expectations and estimated the NAIRU from what he calls the triangle model of inflation. According to this model, the inflation rate depends on three basic determinants: inertia, demand, and supply. Staiger, Stock, and Watson (1997a) develop another interpretation: the random-walk model for inflation expectations, i.e., $\pi_t^e = \pi_{t-1}$, and thus $\pi_t - \pi_t^e = \Delta\pi_t$. Under this assumption, inflation expectations are equal to past inflation. Laubach (2001) also uses the first difference of inflation, but justifies its use because it is the stationary transformation of

inflation according to his data.[6] Finally, as discussed in Restrepo (2008), when inflation is stable, this particular case is also consistent with a model of adaptive expectations. Here, following this literature, we use the specification in equation (1) in our estimates.[7]

Our methodological strategy is first to estimate a version of equation (1) for each of our two measures of unemployment in Mexico, assuming the NAIRU is constant. From this estimation, we conduct a simple statistical test with the null hypothesis of constant parameters (Chow test) that suggest that the NAIRU in Mexico might have changed in recent years. From these first results, we estimate models that allow us to obtain a time-varying NAIRU. Specifically, we consider two reduced-form approaches widely used in the literature: i) a deterministic NAIRU, i.e., a recursive estimation from equation (1), and ii) state-space specifications, which provide further flexibility regarding the dynamic properties of the NAIRU. We explain these specifications in further detail below.

NAIRU Recursive Estimation

In the specification of equation (1), the unemployment gap could have a contemporaneous and a lagged impact on inflation. In order to simplify the NAIRU estimation, we assume that $\beta(L) = \beta$, i.e., that the relationship is contemporaneous. We will see below that this is the resulting specification in our empirical application. We infer the NAIRU as follows:

$$\Delta\pi_t = \alpha + \beta(u_t) + \gamma(L)\Delta\pi_{t-1} + \delta(L)X_t + \varepsilon_t, \tag{2}$$

$$\beta(u_t - \bar{u}) = \alpha + \beta(u_t), \quad \Rightarrow \ \alpha = -\beta(\bar{u})$$

such that if $\hat{\alpha}$ and $\hat{\beta}$ are the OLS estimators in (2), the NAIRU (i.e., the unemployment rate that accomplishes $\Delta\pi_t = \Delta\pi_{t-1} = 0$) can be estimated through the following relationship:

$$\hat{\bar{u}} = -\hat{\alpha}/\hat{\beta}$$

[6] Laubach (2001) presents a statistical perspective, conducting unit root tests on the inflation series for all countries included in his paper, and concluding that the null hypothesis cannot be rejected. He thus uses the stationary transformation of inflation, i.e., the first difference, introducing another way of justifying the implementation of the assumption $\pi_t^e = \pi_{t-1}$.

[7] In this conceptual framework of the NAIRU estimation from a Phillips curve-type equation, we test different ways of managing inflation expectations in our estimates. We obtain the best results—in terms of obtaining economically reasonable values from the NAIRU—with the first difference of the annual inflation rate, implicitly modeling inflation expectations under the random-walk model for inflation expectations.

However, in order to allow the relationship between unemployment and inflation to vary over time, we compute the path of the NAIRU through a recursive estimation of equation (2), leaving the starting point of the sample fixed as follows:

$$\hat{\bar{u}}_t = -\hat{\alpha}_t/\hat{\beta}_t$$

Through this estimation, it is possible to infer the evolution of the NAIRU over time, since the most recent information is incorporated into the model. An alternative strategy could be a rolling window estimation of the model, but the size of the sample and the drastic behavior of the unemployment rate in the international financial crisis make these estimates very volatile.[8]

We model the NAIRU as an unobserved stochastic process, where we assume that its determinants are unknown but persistent (i.e., they follow a random walk). Starting from the simplest case, components that further explain the dynamics of the unemployment rate, such as lags and the output gap, can be gradually added to the system of equations to introduce additional structure into the model. We describe below the three cases we explore.[9]

NAIRU Random Walk

As in Gordon (1997), the evolution of the NAIRU is obtained from the following system of equations:

$$\Delta\pi_t = \beta(u_t - \bar{u}_t) + \gamma(L)\Delta\pi_{t-1} + \delta(L)X_t + \varepsilon_t$$

$$\bar{u}_t = \bar{u}_{t-1} + e_t \qquad (3)$$

where errors are assumed to be i.i.d. N$(0, \sigma_\varepsilon^2)$ and uncorrelated.[10]

[8] In general, results with relatively small windows (24, 36, and 48 month) are too volatile to provide plausible economic interpretations. In estimations with windows of up to 5 or 6 years, the results are less volatile but at the expense of much information, and thus of any possibility of making an inference regarding the level of the NAIRU prior to the international financial crisis. In fact, it is of particular interest to analyze the period starting in 2008 in order to obtain information on at least one complete business cycle. Results using the rolling window approach can be requested from the authors.

[9] See, for example, Laubach (2001) for a broad discussion of these different models.

[10] This is a standard regression model for a stochastic parameter that changes over time, estimated with maximum likelihood and a Kalman filter.

NAIRU Random Walk and AR(2) Unemployment Gap

In addition to assuming a random-walk NAIRU, this methodology models the dynamics of the unemployment gap $(u_t - \bar{u}_t)$ following Laubach (2001). We model this gap as an autoregressive process, which prevents the unemployment rate from deviating permanently from the NAIRU. In other words, the unemployment gap is a mean-reverting process. The system of equations to estimate the NAIRU is given by:

$$\Delta\pi_t = \beta(u_t - \bar{u}_t) + \gamma(L)\Delta\pi_{t-1} + \delta(L)X_t + \varepsilon_t$$

$$\bar{u}_t = \bar{u}_{t-1} + e_t$$

$$(u_t - \bar{u}_t) = \rho_1(u_{t-1} - \bar{u}_{t-1}) + \rho_2(u_{t-2} - \bar{u}_{t-2}) + \epsilon_t \quad (4)$$

where ρ_1 and ρ_2 are parameters to be estimated, and the errors are assumed $N(0, \sigma_i^2)$ and uncorrelated, with $i = e,\ \epsilon$.

NAIRU Random Walk and Unemployment Gap (Okun's Law)

We expand the previous system of equations with the inclusion of an equation relating the unemployment gap to the output gap (Okun's Law). The system of equations we use to estimate the NAIRU is the following:

$$\Delta\pi_t = \beta(u_t - \bar{u}_t) + \gamma(L)\Delta\pi_{t-1} + \delta(L)X_t + \varepsilon_t$$

$$\bar{u}_t = \bar{u}_{t-1} + e_t$$

$$(u_t - \bar{u}_t) = \varphi_t y_t^{gap} + \epsilon_t \quad (5)$$

$$\varphi_t = \varphi_{t-1} + r_t \quad (5.1)$$

where φ_t is the time-varying Okun coefficient, modeled as a random walk, and errors are assumed to be $N(0, \sigma_i^2)$ and uncorrelated, with $i = e, \epsilon, r$.[11] In this specification, we consider the output gap as an exogenous variable within the model, and estimate it using the Hodrick-Prescott (HP) filter with a tail correction method (St-Amant and van Norden 1997).[12]

[11] In the state-space specifications, we also estimate a version with the parameter φ_t modeled as a constant over time. We will show evidence below suggesting that the relationship between the unemployment gap and the output gap has changed over time. Given this evidence, and for reasons of space and clarity, we show this result only in Section 4.

[12] For more details, see Banco de México (2009), "Inflation Report April-June 2009," p. 69.

3.2 Data

We use monthly, seasonally-adjusted data for unemployment and prices from January 2005 to December 2016, obtained from the Mexican National Institute of Statistics and Geography (INEGI). In all estimations, inflation (π_t) corresponds to monthly core inflation, calculated as the annual change in the seasonally-adjusted Consumer Price Index (CPI).[13] We use INEGI's monthly statistics on unemployed workers, which are based on the international definition.[14]

The data on informal wage earners comes from INEGI's National Occupation and Employment Survey (*Encuesta Nacional de Ocupación y Empleo*, ENOE), a quarterly household survey with a rotating panel structure, from 2005 to 2016. Every quarter, INEGI replaces one-fifth of the sample: each household is thus followed for five consecutive quarters. The purpose of the survey is to collect data on the employment situation of Mexicans aged 15 and older in rural and urban areas. It is possible to identify informal wage earners in this survey, as defined by the International Labour Organization (ILO 2003). We assume that workers are informal if they are wage earners without any of the following mandatory benefits: IMSS (social security), ISSSTE (social security for government employees), Afore (retirement benefits), INFONAVIT (home loan), or private health insurance. For comparability purposes, we convert the quarterly informal labor data to monthly data using linear interpolation[15] because the rest of the variables considered are available as monthly data.[16]

In the baseline estimation, unemployment (u_t) corresponds to INEGI's national unemployment rate, $u_t = 100 * \left[\frac{Unemp_t}{EAP_t}\right]$, where $Unemp_t$ is the number of people without a

[13] This price index excludes certain goods and services whose prices are excessively volatile, or whose determination process does not respond to market conditions: agriculture, energy and government tariffs.

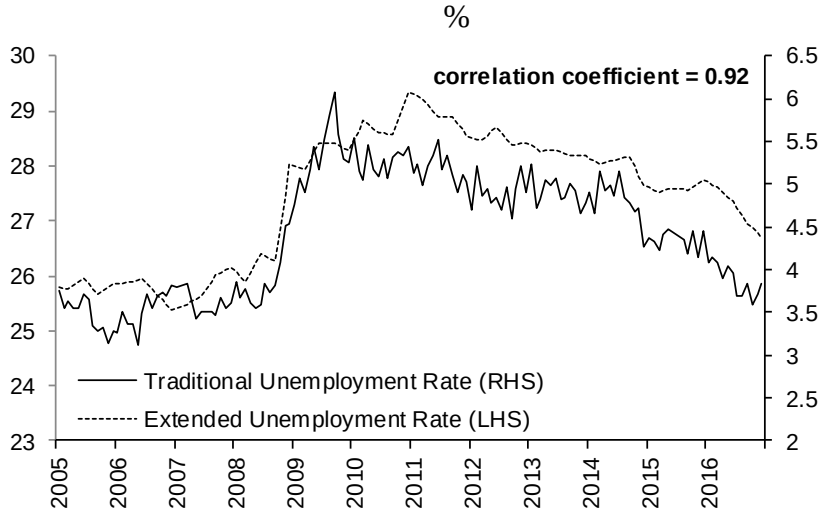
[14] Unemployed workers are those who during the week before the execution of the survey were: (a) without work, either in paid employment or self-employed; (b) currently available for paid employment or self-employment; and (c) seeking work, i.e., they had taken specific steps in a recent period to seek paid employment or self-employment.

[15] Both the wage earner and the unemployment series come from the ENOE. However, we obtained the unemployment rate from monthly subsamples of the ENOE published by INEGI. The unemployment rate series is published monthly, while the wage earners series is published quarterly.

[16] To verify that the interpolation would not cause any bias in the estimation of the NAIRU, we also perform estimates with the monthly data transformed to quarterly and found no important differences. Detailed results are available upon request from the authors.

job and actively searching for one, and EAP_t is the economically active population[17] (unemployed plus employed) within the total population aged 15 or older. In the estimation including informal employment (NAIRU-inf), we calculate an extended measure of unemployment $(u - extended_t)$, which includes INEGI's national series for both unemployment and informal wage earners, $u - extended_t = 100 * \left[\frac{Unemp_t + Inf_t}{EAP_t}\right]$, where Inf_t is the number of informal wage earners within the EAP_t. Figure 3 shows both the traditional unemployment rate and the extended unemployment rate used in our estimation. These variables show a high level of correlation: 0.92. However, unlike the traditional unemployment rate, it seems that the extended unemployment indicator did not return to levels observed prior to the 2009 crisis.

Figure 3. Traditional and Extended Unemployment Rate



Source: INEGI and authors' calculations with data from ENOE, INEGI.

We estimate the output gap (y_t^{gap}) using the HP filter with tail-correction on INEGI's economic activity index (IGAE). Some of the variables tested as alternatives to control for supply shocks in equation (1) include the monthly annual change in the following series: the BIS real effective exchange rate index for Mexico, the Banco de México Mexican import price index, the West Texas Intermediate and Mexican mix oil prices in U.S. dollars per barrel, the U.S. CPI, and the telecommunications component of the Mexican CPI. These variables are not included in the estimation simultaneously, but are tested as alternatives to

[17] INEGI defines EAP as the number of people who performed an economic activity (employed) or actively searched for a job during the month before the interview date (unemployed).

obtain a parsimonious and statistically valid model according to the diagnostic and specification tests described in Section 4. Using the conventions of the NAIRU-related literature, we subtract the mean from X_t to induce a zero-mean sample, avoiding bias from the constant component. Thus, supply shocks are zero, on average, in the specification for inflation dynamics.

4. Estimates of the NAIRU

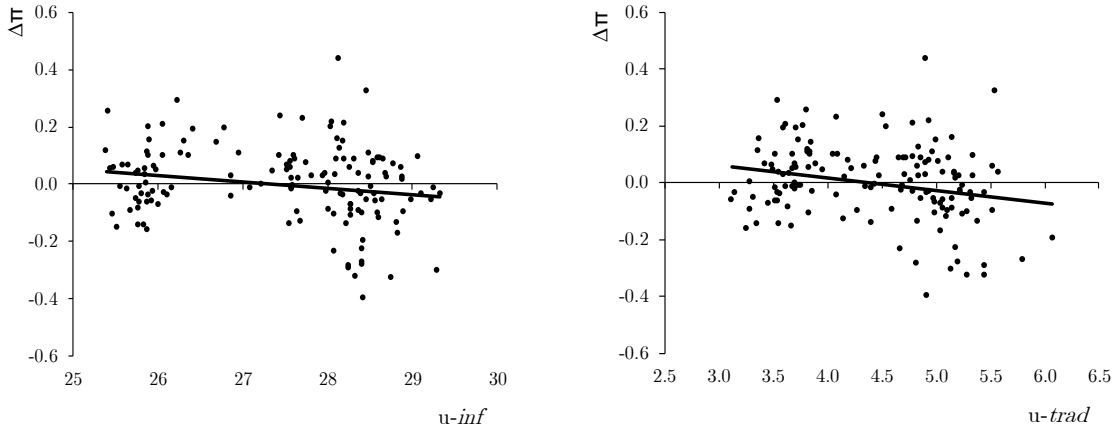
4.1 Results

A First Approach to the NAIRU

Figure 4 shows scatter plots of the change in annual inflation against the two measures of unemployment. First, it should be noted that there is indeed a negative relationship between the variables. The correlation between the changes in annual inflation and $u - extended_t$ is -0.18 and with u_t is -0.21, both statistically different from zero at the 5 percent level. Thus, lower levels of unemployment, in any of its measurements, are associated with higher inflation.

Figure 4. Relationship Between the Change in Annual Inflation and Unemployment in Mexico, 2005:01-2016:12

A. Unemployment (extended) B. Unemployment



Source: Authors' calculations with data from INEGI.

From the intersection of the line of best fit with the x-axis (i.e., when the change in inflation is zero), we can infer that the NAIRU-trad is 4.4 and the NAIRU-inf is 27.3.[18] However, this analysis would omit the inertial effects of inflation and the possible effect of supply shocks. The results of the estimation of equation (1) for both measures of unemployment are shown below.[19]

NAIRU-inf:

$$\Delta\pi_t = \underset{(0.226)}{0.531} - \underset{(0.008)}{0.0193}u_t^{inf} + \underset{(0.066)}{0.222}\Delta\pi_{t-1} + \underset{(0.066)}{0.017}\Delta\pi_{t-2} - \underset{(0.003)}{0.006}\Delta rec_{t-1} - \underset{(0.003)}{0.007}\Delta rec_{t-2}$$

LS estimation, 2005:1-2016:12 ($T = 144$), $\bar{R}^2 = 0.440$, $\hat{\sigma}_\varepsilon = 0.115$,

$F_{ARCH(1)} = 0.987$, $F_{het} = 0.115$, $F_{ar(1)} = 0.168$, $JB = 0.402$.

NAIRU-trad:

$$\Delta\pi_t = \underset{(0.061)}{0.177} - \underset{(0.014)}{0.040}u_t^{trad} + \underset{(0.066)}{0.205}\Delta\pi_{t-1} + \underset{(0.066)}{0.011}\Delta\pi_{t-2} - \underset{(0.003)}{0.006}\Delta rec_{t-1} - \underset{(0.003)}{0.007}\Delta rec_{t-2}$$

LS estimation, 2005:1-2016:12 ($T = 144$), $\bar{R}^2 = 0.452$, $\hat{\sigma}_\varepsilon = 0.114$,

$F_{ARCH(1)} = 0.827$, $F_{het} = 0.202$, $F_{ar(1)} = 0.275$, $JB = 0.434$.

where π_t is core annual inflation and $\Delta\pi_t$ its first difference, u_t^i (for $i\epsilon\{inf, trad\}$) is the traditional ($trad$) or extended (inf) unemployment rate, and Δrec_t is the first difference of the annual change of the real exchange rate (increase means appreciation). The standard errors are shown in parentheses. The sum of the coefficients related to the lags of the control variables is statistically significant and shows the expected sign, and there are no substantial changes in its magnitude when different unemployment measures are used.[20] $\bar{R}^2$ is the R-

[18] These values should be considered a simple, intuitive approach to approximating the NAIRU. However, they involve a statistical estimate with a standard error of 0.29 in the case of the NAIRU-trad and 0.56 for the NAIRU-inf.

[19] We test the model with a broad set of combinations of unemployment lags, inflation, and the control variables described in Section 3 in order to select a parsimonious and statistically robust model for the dynamics of inflation. In other words, we seek a solid model for all NAIRU estimates based on statistical and economic significance of the variables (i.e., coefficients with the appropriate sign), where the residuals of the model complied with the diagnostic tests (normality, serial correlation, and heteroskedasticity). In this manner, we obtain the specifications for the dynamics of inflation (based on the Phillips curve) that are estimated throughout the paper.

[20] Although in both equations the second lag of inflation is not statistically different from zero, it is included in the specifications because the sum of the lags of inflation is statistically different from zero. The results of the estimated NAIRUs do not depend on the inclusion or not of this second lag.

squared measure adjusted by the number of predictors, and $\hat{\sigma}_\varepsilon$ is the standard error of the model. We include two tests for heteroskedasticity: the autoregressive conditional heteroskedasticity test, $F_{ARCH(1)}$, and the White test, F_{het}. For serial correlation, we run a Lagrange multiplier test, $F_{ar(1)}$, and we use the Jarque-Bera test, JB, for normality. All tests indicate that the model presents no problems of ARCH errors, autocorrelation, heteroskedasticity, or non-normality.[21] We report the *p*-values of these diagnostic tests. To arrive at these well-behaved equations of inflation dynamics, we test different numbers of lags for all supply-shock variables, unemployment, and inflation. We use this same specification of inflation dynamics for all methodologies (including the state-space models), so that in all cases the variables included and the structure of lags are the same.

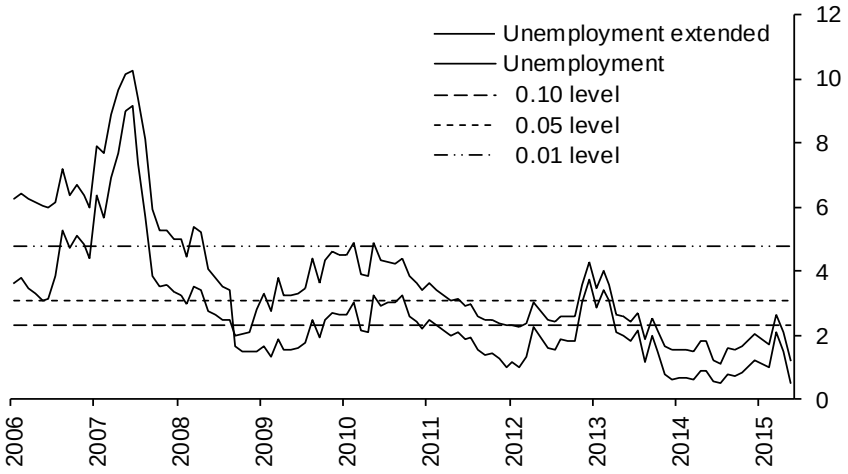
From these results, we observe that both the traditional unemployment measure and the proposed indicator have statistically significant effects on inflation. We also obtain a first estimate of the NAIRU, where we assume it is constant over time. Under this assumption we obtain NAIRU-trad = 4.43 (0.27) and NAIRU-inf = 27.46 (0.48).[22] We test the assumption of a constant NAIRU by applying a test of structural change, the classical Chow test of structural change with the null hypothesis of constant parameters,[23] which divides the sample in two and tests whether the coefficients related to the NAIRU estimation are equal in both subsamples. Figure 5 illustrates the results of this test for different periods. In most periods the null hypothesis of constant parameters is rejected at the conventional significance levels. We can thus conclude from the analysis that the NAIRU-trad and the NAIRU-inf show trajectories that vary over time.

[21] It is also necessary to include three pulse dummy variables in the equations for outliers in January 2010, 2014, and 2015. These dummies are associated with the fiscal reforms that came into effect in January 2010 and 2014, and with the decrease in the prices of telecommunication and energy services resulting from structural reforms.

[22] Standard errors calculated using the delta method are shown in parentheses.

[23] We also conducted other structural change tests, including the forecast Chow test, the breakpoint Chow test, and the 1-step recursive Chow test. In addition to the F-statistic, we also consider the Log-likelihood ratio and Wald test statistics. It should be noted that the F-statistic from the structural change test differs from the F-statistic of overall significance in a linear regression model. Almost all the results point to the rejection of the null hypothesis of constant parameters.

Figure 5. Evidence of Time-Varying NAIRU for Mexico, 2005:01-2016:12
F-Statistic



Source: Authors' calculations using data from INEGI.

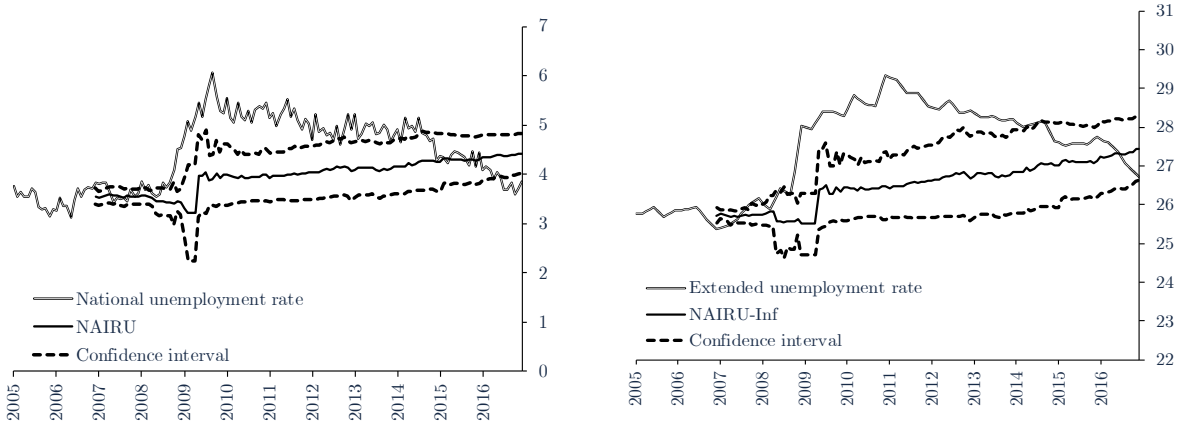
Time-Varying NAIRU

We next present in graphical form the results of the methodologies for estimating a time-varying NAIRU for both measures of unemployment. Appendix B presents detailed results for each estimated model. In Figure 6, we show the results of the NAIRU and labor market slack using both the traditional indicator of labor underutilization, unemployment (*slack-trad*), and the extended indicator (*slack-inf*), estimated with the four models described in the previous section. In general, our results show that the estimations of both NAIRU-trad and NAIRU-inf increase slightly over time, and that *slack-trad* and *slack-inf* follow a similar trajectory.

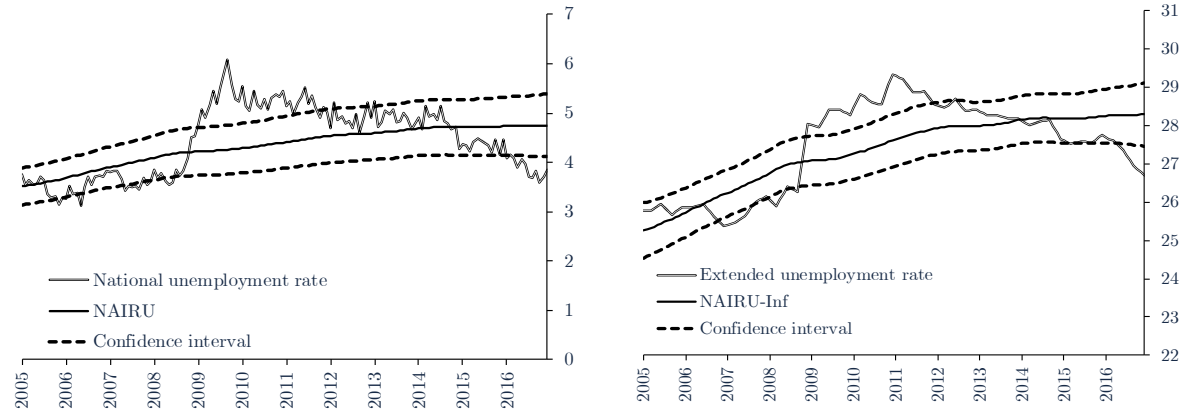
Figure 6. Estimation of NAIRU and NAIRU-inf[1/]

%, s.a.

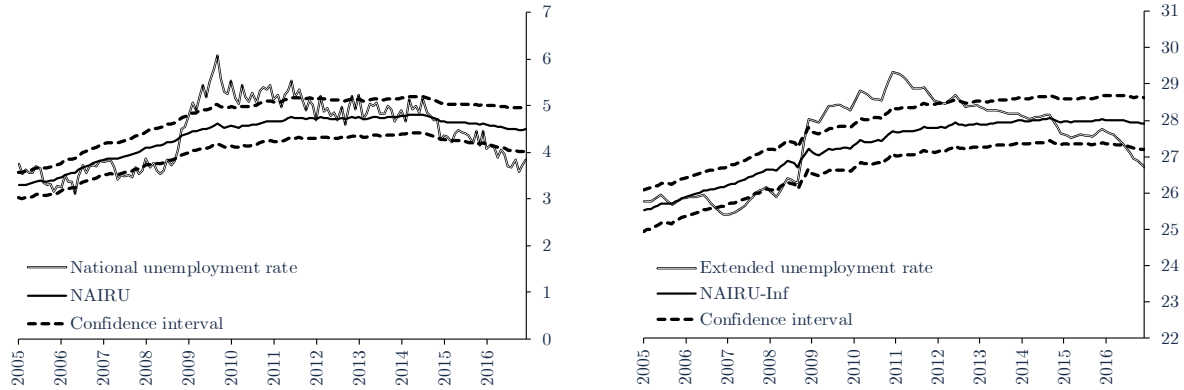
A. Recursive Estimation



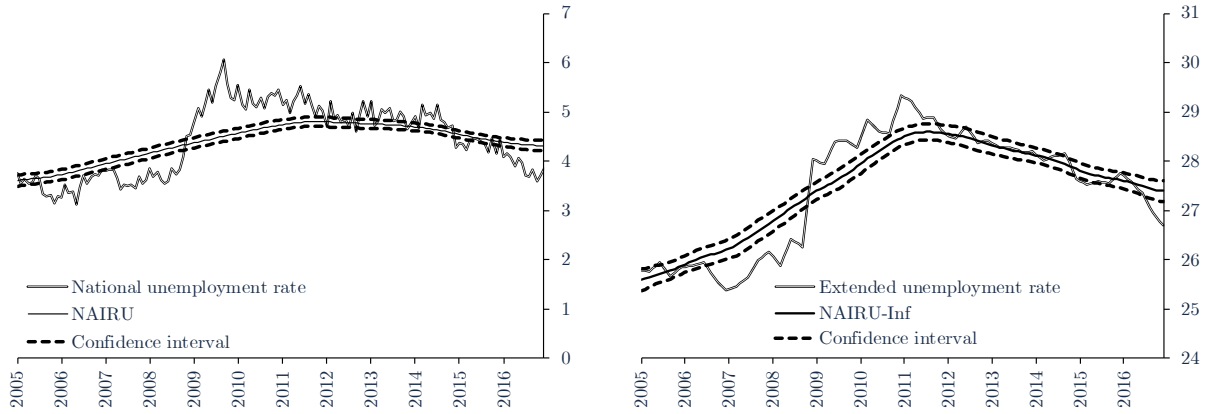
B. Random Walk



C. Random Walk and Unemployment Gap AR(2)



D. Random Walk and Unemployment Gap (Okun's Law)



Note: 90% confidence interval. Seasonally adjusted data.
Source: Authors' calculations with data from INEGI.

Now we compare the four estimations, highlighting their major differences. The recursive estimation seems to jump slightly in mid-2009 and then start a slight upward trend through the end of the sample period. These jumps are not observed in any of the state-space models because those are estimated with double smoothing using the Kalman filter. However, we can see that all the specifications coincide in a final NAIRU that is greater than at the beginning of the period. If we focus on the three state-space models, which differ only in how we model non-observable variables, we can distinguish some of the modeling differences. For example, the results of the random-walk model show an NAIRU with a clear upward trend, which slows down in the final years of the sample. These results contrast with those of the model in which the unemployment gap follows a second-order autoregressive process (see equation 4). In this specification, the unemployment gap tends to revert to its zero mean, which makes the slope of the NAIRU flatter than that of the random-walk models.

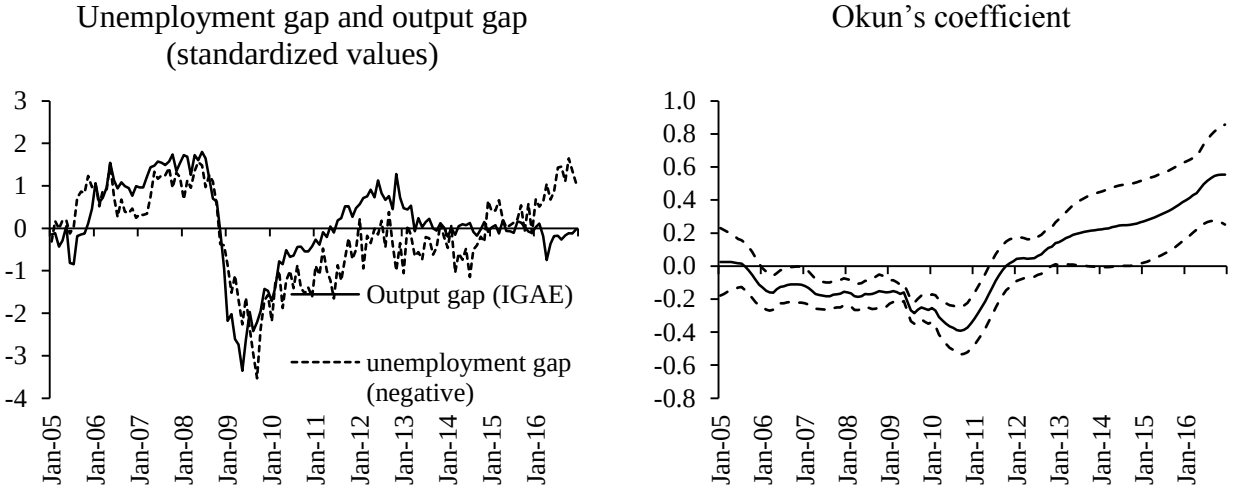
Finally, in contrast to the other three models, when we include the relationship between the unemployment gap and the output gap, as described by equations 5 and 5.1, the NAIRU drops after 2011, particularly when the extended unemployment measure is used. Figure 7 shows the output gap and the unemployment gaps for both indicators of slack in this estimation, and the trajectory over time of Okun's coefficient (φ_t). The results show that toward the end of the sample period, although the output gap suggests the existence of slack in the goods and services market, the gap in the labor market has been closed. This result can

be explained, in part, by the fact that the statistical relationship established by Okun's Law has changed over time and, in particular, has weakened in the final years of the estimation period. In fact, this relationship becomes positive although statistically significant only in the case of the model that uses the traditional unemployment rate. It is noteworthy that these estimates of the NAIRU modeling Okun's Law have smaller confidence intervals than the rest of the estimates (see Figure 6D). In this model, we are not estimating the output-gap endogenously, but with an HP filter with tail-correction, and the greater rigidity in the structure of this model could explain this result. As the results of Laubach (2001) suggest, providing more structure to the model reduces the confidence intervals.

Despite these differences, all our measures of labor slack seem to be consistent with the economic cycle, i.e., a first period characterized by tightness in the labor market, a post-crisis period with important labor slack, and a reduction in this slack beginning in 2014. In addition, the indicators derived from both indicators of slack show a gradual decrease that becomes more pronounced in the final year, when the unemployment rate is below NAIRU, a difference that is statistically significant. Figure 8 shows the average of all estimations. For the sake of simplicity, in Sections 4.3 and 5 we use these averages to analyze employment in the economic cycle with both indicators of labor slack, the traditional measure and the one including informal employment.

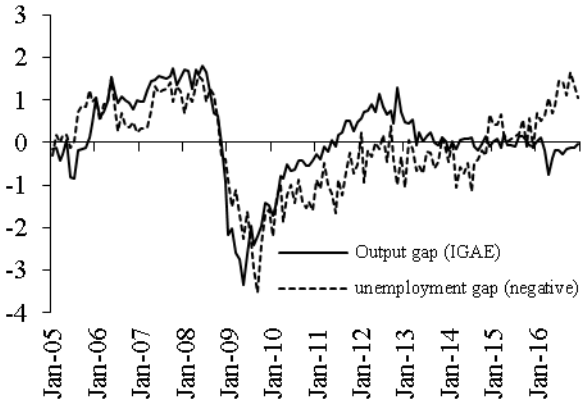
Figure 7. Output Gap, Unemployment Gap and Okun's Coefficient

A. Unemployment

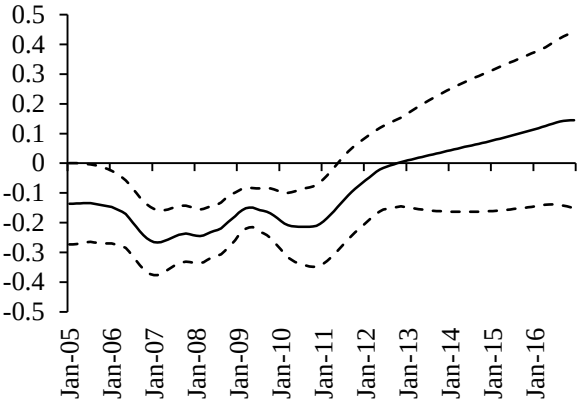


B. Unemployment extended

Unemployment extended gap and output gap (standardized values)



Okun's coefficient

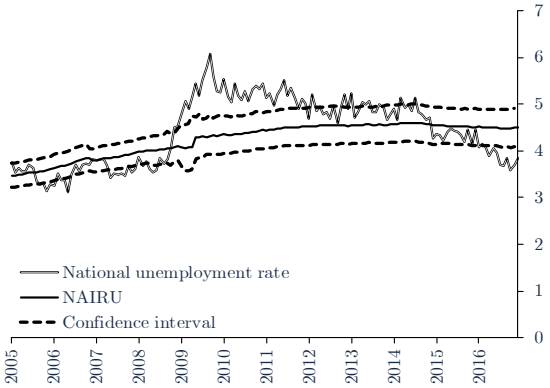


Note: 90% confidence interval. Seasonally adjusted data.
Source: Authors' calculations with data from INEGI.

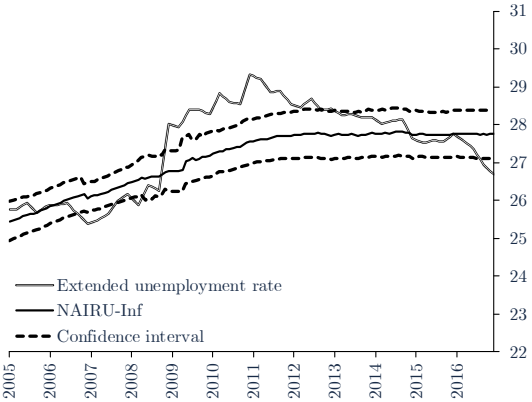
Figure 8. Average Estimations of NAIRU-trad and NAIRU-inf

%, s.a.

a. NAIRU-trad



b. NAIRU-inf



Note: The confidence interval corresponds to two average standard deviations among all estimations. Seasonally adjusted data. Source: Banco de México.

4.2 Inflation-Predicting Performance of Each Measure of the Unemployment Gap

In this section, we evaluate the forecasting accuracy of the eight unemployment gaps estimated in the previous subsection. We use the methodology developed by Hansen et al. (2011) that allows us to obtain a subset of superior models for its predictive capacity. The methodology identifies the subset of the models we use that have the best inflation forecasting ability, using the confidence interval acquired through the estimation of a

parameter to obtain the model confidence set (MCS) constructed from a predictive equivalence test and elimination rule. This procedure can be summarized as follows: (i) the set of models to be evaluated is chosen in terms of their predictive capacity; (ii) the null hypothesis is that all models have the same predictive ability, while the alternative is that at least one of the models is inferior; and (iii) if the null hypothesis is not rejected, we have a superior set of models. If the null hypothesis is rejected, then the inferior model is removed from the procedure and we return to the previous step. This procedure, unlike other predictive equivalence tests, does not require the choice of a reference model to implement the test.

Specifically, to test whether the models have equivalent predictive performance, Hansen et al. (2011) propose the following test statistic:

$$H_0: T_{R,\mathcal{M}} = \max_{i,j \in \mathcal{M}} \left| \frac{\bar{d}_{ij}}{\left(\widehat{var}(\bar{d}_{ij})\right)^{1/2}} \right| = 0,$$

where $\mathcal{M}$ is the full set of models considered in the predictive evaluation, $\bar{d}_{ij} = n^{-1} \sum_{t=1}^{n} d_{ij,t}$, $d_{ij,t} = L_{i,t} - L_{j,t}$, and $L_{i,t}$ is the loss function of model i in the period t, which in our case is a quadratic loss function. Thus, $\bar{d}_{ij}$ is the mean squared error (MSE) of model i relative to the MSE of model j. The $\widehat{var}(\bar{d}_{ij})$ statistics is calculated using bootstrap. $T_{R,\mathcal{M}}$ compares pairs of models.

The exercises are carried out to evaluate the predictive capacity of the models with different measures of unemployment gaps. This is a pseudo-out-of-sample exercise for different forecast horizons, $h = 1,2,\ldots 12$, and the average of these horizons. For this exercise, we use the subsample that covers from 2006:12 to 2016:12, with a rolling window of 60 observations.[24] The sample for the forecast evaluation considers approximately 35 percent of the full sample (2013:1-2016:12), which corresponds to 48 forecast periods.

Table 2 shows the results of this exercise. Practically all the models for all horizons show an equivalent predictive capacity. A possible exception is the Okun's law model with the informality unemployment rate that is discarded in some horizons. Thus, the results do

[24] Given that the corresponding estimates of the NAIRU from the recursive models have fewer observations, and in order to fairly examine each of the unemployment gaps calculated, all of the Phillips curve models take as given the gap of the NAIRU and are estimated by OLS in the corresponding subsample.

not indicate a clear difference in the ability of the unemployment gaps to predict the dynamics of inflation.

Table 2. RMSE and Results of the Test for Predictive Ability. MCS procedure: $T_{R,\mathcal{M}}$.

Unemployment gaps with respect to the NAIRU		Pseudo-out-sample						
Variable	Model	h=2	h=4	h=6	h=8	h=10	h=12	Average (h=1..12)
Traditional Unemployment Rate	Recursive	0.194	0.197	0.197	0.197	0.200	0.200	0.197
	RW	0.192	0.195	0.196	0.195	0.197	0.197	0.195
	RW+AR(2)	0.192	0.195	0.196	0.195	0.197	0.197	0.195
	Okun's law	0.193	0.196	0.197	0.196	0.197	0.197	0.195
Extended measure of unemployment	Recursive	0.195	0.198	0.198	0.198	0.201	0.202	0.198
	RW	0.192	0.195	0.196	0.196	0.198	0.198	0.195
	RW+AR(2)	0.194	0.197	0.197	0.197	0.200	0.200	0.197
	Okun's law	0.196	0.201	0.201	0.199	0.199	0.198	0.198

The entries shaded in gray represent the models that are elements of the MCS selected by the

4.3 Measuring Inflationary Pressures in Difficult Times

As shown in the previous analysis, there is no clear statistical difference between the two measurements of labor slack in predicting inflation. However, from the policymaker's point of view, there could be periods when it is especially important to have accurate indicators of inflationary pressures, such as when the unemployment gap is declining and approaching toward zero. Because this type of situation could trigger demand pressures, the policymaker needs the most accurate possible indicator of the unemployment gap. On the other hand, when unemployment is well above the natural unemployment rate, there is little uncertainty that there are no inflationary pressures coming from the labor market.

In this section we evaluate which labor market slack indicator is more accurate in detecting inflationary pressures when the unemployment gap is close to zero. We use the threshold regression model of the inflation equation that we have used in the previous estimates. The threshold is endogenously estimated in the model. First, as baseline regression we estimate a basic model with no thresholds:

$$\Delta\pi_t = \beta_{trad} Slack_t^{trad} + \beta_{inf} Slack_t^{inf} + \gamma(L)\Delta\pi_{t-1} + \delta(L)X_t + \varepsilon_t$$

where $Slack_t^{trad}$ and $Slack_t^{inf}$ are the average gaps of the traditional and expanded unemployment rate (with informality), respectively.

In this subsection we use the average of the four estimation models for each unemployment measurement. Table 3 shows the results. Column (1) exhibits the results of the traditional unemployment gap, column (2) of the extended unemployment gap, and column (3) shows the results with both unemployment measures in the same equation. When the coefficients of the gaps are estimated separately they are significant and their levels are not statistically different. However, when both measures are included in the inflation specification, their magnitude is reduced by almost half and their standard error more than doubled,[25] an obvious indication that the two measures of labor market slack are closely related.[26] Figure 9 illustrates the unemployment gaps from the average of the estimates, that is, the gaps calculated from the average estimates of NAIRU-trad and NAIRU-inf reported in Figure 8. The gaps are standardized (divided by their standard deviation in the sample) so that their magnitudes can be directly compared. Throughout the sample period the gaps show similar trajectories, but there are some periods with more than subtle differences.

We then estimate the threshold regression model. This model allows us to specify a regime change that occurs when a predetermined variable crosses an unknown threshold to be estimated. In particular, we focus on the simplest case of a single threshold (τ), that is, a model with two regimes described below:

$$\Delta\pi_t = \beta_{trad}^1 Slack_t^{trad} + \beta_{inf}^1 Slack_t^{inf} + \gamma(L)\Delta\pi_{t-1} + \delta(L)X_t + \varepsilon_t, \text{ if } -\infty < (Slack_t^{trad})^2 < \tau$$

$$\Delta\pi_t = \beta_{trad}^2 Slack_t^{trad} + \beta_{inf}^2 Slack_t^{inf} + \gamma(L)\Delta\pi_{t-1} + \delta(L)X_t + \varepsilon_t, \text{ if } \tau \leq (Slack_t^{trad})^2 < \infty$$

[25] This result shows a typical case of multicollinearity. In fact, the sum of the coefficients is -0.037 and the joint test with the F-statistic rejects the null hypothesis that the sum is zero.

[26] In fact, at the suggestion of an anonymous reviewer, estimations were carried out to complement this result that included both measures of gaps, with both contemporary and lagging values. Then, through the implementation of the general-to-specific method, we look for a parsimonious model in which at least one of the two gap measures is significant. For the application of the general-to-specific method, it is necessary to choose different diagnostic and specification tests to which the econometric model is submitted, in addition to choosing the corresponding level of significance to perform these tests. Our results indicate that the final model, and, therefore, the measure of unemployment that survives the procedure, depends significantly on both the diagnostic and specification tests selected and the level of significance. This method thus does not help to answer which measure is more pertinent. The estimates were made using the Autometrics algorithm, perhaps the most robust and documented procedure for the general-to-specific method in econometrics, which is available in PcGive in OxMetrics 6 software. Detailed results are available upon request from the authors.

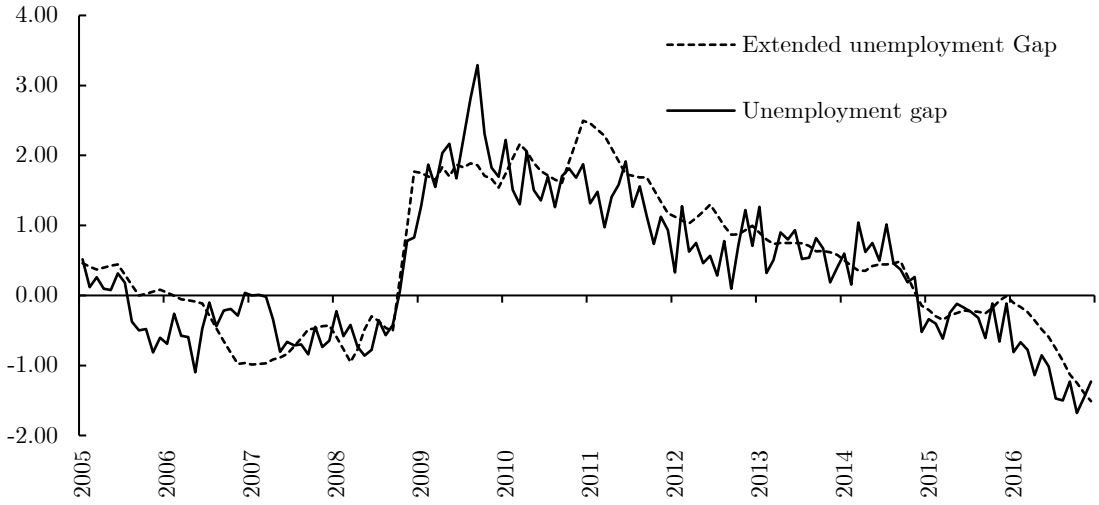
where β_{trad}^{j} and β_{inf}^{j} are the coefficients related to the gaps in each regime j, for $j = 1,2$. Note that between regimes only the coefficients related to the gaps change; those related to the control variables are not a function of the threshold.

Table 3. OLS Estimations of Inflation Equation

Slack Variables ($Slack_t$) (Average of the four estimates)		**Equation**		
		(1)	(2)	(3)
Unemployment Gap	Coeff. (β)	**-0.036**	-	**-0.018**
	Std. error	0.009	-	0.021
	t-statistic	-3.880	-	-0.866
Extended unemployment gap	Coeff. (β)	-	**-0.034**	**-0.019**
	Std. error	-	0.009	0.020
	t-statistic	-	-3.908	-0.973
	AIC	-1.51	-1.51	-1.50
	BIC	-1.35	-1.35	-1.32
	HQIC	-1.44	-1.45	-1.43
	R^2 Adj	0.48	0.48	0.48

Note: All estimates include two lags of the change in inflation and the change in the annual depreciation of the real exchange rate, plus three pulse dummies for outliers.
Source: Authors' calculations with data from INEGI.

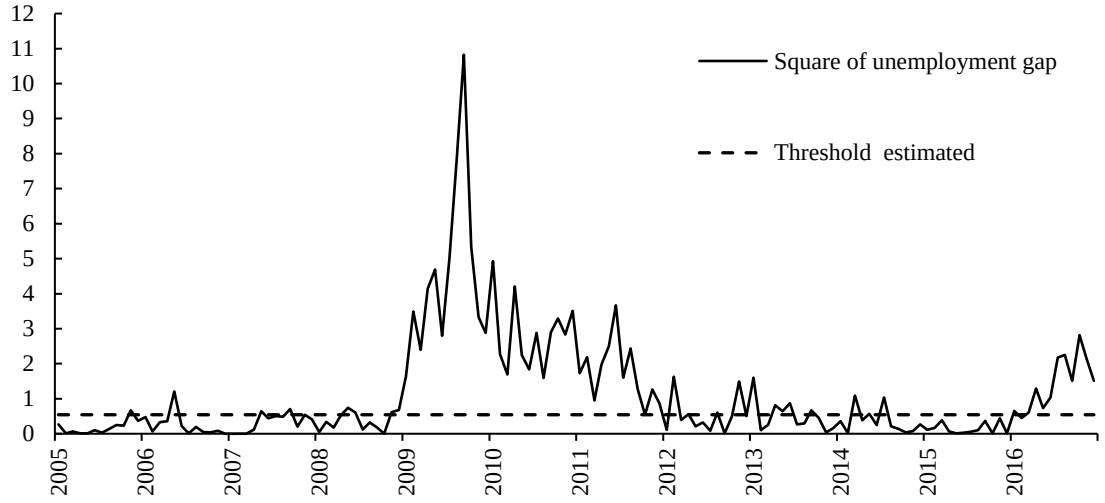
Figure 9. Average Estimations of the Unemployment Gap
(standardized values)



Source: Authors' calculations with data from INEGI.

The predetermined variable which helps us to determine the threshold is the square of the traditional unemployment rate gap, $(Slack_t^{trad})^2$, which is illustrated in Figure 10.[27] This is intuitively simple: $(Slack_t^{trad})^2$ represents how far the slack in the labor market is from zero. We analyze whether for periods in which $(Slack_t^{trad})^2$ is close to zero (values, regardless of the sign, of the traditional unemployment gap closer to zero) there is a statistically valid partition in which the information of each gap is exploited. A model with its corresponding threshold is estimated for each constraint, and we choose the best model according to the information criteria. Table 4 reports the main results; the full results and constraints can be found in Appendix C. In this methodology (Bai and Perron 2003), the threshold is determined endogenously using the information criteria from the global minimization procedure.

Figure 10. Variable of Interest to Determine the Regimes: Square of the Traditional Unemployment Gap, τ= 0.52



Source: Authors' calculations with data from INEGI.

Column (1) of Table 4 shows the result of the non-constrained classical threshold regression model, in which a regime change is permitted in the parameters β_{trad}^{j} and β_{inf}^{j}. $Slack_t^{trad}$ is only significant in regime 2 [$\hat{\tau} \leq (Slack_t^{trad})^2$], whereas $Slack_t^{inf}$ is marginal in regime 1 [$(Slack_t^{trad})^2 < \hat{\tau}$] and not statistically significant in regime 2.

[27] The results are the same if we use $(Slack_t^{inf})^2$ to choose the threshold.

Column (2) shows a restricted version of the model, in which we assume that $\beta_{trad}^{1} = 0$ and $\beta_{inf}^{2} = 0$. In this case, $Slack_t^{inf}$ has a significant impact on inflation when the variable $(Slack_t^{trad})^2$ is less than the estimated threshold, while $Slack_t^{trad}$ is significant in regime 2 when $\hat{\tau} \leq (Slack_t^{trad})^2$. In fact, according to the information criteria (AIC, BIC, and HQ) and the $\overline{R^2}$, this is the best model among those considered. The estimated threshold value ($\hat{\tau} = 0.54$) is shown in Figure 10. Finally, columns (3) and (4) present other variants of the model in which just one of the gaps is a function of the threshold, while the coefficient of the other remains constant between regimes. Column (3) assumes that only $Slack_t^{inf}$ depends on the regimes, while in column (4) $Slack_t^{trad}$ remains constant between regimes. In none of these variants are the coefficients significant. Thus, according to our results, the best partitioned specification, the one in column (2), implies that $Slack_t^{inf}$ is relatively better suited to explain inflation than $Slack_t^{trad}$ in periods where it is more difficult to know if there is slack or not.

These results might be explained by a period with a high rate of job creation where *slack-trad* reflects a tight labor market. However, if this period also showed a high rate of low-quality informal labor growth, *slack-inf* might show a different history, one with a higher level of slack, given that it accounts for this low-quality employment. In such a case, *slack-inf* could reflect inflationary pressures more accurately.[28] The specification of the inflation equation can be decomposed into terms for the determinants of slack, inertia, and supply shocks. In Figure 11 we compare the contribution to inflation of the slack components of models (1) and (2) in Table 3 with that of the preferred model resulting from threshold regression analysis in Table 4. We see that around 2007 the $Slack_t^{trad}$ measure does not indicate inflationary pressures, while the $Slack_t^{inf}$ measure does. Towards the end of the sample period, beginning in 2016, we see the opposite: the $Slack_t^{trad}$ measure shows inflationary pressures, while $Slack_t^{inf}$ shows no upward pressures until the end of the year. In the following section we analyze these observations in more detail.

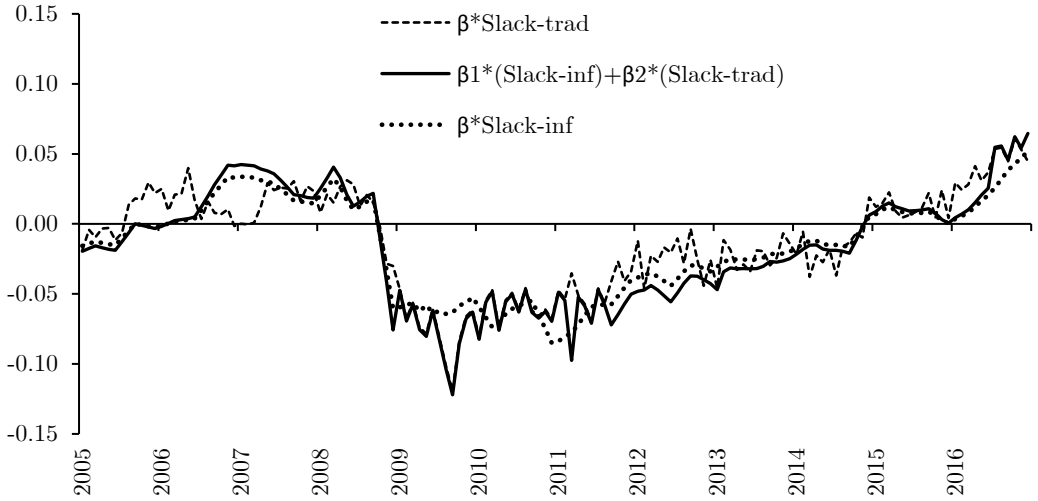
[28] In an emerging economy like Mexico, people with few resources may be forced to work because they do not have the option to remain unemployed or out of the labor force. This could push the unemployment rate to low levels with no significant pressure on wages or inflation.

Table 4. Threshold Regression Results

			Constraints			
			(1)	(2)	(3)	(4)
Regime			**None**	$\beta_{trad}^{1}=0;$ $\beta_{inf}^{2}=0$	$\beta_{trad}^{1}=\beta_{trad}^{2}$	$\beta_{inf}^{1}=\beta_{inf}^{2}$
Unemployment Gap	-	**Coeff.**	-	-	-0.027	-
		t-stat.	-	-	-1.196	-
	[1]	**Coeff.**	-0.003	-	-	0.130
		t-stat.	-0.103	-	-	1.261
	[2]	**Coeff.**	-0.101	-0.037	-	-0.013
		t-stat.	-2.027	-3.764	-	-0.592
Extended unemployment gap	-	**Coeff.**	-	-	-	-0.026
		t-stat.	-	-	-	-1.312
	[1]	**Coeff.**	-0.034	-0.043	-0.021	-
		t-stat.	-1.602	-2.057	-1.053	-
	[2]	**Coeff.**	0.072	-	-0.001	-
		t-stat.	1.347	-	-0.047	-
		AIC	-1.501	-1.518	-1.498	-1.506
		BIC	-1.274	-1.332	-1.292	-1.300
		HQIC	-1.409	-1.442	-1.414	-1.422
		$\overline{R^2}$	0.485	0.487	0.480	0.484
		$\hat{\tau}$	2.254	0.542	2.173	0.124

Note: All estimates include two lags of the change in inflation and the change in the annual depreciation of the real exchange rate, plus three pulse dummies for outliers.
Source: Authors' calculations with data from INEGI.

Figure 11. Comparison of the Contribution to Inflation of the Unemployment Gap Measures

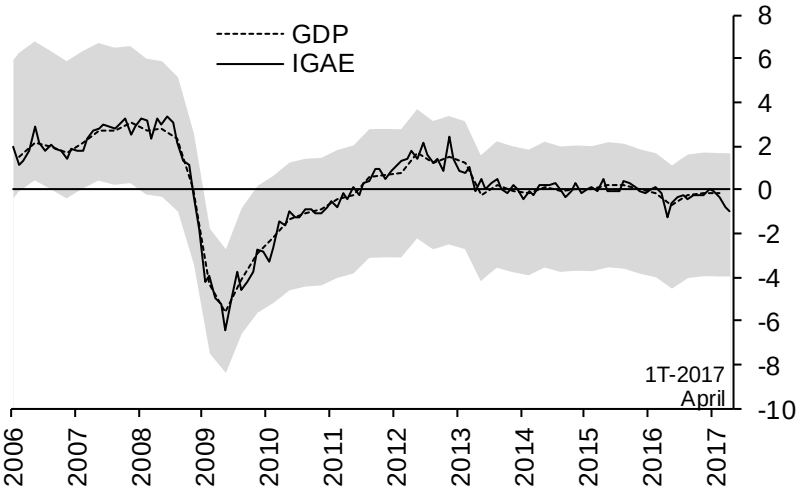


Source: Authors' calculations with data from INEGI.

5. The Mexican Labor Market over the Economic Cycle

In this section, we compare the trajectories of *slack-trad* and *slack-inf* with the main employment-related economic variables to assess and compare their effectiveness in anticipating demand-driven inflationary pressures. In order to facilitate the analysis, we divide the time span into three periods that take into account the economic cycle in Mexico (Figure 12). The first is the pre-crisis period, from 2005Q1 to 2008Q4, which was characterized by inflationary pressures: the GDP gap was positive with the lower bound of the confidence interval close to zero. The second period spans 2009Q1 and 2014Q2, the post-crisis economic slack. The third, from 2014Q3 to 2016Q4, starts with the output gap near zero, and remains close to zero until the end of the study period.

Figure 12. Output Gap
% of potential output; s.a.



Note: Calculated with seasonally adjusted data. Estimated using the Hodrick-Prescott (HP) filter with tail correction method; see Banco de México (2009), "Inflation Report April-June 2009." p. 69. The shaded area is the 95% confidence interval of the output gap, calculated with an unobserved components method.
Source: Calculated by Banco de México with data from INEGI.

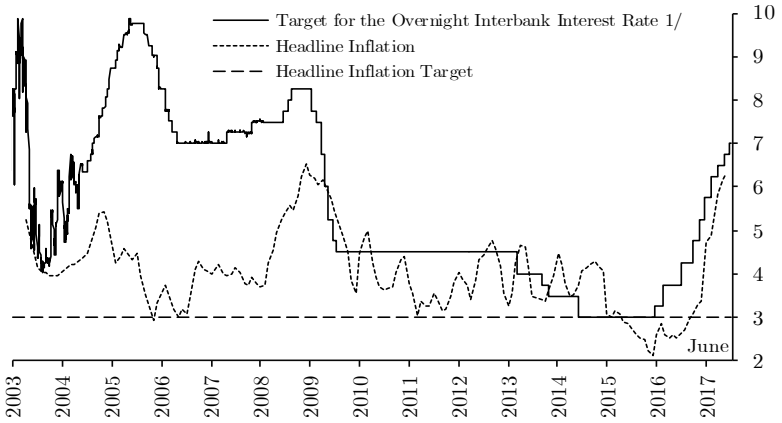
We illustrate the main features of the Mexican labor market in each period by describing inflation and monetary policy rates in these periods, and comparing the measures of labor slack with relevant variables such as wages, labor costs, and the GDP gap. Since 2005, there have been two periods of accelerated inflation (2008 and 2017) where Banco de México responded by increasing the reference rate (Figure 13). Another event of interest for our analysis is the deflationary period after the worldwide crisis of 2009.

Period I (2005Q1-2008Q4)

During this period, inflation began to pick up (Figure 13). The Mexican economy showed some tightness: the GDP gap was positive and statistically significant (Figure 12) and wages showed important gains (Figure 14d). In addition, unit labor costs in both the manufacturing and service sectors were particularly high throughout this period (Figure 14e and 14f).[29] However, increases in international food and energy prices also contributed to local inflation (Banco de México 2008). *Slack-inf* showed greater tightness than *slack-trad*, particularly in 2008 (Figure 8), which is consistent with the inflationary pressures suggested by other sources of information in the economy. This may indicate that through this period, *slack-inf* was a better indicator of the Mexican labor market than *slack-trad* to detect inflationary pressures.

Figure 13. Monetary Policy Rate and Consumer Price Index

% and annual % change



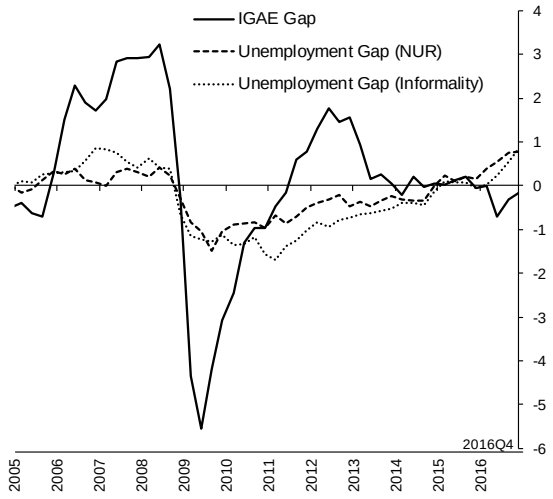
Note: Data before January 20, 2008 refers to the observed Overnight Interbank Interest Rate.
Source: INEGI and Banco de México.

[29] Labor cost information is available from 2007.

Figure 14. The Context of the Mexican Labor Market

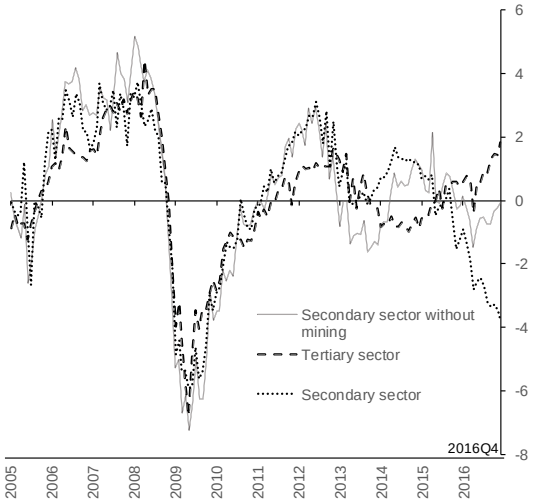
A. **IGAE Gap and the Negative of the Unemployment Gap [1/]**

%



B. IGAE Gap [2/]

%, s.a.



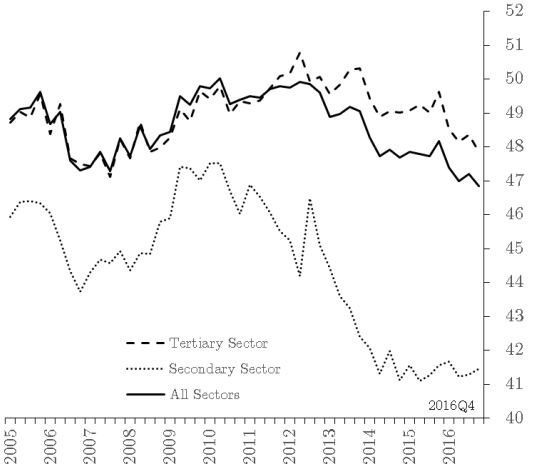
1/ The IGAE gap is shown as a percentage of the potential output. The negative of the unemployment gap refers to the average estimation for the NAIRU less the observed rate of unemployment.

2/ We present the IGAE gap, measured as a percentage of potential output, by sector.

Source: Banco de Mexico estimates with data from INEGI.

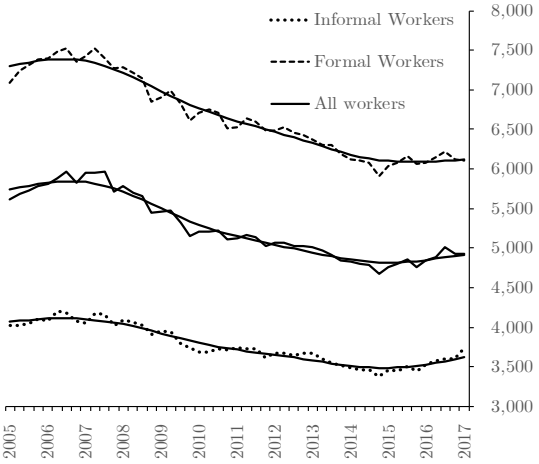
C. Informality rate by sector [3/]

%



D. Average monthly wages of the urban employed population[4/]

Real, MXN December 2010

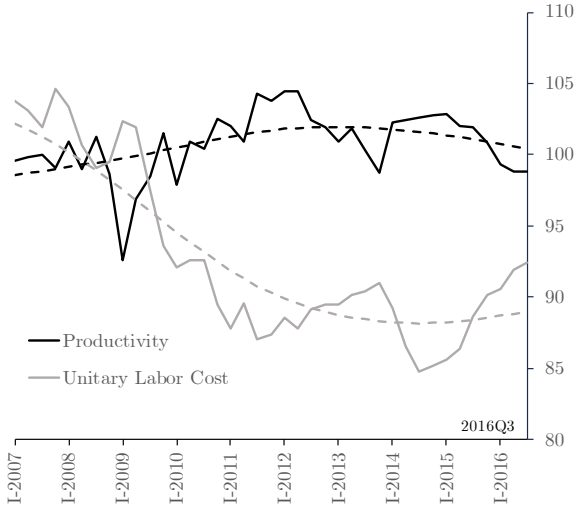


3/ Quarterly series. The graph shows the informality rate for the employed population aged 15 or older in urban areas with a population greater than 15,000.

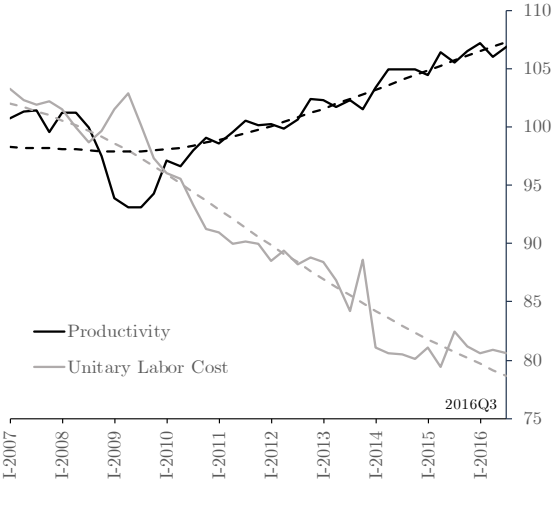
4/ Quarterly data with and without Hodrick-Prescott filter (smooth line, λ=200). Employed population aged 15 or older in urban areas with a population greater than 15,000. We eliminate wages lower than the 1st and greater than the 99th percentile. When the interviewee did not answer the question about wages with an actual figure, but answered in terms of the minimum wage equivalent, we calculated the monthly wage equivalent.

Source: Authors' estimations with data from ENOE, INEGI.

E. Labor Productivity and Unit Labor Cost [5/]
Manufactures
2008=100, s.a.

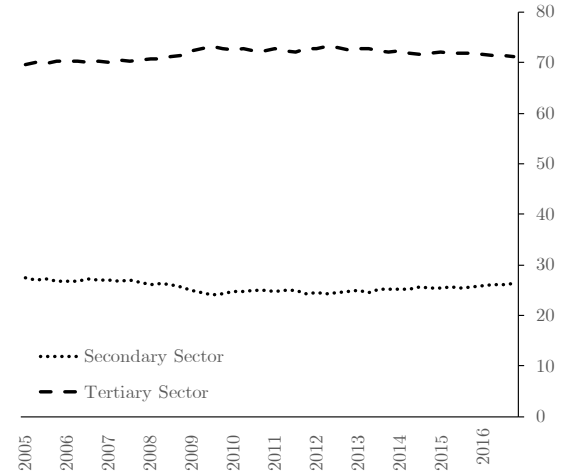


F. Labor Productivity and Unit Labor Cost [5/]
Services
2008=100, s.a.

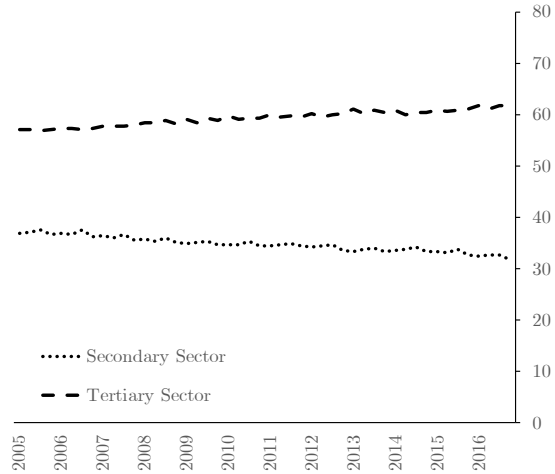


5/ Productivity based on hours worked. Seasonally adjusted series. Trends and seasonal adjustment estimated by Banco de México.
Source: Banco de México using SCNM, ENOE, and INEGI data.

G. Urban Employment by Sector [6/]
% of total employment



H. GDP by Sector [7/]
% of total GDP



6/ Quarterly data. Employed population aged 15 years and older in urban areas with a population greater than 15,000.
7/ Using original quarterly series on GDP at 2008 market prices.
Source: Authors' estimations with INEGI data: ENOE and Economic Information Bank.

Period II (2009Q1-2014Q2)

During Period II, Mexican economic activity decelerated significantly and went through an important recession as a consequence of the international financial crisis. Wages and labor costs plunged deeply (Figures 14d, 14e, and 14f) and are still today far from their pre-crisis levels. Banco de México quickly loosened monetary conditions by decreasing the policy interest rate from 8.25 to 4.5 percent (Figure 13). In this period, both measures of slack showed an important increase. However, unlike during Period I, *slack-inf* suggested a greater degree of slack than *slack-trad*. Again, it appears that *slack-inf* better reflected the reality of the Mexican labor market.

Period III (2014Q3-2016Q4)

Five years after the beginning of the crisis, the slack in the labor market, as measured both by NAIRU-trad and by NAIRU-inf, started declining and continued with this trend until the end of the period (Figure 8). At first glance, the latter would suggest the presence of demand-pull inflationary pressures. However, the fact that wages barely grew during this period (Figure 14d) and the output gap was still negative suggest no inflationary pressures coming from aggregate demand (Figure 14a).

In order to understand this conundrum, we analyze this part of the cycle by separating economic activity in the service and industrial sectors. The slack in the IGAE during Period III is fully accounted for by the negative output gap in the secondary sector (with and without mining) since the end of 2015. In contrast, the tertiary sector (services) output gap closed and crossed into positive territory toward the end of the period (Figure 14b). The tertiary sector is also more labor intensive and has a higher level of informal employment than the secondary sector (Figures 14c, 14g, and 14h). Finally, the informal sector has considerably lower wages than the formal sector (Figure 14d). These three factors provide a plausible explanation of why labor market conditions during this period did not translate into demand-pull inflationary pressures: the service sector, with the highest degree of informal employment and significantly lower wages, was the only productive sector that tightened. Thus, the labor market in Mexico seems to have allowed an adjustment in which workers without formal employment could be absorbed by the service sector into lower-paying jobs, without implying significant inflationary pressures from aggregate demand. During this period, both

measures of slack start to suggest tighter labor market conditions. However, once again, *slack–inf* shows a subtle difference from *slack-trad*. Figure 8 shows that *slack-inf* suggests less tightness in the labor market than *slack-trad*, which is consistent with an absence of wage pressures and lower labor costs, both in the service and industrial sectors.

Finally, it is important to note that Banco de México started tightening monetary policy conditions in December 2015 (Figure 13). However, it was emphatic that such pre-emptive policy rate increases were driven by other exogenous shocks at the time (most importantly, exchange rate depreciation) and not by demand-pull inflationary pressures (see Banco de México 2016).

6. Final Remarks

In this study, we estimate two measures of labor market slack for the Mexican economy using traditional NAIRU estimation frameworks. In particular, using traditional methodologies to estimate the non-accelerating inflation rate of unemployment (NAIRU), we compute two measures of NAIRU, a traditional NAIRU based on the unemployment rate and an alternative measure (NAIRU-inf), that not only considers the unemployment rate, but also informal wage earners. Our results show no drastic differences in the labor market slack between both indicators over the economic cycle. However, we find subtle differences in some periods. For example, during adverse shocks, differences become significant, since the labor market in Mexico seems to allow an adjustment in which the informal sector can absorb workers without formal employment in lower-paying jobs. During the period of sustained economic growth, informal workers might move to the formal sector, suggesting that the unemployment rate in developing countries with a significant informal labor force could show a relatively lower level and less variation than in advanced economies, where informal sectors tend to be small. With these developments in mind, we propose a complementary analysis of labor market slack using the unemployment rate, with additional information that takes into account the high informality rates that are important in developing economies.

Our results also show that both measures of the NAIRU increased slightly over our study period, and the labor market slack measured with both indicators of labor underutilization showed a similar cyclical pattern. However, consistent with an endogenous threshold model, the slack in the labor market estimated with the indicator including

informality seems to predict inflationary pressures more accurately when the unemployment gap is close to zero. For example, *slack-inf* better anticipated the inflationary pressures observed in 2007–2008. In addition, during 2016, this alternative measure showed a greater degree of slack than the traditional one, which is consistent with the absence of considerable wage pressures observed during this period.

We do not suggest replacing the use of the traditional labor-market slack indicator (*slack-trad*) with the indicator that includes informal employment (*slack-inf*) for analytical purposes, but we do propose using it as an additional measure to complement the analysis. First, economic situations may be exposed to diverse factors at different times: a particular situation, for example, could lead to an overweighting of a specific slack indicator. Second, *slack-trad* is calculated with monthly data, while *slack-inf* is calculated quarterly. Thus, *slack-trad* offers policymakers a timelier indicator of labor market slack than *slack-inf*, since monetary policy decisions are made approximately every month and a half.

Finally, we consider that the subtle differences between the indicators identified in this paper may be useful for policymakers evaluating labor conditions at a particular moment in time, particularly when unemployment gap is close to zero. We conclude that the inclusion of informal employment can complement the analysis of the Mexican economic cycle and can be a useful tool for monetary policy formulation not only in Mexico, but also in other developing countries.

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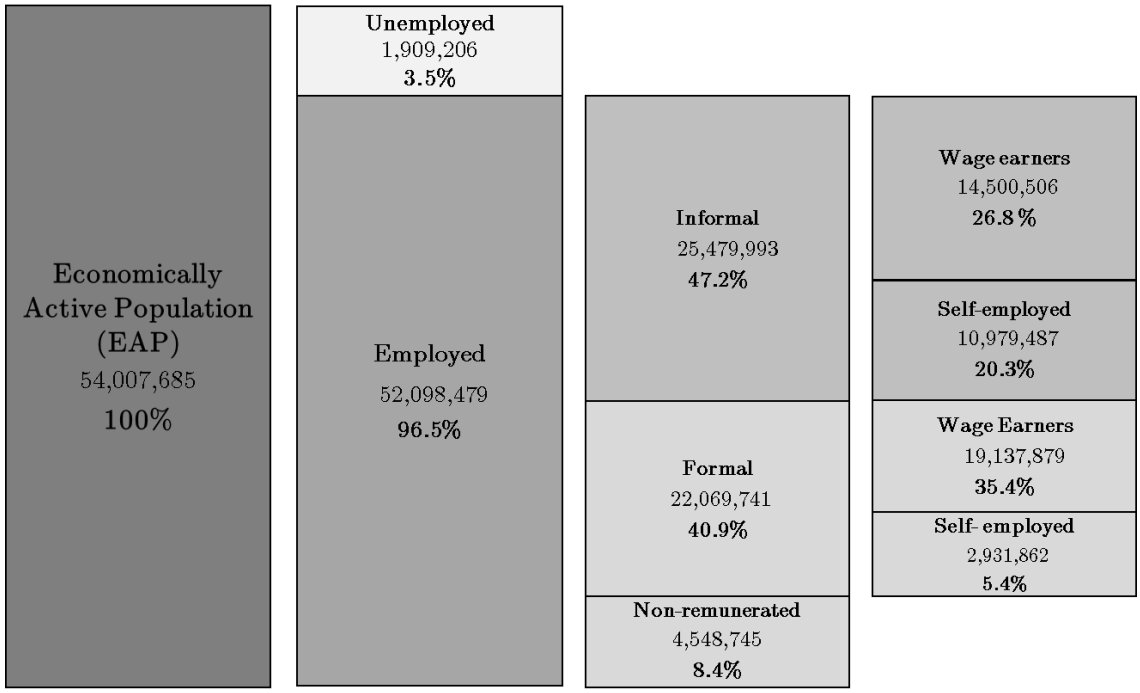
Appendix A

Labor Market Composition, ENOE (Q4-2016)

Percentage of the Total Economically Active Population (EAP), Aged 15 and Older.



Note: Survey weights were used to obtain the population-representative figures.
Source: Authors' calculations with data from INEGI.

Appendix B: Estimation Results

As we discuss in the text, the models described in equations (3) to (5) have a state-space representation and are estimated by maximum likelihood and the Kalman filter. For this type of econometric estimate there are some details that should be clarified. First, the NAIRU is modeled in all cases as a random walk. However, in the estimation of this type of model there is the so-called "pile-up problem" (see, for example, Stock 1994). This problem consists of difficulty in estimating the variance of the error term of the NAIRU, σ_e^2, because the estimator has point mass at zero. This parameter, σ_e , captures the smoothness of the NAIRU: $\sigma_e = 0$ implies a constant NAIRU, whereas high values imply NAIRU values that make no sense for a variable meant to measure the low frequency component.

The choice of the value of σ_e , as mentioned by Gordon (1997), is similar to choosing the value of the smoothing parameter of the Hodrick-Prescott filter. To obtain a value of this parameter we test a grid in a range of feasible values, using as reference values other measurements of the low frequency component of the unemployment series, such as the Hodrick-Prescott filter (with a lambda of 14400 usually used for monthly series), and moving averages between 4 and 8 years. The choice is made taking into account both the economic importance of the result, that is, whether the effect of unemployment on the Phillips curve is statistically different from zero (at a significance level of at least 0.10), as well as the ability of the model to forecast inflation (evaluated in a dynamic simulation exercise within the sample). Second, as Hamilton (1986) shows, the estimation of the variance of the state variables or non-observables in this kind of model has two sources of uncertainty: (i) filter uncertainty, the uncertainty intrinsic to the use of the Kalman filter in itself; and (ii) parameter uncertainty, which reflects the fact that the parameters of the model are unknown and have to be estimated. Thus, for the calculation of the standard errors of the state variables we follow the algorithm proposed by Hamilton (1986) through the use of Monte Carlo methods.

Table B1. Summary of NAIRU and NAIRU-Inf Estimations, 2005M01-2016M12

NAIRU current estimation

Dependent variable: $\Delta\pi_{core,t}$	(1) NAIRU	(2) NAIRU-Inf
Recursive estimation	4.43***	27.46***
	(0.239)	(0.498)
Random Walk	4.75***	28.29***
	(0.304)	(0.483)
Random Walk & Unemployment Gap	4.50***	27.90***
	(0.248)	(0.368)
Random Walk & Unemployment Gap (Okun s Law)	4.32***	27.40***
	(0.067)	(0.138)
N	144	144

Note: Standard errors are reported in parentheses for the recursive estimation and root mean squared errors are reported in parentheses in the rest of the estimations. We include dummy variables for 2010M1, the period 2013M1-2014M1, and 2015M1.
*, **, *** indicate significance at the 90%, 95%, and 99% level, respectively.

Table B2. NAIRU Recursive Estimation, 2005M01-2016M12

Final period of the recursive estimation

Dependent variable: $\Delta\pi_{core,t}$	(1) Traditional Unemployment Rate	(2) Extended Unemployment Rate
u_t	-0.04**	-0.02**
	(0.014)	(0.008)
$\Delta\pi_{core,t-1}$	0.21**	0.22***
	(0.066)	(0.066)
$\Delta\pi_{core,t-2}$	0.01	0.02
	(0.066)	(0.066)
ΔReal depreciation$_{t-1}$	-0.01*	-0.01*
	(0.003)	(0.003)
ΔReal depreciation$_{t-2}$	-0.01**	-0.01**
	(0.003)	(0.003)
$\_cons$	0.18**	0.53**
	(0.062)	(0.226)
NAIRU	4.43***	27.46***
	(0.239)	(0.498)
N	144	144
R-squared	0.48	0.47
Adjusted R-squared	0.45	0.44
S.E. of regression	0.11	0.11
Log likelihood	113.58	112.11

Note: Standard errors are reported in parentheses. We include dummy variables for 2010M1, the period 2013M1-2014M1, and 2015M1.
*, **, *** indicate significance at the 90%, 95%, and 99% level, respectively.

Table B3. NAIRU Random Walk, 2005M01-2016M12

Dependent variable: $\Delta\pi_{core,t}$	(1) Traditional Unemployment Rate	(2) Extended Unemployment Rate
$u_t - \bar{u}$	-0.06**	-0.05***
	(0.021)	(0.012)
$\Delta\pi_{core,t-1}$	0.18**	0.19***
	(0.058)	(0.056)
$\Delta\pi_{core,t-2}$	0.00	-0.01
	(0.078)	(0.073)
ΔReal depreciation$_{t-1}$	-0.01**	-0.01**
	(0.003)	(0.002)
ΔReal depreciation$_{t-2}$	-0.01**	-0.01**
	(0.003)	(0.003)
NAIRU	4.75***	28.29***
Root MSE	(0.304)	(0.483)
N	144	144
Log likelihood	112.03	105.85

Note: Standard errors are reported in parentheses. We include dummy variables for 2010M1, the period 2013M1-2014M1, and 2015M1.
*, **, *** indicate significance at the 90%, 95%, and 99% level, respectively.

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Table B4. NAIRU Random Walk & AR(2) Unemployment Gap, 2005M01-2016M12

Dependent variable: $\Delta\pi_{core,t}$	(1) Traditional Unemployment Rate	(2) Extended Unemployment Rate
$u_t - \bar{u}$	-0.08**	-0.05***
	(0.030)	(0.014)
$\Delta\pi_{core,t-1}$	0.17**	0.19***
	(0.062)	(0.055)
$\Delta\pi_{core,t-2}$	-0.01	0.00
	(0.086)	(0.073)
ΔReal depreciation$_{t-1}$	-0.01*	-0.01**
	(0.003)	(0.003)
ΔReal depreciation$_{t-2}$	-0.01**	-0.01**
	(0.003)	(0.003)
NAIRU	4.50***	27.90***
Root MSE	(0.248)	(0.368)
$u_{t-1} - \bar{u}$	0.60***	1.66***
	(0.090)	(0.044)
$u_{t-2} - \bar{u}$	0.35***	-0.67***
	(0.092)	(0.046)
Unemployment gap	-0.66**	-1.24***
Root MSE	(0.294)	(0.372)
N	144	144
Log likelihood	138.60	225.32

Note: Standard errors are reported in parentheses. We include dummy variables for 2010M1, the period 2013M1-2014M1, and 2015M1.
*, **, *** indicate significance at the 90%, 95%, and 99% level, respectively.

Table B5. NAIRU Random Walk & Unemployment Gap (Okun's Law), 2005M01-2016M12

Dependent variable: $\Delta\pi_{core,t}$	(1) Traditional Unemployment Rate	(2) Extended Unemployment Rate
$u_t - \bar{u}$	-0.09***	-0.10***
	(0.015)	(0.006)
$\Delta\pi_{core,t-1}$	0.17**	0.18***
	(0.059)	(0.053)
$\Delta\pi_{core,t-2}$	-0.01	-0.01
	(0.077)	(0.069)
ΔReal depreciation$_{t-1}$	-0.01**	-0.01**
	(0.002)	(0.002)
ΔReal depreciation$_{t-2}$	-0.01**	-0.01***
	(0.003)	(0.002)
NAIRU	4.32***	27.40***
Root MSE	(0.067)	(0.138)
Unemployment gap	-0.02	-0.01
Root MSE	(0.259)	(0.425)
Okun	0.55**	0.14
Root MSE	(0.189)	(0.182)
N	144	144
Log likelihood	-17.37	-296.69

Note: Standard errors are reported in parentheses. We include dummy variables for 2010M1, the period 2013M1-2014M1, and 2015M1.
*, **, *** indicate significance at the 90%, 95%, and 99% level, respectively.

Appendix C. Threshold Regression Results

Table C. Threshold Regression Results

Regime			Constrains								
			None	$\beta_{trad}^1 = 0; \beta_{inf}^2 = 0$	$\beta_{trad}^1 = \beta_{trad}^2$	$\beta_{inf}^1 = \beta_{inf}^2$	$\beta_{trad}^1 = \beta_{trad}^2; \beta_{inf}^2 = 0$	$\beta_{inf}^1 = \beta_{inf}^2; \beta_{trad}^1 = 0$	$\beta_{trad}^1 = \beta_{trad}^2; \beta_{inf}^1 = 0$	$\beta_{trad}^2 = 0; \beta_{inf}^1 = 0$	$\beta_{inf}^1 = \beta_{inf}^2; \beta_{trad}^2 = 0$
	-	**Coeff.**	-	-	-0.027	-	-0.028	-	-0.012	-	-
		t-stat.	-	-	-1.196	-	-2.547	-	-0.541	-	-
Unemployment gap	[1]	**Coeff.**	-0.003	-	-	0.130	-	-	-	0.074	0.153
		t-stat.	-0.103	-	-	1.261	-	-	-	0.784	1.602
	[2]	**Coeff.**	-0.101	**-0.037**	-	-0.013	-	-0.025	-	-	-
		t-stat.	-2.027	**-3.764**	-	-0.592	-	-1.313	-	-	-
	-	**Coeff.**	-	-	-	-0.026	-	-0.014	-	-	-0.037
		t-stat.	-	-	-	-1.312	-	-0.797	-	-	-4.175
Extended unemployment gap	[1]	**Coeff.**	-0.034	**-0.043**	-0.021	-	-0.020	-	-	-	-
		t-stat.	-1.602	**-2.057**	-1.053	-	-1.423	-	-	-	-
	[2]	**Coeff.**	0.072	-	-0.001	-	-	-	-0.026	-0.036	-
		t-stat.	1.347	-	-0.047	-	-	-	-1.155	-4.026	-
		AIC	-1.501	**-1.518**	-1.498	-1.506	-1.512	-1.511	-1.507	-1.509	-1.517
		BIC	-1.274	**-1.332**	-1.292	-1.300	-1.326	-1.326	-1.321	-1.324	-1.332
		HQIC	-1.409	**-1.442**	-1.414	-1.422	-1.436	-1.436	-1.431	-1.434	-1.442
		$\overline{R^2}$	0.485	**0.487**	0.480	0.484	0.484	0.483	0.481	0.482	0.487
		$\hat{\tau}$	2.254	**0.542**	2.173	0.124	2.173	0.269	0.177	0.124	0.124

Note: All estimates include two lags of the change in inflation and the change in the annual depreciation of the real exchange rate, plus three pulse dummies for outliers.