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Seen and Unseen: NAIRU, informal labor market and talking points for monetary policy

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Seen and Unseen: NAIRU, informal labor market and talking points for monetary policy †

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Abstract:

This paper examines how labor-market informality alters the estimation and policy interpretation of the Non-Accelerating Inflation Rate of Unemployment (NAIRU) in an emerging-market context. Using quarterly Peruvian data from 2007 to 2024, we estimate a time-varying parameter unobserved-components model with stochastic volatility following Chan, Koop, and Potter (2016). Bayesian MCMC techniques jointly recover trend inflation, the NAIRU, and the Phillips-curve slope under two alternative measures of slack: the standard unemployment rate and an extended measure incorporating informal workers. The conventional specification implies a rising NAIRU and persistent inflationary pressure. In contrast, the informality-adjusted NAIRU declines, and the Phillips-curve slope flattens, indicating that informal employment absorbs slack and dampens inflationary dynamics. These results suggest that ignoring informality overstates inflation risks and the power of monetary policy, with significant implications for inflation-targeting frameworks in economies with large informal sectors.

JEL Classification: E24, E31, E32, E52, O17, C11, C32

Key words: NAIRU, Informal employment, Phillips curve, Monetary policy, Inflation dynamics, Emerging markets, State-space model, Bayesian estimation

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1. INTRODUCTION

Policymakers whether in developed countries or emerging economies face different types of challenges in identifying the factors and events that lead to unfavorable outcomes, such as high inflation or a prolonged recession. When uncertainty becomes an important variable to consider, the non-accelerating inflation rate of unemployment (NAIRU) seems to be one of those critical and unobservable measures that underpins the long-term relationship between inflation and the level of unemployment (in line with the Phillips curve literature). In that regard, labor markets tend to differ between countries and regions. While aggregate unemployment is adequate for a clear assessment of the economy in terms of NAIRU, it is not sufficient when a significant number of informal workers are present in the labor force (which is the case for most emerging economies). Ignoring the informal labor market may mislead the optimal path for monetary policy.

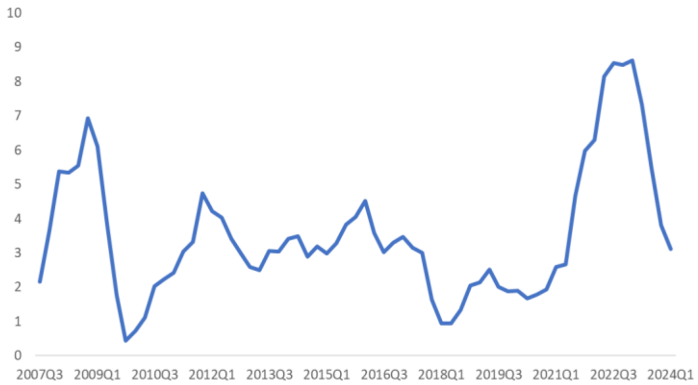
In line with an optimal monetary policy in a developing country, central banks need to pay attention to informal labor markets because they are large enough to absorb most of the labor force and, by doing so, influence the transmission mechanisms available for policymakers. Rather than just "employed" and "unemployed," there is a third important category: the underemployed (those employed in the informal labor market). Alberola and Urrutia (2020) and Castillo and Montoro (2012) argue that the informal labor market functions as a buffer for the monetary policy: when a monetary policy shock impacts the economy, part of the affected labor force goes into informality rather than directly becoming unemployed. Since this market has lower productivity, its large presence diminishes the intended final effect on inflation and output, which in turn requires the central bank to exert greater effort to meet its targets. Moreover, the monetary authority requires a clear understanding of this market in an environment shaped by central bank reputation, accountability for inflation targeting, and the impact of different types of shocks that hit the economy in order to conduct a reliable monetary policy.

It is also worth considering the COVID-19 pandemic as a unique case in which the labor market was directly hit. As shown in Figure 1, inflation in Peru was around 2 percent between 2020 and 2021, while the unemployment rate peaked around 10 percent at the same time. If the unemployment data are extended with informal workers (as in Aguilar-Argaez et al., 2022), a different pattern emerges. The transition from formal to informal labor market was a direct effect of regulations that limited the number of people in the same place and the need for those unemployed to generate income in order to cope with pandemic-related expenditures. In this context, the informal market absorbed a significant portion of the labor force when the COVID-19 pandemic struck the economy, buffering the real effects of the shock, and limiting the final effect on prices. This fact is in line with the more general case reported in Armas et al. (2023) in which workers who cannot find jobs in the formal sector accept jobs in the informal sector. Thus, as we include informal wage earners in our measure of the unemployment rate, we may expect that, whenever there is an opportunity to join the formal sector, an informal worker will take it.

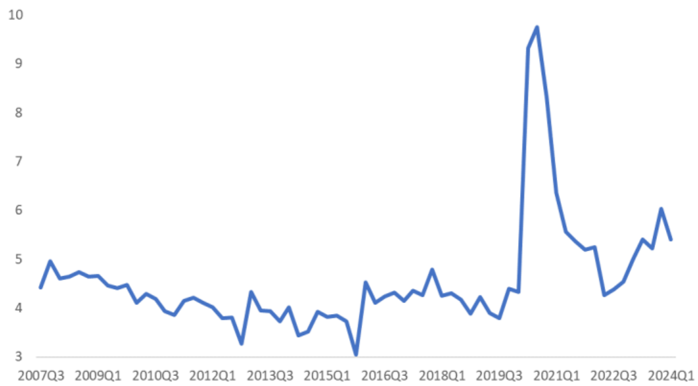
Different strategies have been applied for estimating the NAIRU ranging from time-series methods to steady-state representations. We closely follow Chan et al. (2016) and Stella and Stock (2016) in terms of modeling, i.e., we estimate a bivariate model with latent states such as trend unemployment (interpreted as the NAIRU) and trend inflation, which are time-varying. The modeling strategy is based on a Phillips curve that also has a time-varying slope. The main distinction of Chan et al. (2016) from previous steady-state representations is the inclusion of bounds for the model so that the NAIRU lies within a framework in which the central bank keeps trend inflation within a range. This allows us to better distinguish between cyclical and trend movements in unemployment and inflation.

FIGURE 1 – INFLATION AND UNEMPLOYMENT MEASURES

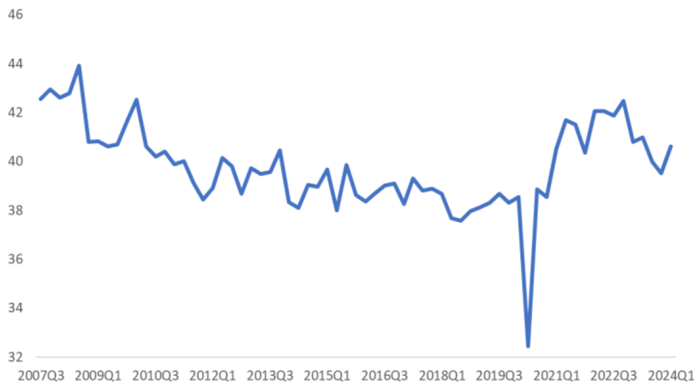
INFLATION



UNEMPLOYMENT RATE



EXTENDED UNEMPLOYMENT RATE



Notes: Inflation is quarterly percentage change of the Consumer Price Index. The unemployment rate measures the people who are not employed, while the extended unemployment rate includes those not employed in the formal sector or as dependent workers in the informal sector.

The remainder of the paper is organized as follows. Section 2 presents the method and estimation in a state-space representation. Section 3 describes the data, priors, and posteriors for the estimation of the NAIRU, as well as other key parameters. Section 4 presents the results. Section 5 discusses the policy implications of our results in terms of the literature associated with the Phillips curve and monetary policy. Section 6 presents the conclusions.

2. STATE – SPACE REPRESENTATION

Following Chan et al. (2016), we estimate a bivariate unobserved components model for inflation (π_t) and unemployment (u_t). The framework is specified as follows:

$$(\pi_t - \tau_t^{\pi}) = \rho_t^{\pi}(\pi_{t-1} - \tau_{t-1}^{\pi}) + \lambda_t(u_t - \tau_t^{u}) + \varepsilon_t^{\pi} exp\left(\frac{h_t}{2}\right) \tag{1}$$

$$(u_t - \tau_t^{u}) = \rho_1^{u}(u_{t-1} - \tau_{t-1}^{u}) + \rho_2^{u}(u_{t-2} - \tau_{t-2}^{u}) + \varepsilon_t^{u} \tag{2}$$

$$\tau_t^{\pi} = \tau_{t-1}^{\pi} + \varepsilon_t^{\tau\pi} \tag{3}$$

$$\tau_t^{u} = \tau_{t-1}^{u} + \varepsilon_t^{\tau u} \tag{4}$$

$$\rho_t^{\pi} = \rho_{t-1}^{\pi} + \varepsilon_t^{\rho\pi} \tag{5}$$

$$\lambda_t = \lambda_{t-1} + \varepsilon_t^{\lambda} \tag{6}$$

$$h_t = h_{t-1} + \varepsilon_t^{h} \tag{7}$$

where ρ_t^{π} represents inflation gap persistence, h_t reflects the volatility of the inflation gap which depends on both $\varepsilon_t^{\pi} \backsim N(0,1)$ and $\varepsilon_t^{h} \backsim N(0, \sigma_h^2)$. Notice also that both dependent variables are written as deviations from their trends, τ_t^{π} and τ_t^{u}, which are interpreted as trend inflation and NAIRU, respectively. The errors affecting trend inflation are $\varepsilon_t^{\tau\pi} \sim TN(a_{\pi} - \tau_{t-1}^{\pi}, b_{\pi} - \tau_{t-1}^{\pi}; 0, \sigma_{\tau\pi}^2)$, as for NAIRU, they are $\varepsilon_t^{\tau u} \sim TN(a_u - \tau_{t-1}^{u}, b_u - \tau_{t-1}^{u}; 0, \sigma_{\tau u}^2)$. Here a and b represent the trend bands, and $TN(a, b; \mu, \sigma^2)$ represents a truncated Gaussian distribution between a and b with mean μ and variance σ^2. Given this specification, the one-period-ahead conditional expectation for trend inflation and NAIRU satisfies the following properties:

$$E_t[\tau_{t+1}^{\pi}] = \tau_t^{\pi} + \sigma_{\tau\pi}\left[\frac{\phi\left(\frac{a_\pi-\tau_t^{\pi}}{\sigma_{\tau\pi}}\right)-\phi\left(\frac{b_\pi-\tau_t^{\pi}}{\sigma_{\tau\pi}}\right)}{\Phi\left(\frac{b_\pi-\tau_t^{\pi}}{\sigma_{\tau\pi}}\right)-\Phi\left(\frac{a_\pi-\tau_t^{\pi}}{\sigma_{\tau\pi}}\right)}\right], if\ a_\pi \le \tau_t^{\pi} \le b_\pi \tag{8}$$

$$E_t[\tau_{t+1}^{u}] = \tau_t^{u} + \sigma_{\tau u}\left[\frac{\phi\left(\frac{a_u-\tau_t^{u}}{\sigma_{\tau u}}\right)-\phi\left(\frac{b_u-\tau_t^{u}}{\sigma_{\tau u}}\right)}{\Phi\left(\frac{b_u-\tau_t^{u}}{\sigma_{\tau u}}\right)-\Phi\left(\frac{a_u-\tau_t^{u}}{\sigma_{\tau u}}\right)}\right], if\ a_u \le \tau_t^{u} \le b_u \tag{9}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are the probability and cumulative density function for the standard Gaussian distribution, respectively.

In the model, we set $a_\rho = 0$ and $b_\rho = 1$ for shock persistence in the inflation gap i.e., in $\varepsilon_t^{\rho\pi} \sim TN\left(a_\rho - \rho_{t-1}^{\pi}, b_\rho - \rho_{t-1}^{\pi}; 0, \sigma_{\rho\pi}^2\right)$, so that the estimated coefficient never moves into undesirable regions in the parameter space. We also set $a_\lambda = -1$ and $b_\lambda = 0$ for the shocks associated with the slope of the Phillips curve i.e. $\varepsilon_t^{\lambda} \sim TN\left(a_\lambda - \lambda_{t-1}, b_\lambda - \lambda_{t-1}; 0, \sigma_\lambda^2\right)$ to ensure that the Phillips curve has a negative slope. The one-period-ahead conditional expectation for the inflation persistence and the slope of the Phillips curve is specified as:

$$E_t[\rho_{t+1}^{\pi}] = \rho_t^{\pi} + \sigma_{\rho\pi}\left[\frac{\phi\left(\frac{a_\rho-\rho_t^{\pi}}{\sigma_{\rho\pi}}\right)-\phi\left(\frac{b_\rho-\rho_t^{\pi}}{\sigma_{\rho\pi}}\right)}{\Phi\left(\frac{b_\rho-\rho_t^{\pi}}{\sigma_{\rho\pi}}\right)-\Phi\left(\frac{a_\rho-\rho_t^{\pi}}{\sigma_{\rho\pi}}\right)}\right], if\ a_\rho \le \rho_t^{\pi} \le b_\rho \tag{10}$$

$$E_t[\lambda_{t+1}] = \lambda_t + \sigma_\lambda\left[\frac{\phi\left(\frac{a_\lambda-\lambda_t}{\sigma_\lambda}\right)-\phi\left(\frac{b_\lambda-\lambda_t}{\sigma_\lambda}\right)}{\Phi\left(\frac{b_\lambda-\lambda_t}{\sigma_\lambda}\right)-\Phi\left(\frac{a_\lambda-\lambda_t}{\sigma_\lambda}\right)}\right], if\ a_\lambda \le \lambda_t \le b_\lambda \tag{11}$$

The main focus of the model described by equations (1)–(7) is the unemployment rate. Since we wish to assess the impact of informality, we compare results based on the standard and extended unemployment rates. Moreover, trend inflation, persistence, the slope of the Phillips curve, and expectations are influenced by inflation bounds.[1]

[1] Note that we can also include bounds for the NAIRU, but we chose to bound only trend inflation, setting $a_\pi = 0$ and $b_\pi = 8$. See the Appendix for the implementation of the algorithm.

3. ESTIMATIONS

The data for the bivariate models cover the sample period from 2007 to the first quarter of 2024. We pair inflation and unemployment rate for the estimation of the NAIRU. The extended NAIRU (NAIRU-E) results from combining inflation and the extended unemployment rate. We also estimate a set of key parameters and variables that belong to either NAIRU or NAIRU-E. Inflation is the quarterly variation of the CPI in Peru and comes from the central bank website. The unemployment rate is the ratio of the portion of the labor force (economically active population) to the total labor force. Extended labor force includes the addition of informal workers who are dependent on either a firm or an entrepreneurship (informal wage earners). In this regard, Aguilar-Argaez et al. (2022) suggest that moving from employment to unemployment has an intermediate step: becoming an informal wage earner.

Even though Equation (9) allows for setting bounds for the NAIRU, we only set bounds on Equation (8) for trend inflation at $a_\pi = 0$ and $b_\pi = 8$. Either NAIRU or NAIRU-E becomes more volatile when a crisis hits the economy and heavily affects the labor market. The reshaping of this market was clearer during the COVID-19 pandemic, when informal workers were more susceptible to losing any source of income due to government regulations.

For the priors of the bivariate model, as described in Equations (1) to (7), we set: $\tau_1^\pi \sim TN(a_\pi, b_\pi; \tau_0^\pi, \omega_{\tau\pi}^2)$, $\tau_1^u \sim TN(a_u, b_u; \tau_0^u, \omega_{\tau u}^2)$, $\rho_1^\pi \sim TN\big(0,1; \rho_0^\pi, \omega_{\rho\pi}^2\big)$, $\lambda_1 \sim TN\big(-1,0; \lambda_0, \omega_\lambda^2\big)$, and $h_1 \sim TN(h_0, \omega_h^2)$, where τ_0^π, τ_0^u, ρ_0^π, λ_0, h_0, $\omega_{\tau\pi}^2$, $\omega_{\tau u}^2$, $\omega_{\rho\pi}^2$, ω_λ^2, and ω_h^2 are known constants. The trend inflation prior mean is $\tau_0^\pi = 3$ for the two measures of unemployment. The prior for the NAIRU mean is set as $\tau_0^u = \tau_{-1}^u = 5$ as for the NAIRU-E mean is $\tau_0^u = \tau_{-1}^u = 39$. The hyperparameters for persistence, volatility, and the slope of the

Phillips curve are $\rho_0^\pi = h_0 = \lambda_0 = 0$ and the variances for the unobserved components are $\omega_{\tau\pi}^2 = \omega_{\tau h}^2 = \omega_h^2 = 10$ and $\omega_{\rho\pi}^2 = \omega_\lambda^2 = 1$.

The remaining parameters of the model are defined by $\theta = \left(\sigma_u^2, \sigma_{\tau\pi}^2, \sigma_{\tau u}^2, \sigma_h^2, \sigma_{\rho\pi}^2, \sigma_\lambda^2\right)'$ and we specify their priors as $p(\theta) = p(\sigma_u^2)\, p(\sigma_{\tau\pi}^2)\, p(\sigma_{\tau u}^2)\, p(\sigma_h^2)\, p\left(\sigma_{\rho\pi}^2\right) p\left(\sigma_\lambda^2\right)$ where $\sigma_u^2 \sim IG(v_u, S_u)$, $\sigma_{\tau\pi}^2 \sim IG(v_{\tau\pi}, S_{\tau\pi})$, $\sigma_{\tau u}^2 \sim IG(v_{\tau u}, S_{\tau u})$, $\sigma_h^2 \sim IG(v_h, S_h)$, $\sigma_{\rho\pi}^2 \sim IG\left(v_{\rho\pi}, S_{\rho\pi}\right)$, $\sigma_\lambda^2 \sim IG(v_\lambda, S_\lambda)$, and $IG(.,.)$ denotes the Inverse-Gamma distribution. The parameters for the degrees of freedom are $v_u = v_{\tau\pi} = v_{\tau u} = v_h = v_{\rho\pi} = v_\lambda = 10$ and the scale parameters $S_u = S_h = 0.45$, $S_{\tau\pi} = 0.18$, $S_{\tau u} = 0.09$, $S_{\rho\pi} = S_\lambda = 0.009$.[2]

The conditional posterior distributions of the trend inflation, the NAIRU, and the parameters previously described are estimated using Markov Chain Monte Carlo (MCMC) algorithm, where $\pi = (\pi_1, \dots, \pi_T)'$, $u = (u_1, \dots, u_T)'$, $y = (\pi', u')'$, $\tau^\pi = (\tau_1^\pi, \dots, \tau_T^\pi)'$, $\rho^\pi = (\rho_1^\pi, \dots, \rho_T^\pi)'$, $\lambda = (\lambda_1, \dots, \lambda_T)'$, and $h = (h_1, \dots, h_T)'$.[3]

4. Results

In Figure 2, we present our results for estimating the NAIRU and NAIRU-E. The NAIRU decreases between 2008 and 2013, reaches a turning point, consistently increases until 2020, and then remains stable at a higher level than its initial value. The NAIRU-E also begins with decreasing values, turns around in 2018, and then consistently increases, although its final estimated value remains lower than the initial level. In other words, while the standard measure of unemployment supports the idea that a higher unemployment rate is needed to prevent inflation from accelerating, the extended measure of unemployment points to the need for fewer unemployed individuals or informal workers.

[2] For further information about this setup, refer to the technical appendix at Chan et al. (2016).
[3] See Appendix, for the steps to estimate the bivariate unobserved components model with bounds.

The standard NAIRU rises over time, implying a need for higher unemployment to control inflation while NAIRU-E decreases when informality is included. This result also highlights that the labor market can absorb shocks through informal employment rather than higher unemployment and suggests that monetary policy transmission weakens in economies with large informal sectors i.e. inflation responds less to unemployment changes.[4]

FIGURE 2 – NON-ACCELERATING INFLATION RATE OF UNEMPLOYMENT, NAIRU (τ_t^u)

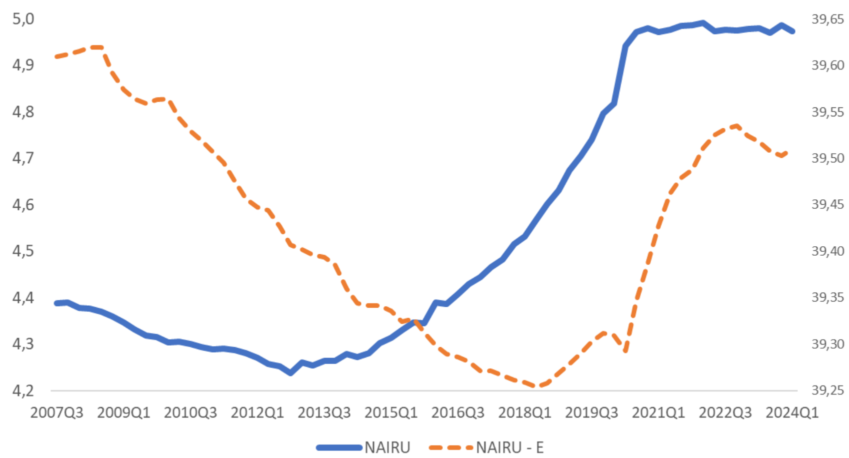
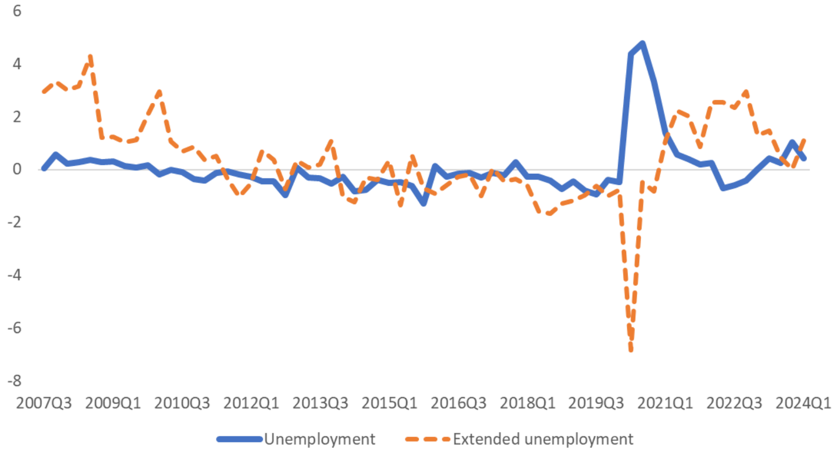


Figure 3 shows that the unemployment gap (difference between the observed unemployment rate and the NAIRU) is less volatile in the case of the extended unemployment data. In general, the deviations from trend are clearer in the case of the NAIRU-E, which relates to the underlying idea of business cycles. The positive gap at the beginning of 2008 - 2012 contrasts with the one in 2021 – 2023 in the NAIRU-E in terms of duration. During the pandemic, this reflects the unusual case where an increase in unemployment translates into a further increase in the already large informal labor force.

[4] See Alberola and Urrutia (2020) and Castillo and Montoro (2012) for a theoretical framework.

FIGURE 3 – UNEMPLOYMENT GAP $(u_t - \tau_t^u)$



In Figure 4, the trend inflation is initially higher under the extended unemployment measure but exhibits lower inflationary pressures in recent years, particularly after COVID-19. These trend measures share similar dynamics, initially decreasing to a turning point, followed by an increase. The similar pattern indicates that unemployment rates are more likely to bring different sets of relevant information for labor markets. Figure 5 shows inflationary pressures given our two measures of unemployment. The standard measure of unemployment seems to generate a higher gap between observed inflation and its trend, which then later significantly decreases, especially after the COVID-19 pandemic. The two gaps seem to agree in identifying higher pressures after two international crises: the Global Financial Crisis and the COVID-19 pandemic.

FIGURE 4 – TREND INFLATION τ_t^{π}

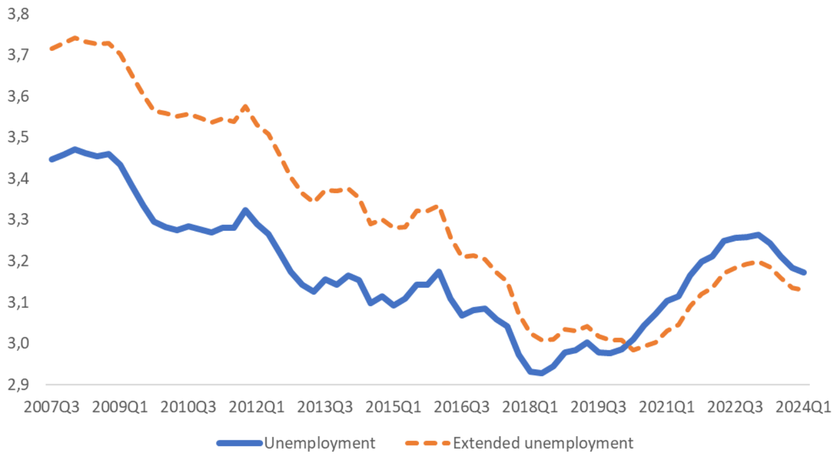
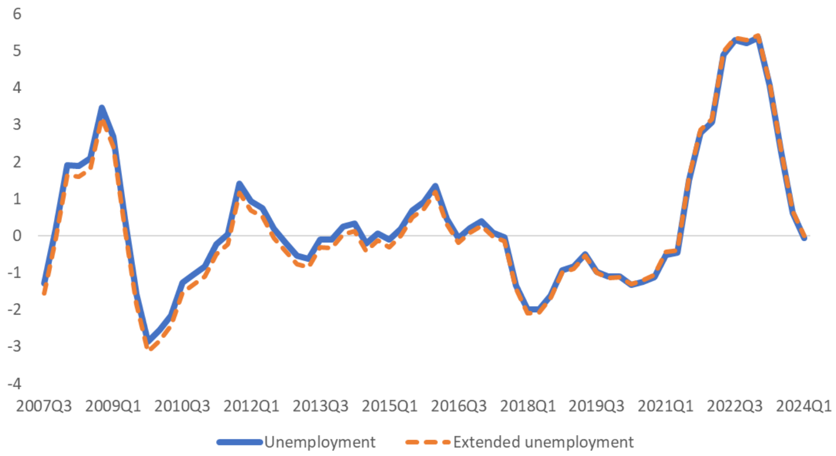


FIGURE 5 – INFLATIONARY PRESSURE $(\pi_t - \tau_t^\pi)$



5. POLICY DISCUSSION

Chan et al. (2016) argue that Equation (1) is a Phillips curve equation describing the relationship between inflation and unemployment by λ_t. Positive unemployment deviations from its trend lead to negative deviations in inflation relative to its trend as well, i.e., λ_t is a measure of how strongly higher unemployment exerts downward pressure on inflation, which is akin to the definition of the slope of the Phillips curve.

In this regard, the slope of the Phillips curve has been estimated by quite a wide range of methods and strategies. In one-equation models, for example, Carrera and Ramirez-Rondan (2017), Coibion (2010), and Khan and Zu (2006) estimate the slope based on non-linear time series analysis. For a bivariate estimation system, Hindrayanto et al. (2019), Xu et al. (2015), Ogunc et al. (2013) and Enders and Hurn (2002) estimate a Phillips curve for different developed economies. In line with Chan et al (2016), Hindrayanto et al. (2019) also rely on the use of an unobserved component model.

Figure 6 presents the slope of the Phillips curve for the standard and the extended measure of unemployment. This estimation suggests a higher impact on inflation from unemployment deviations from trend when the standard unemployment rate is used. The impact on inflation clearly decreases if the extended measure of unemployment is used. This result is consistent with the argument around a weaker monetary policy transmission channel when more informal workers are part of the labor market, in line with the models of Alberola and Urrutia (2020) and Castillo and Montoro (2012).

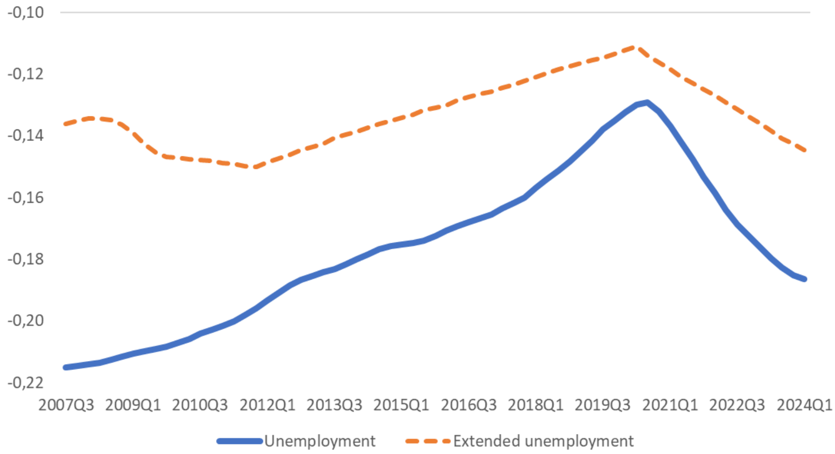
A large informal labor force is an important characteristic of labor markets in developing countries. Central banks committed to an inflation target are also a key component for dealing with different sources of uncertainty and gaining a reputation. Consistent with an optimal monetary policy in a developing country, central banks need to consider informal labor markets because they are large enough that they tend to absorb most of the labor force and, if so, reduce the effectiveness of the transmission mechanisms available for policymakers.

For Castillo and Montoro (2012), the key distinction from a standard New Keynesian model is the composition of households. Some are hand-to-mouth, with no decision-making on how much to consume while the remaining group makes decisions such as how much to work, what to consume, or when to acquire goods and services. If so, rather than having people employed and unemployed, there is a third important category referred to as those employed in the informal labor market. Alberola and Urrutia (2020) and Castillo and Montoro (2012) argue that the informal labor market works as a buffer for monetary policy: when a monetary policy shock impacts the economy, one part of the labor force affected by this shock moves into informality rather than becoming unemployed. Since this market has a lower productivity, the presence of this large group diminishes the intended final effect on inflation as well as on output, which also implies a greater effort by the central bank to achieve its targets.[5]

[5] This stylized fact is consistent with international evidence (e.g., Mexico, Brazil, and Colombia) showing that high informality dilutes the inflation–unemployment trade-off and complicates the calibration of policy interest rates. For example, Alberola & Urrutia (2019) show that in a dual labour-market model informality weakens monetary transmission. Aguilar-Argaez et al. (2022) find in Mexico that an "informality-adjusted" NAIRU is a

Figure 6 also shows that the slope of the Phillips curve for both measures of unemployment shares the same co-movement, trending toward lower values near zero around the COVID-19 event and increasing thereafter. The literature has focused on the reasons behind the Phillips curve becoming flatter, prior to the COVID-19 pandemic, implying a lower transmission from unemployment to inflation (see, for example, Hooper, 2020). Moreover, some research suggests that the Phillips curve becomes steeper and more relevant after the COVID-19 pandemic (see Harding et al., 2023).

FIGURE 6 – SLOPE OF THE PHILLIPS CURVE (λ_t)



6. CONCLUSIONS

Following Chan et al. (2016) and Aguilar-Argaez et al. (2022), we find that informality reshapes both the measurement and meaning of the NAIRU in emerging markets. It weakens the inflation–unemployment link, moderates policy transmission, and cushions shocks at the expense of long-term labor quality and productivity. For policymakers, we highlight that monetary policy cannot be evaluated in isolation from labor market structure. In small open economies like Peru, where informality remains high, accurate assessment of inflationary

better predictor of inflation. Lambert et al. (2020) show in an emerging market context how informality acts as a buffer to unemployment and inflation shocks.

pressures requires extending unemployment definitions and explicitly modeling the informal sector's role in absorbing shocks.

First at all, the interpretation of labor market slack changes by incorporating informality. Our estimations show that including informal workers in the estimation of the NAIRU fundamentally changes how we interpret labor market conditions in Peru. When the analysis relies solely on the formal unemployment rate, the estimated NAIRU follows a rising trend, suggesting that inflation control requires maintaining relatively high unemployment. However, once the extended unemployment rate (NAIRU-E) is used—one that captures the dynamics of informal labor—the trend flattens or even declines in recent years. This result indicates that part of the adjustment previously attributed to rising unemployment is absorbed through transitions between formal and informal employment. Informality thus serves as a buffer mechanism, allowing the economy to absorb shocks without creating excessive formal job loss or inflationary pressure.

Moreover, we estimate a flatter Phillips curve that reflects weaker monetary transmission. The estimated time-varying Phillips curve slope becomes notably flatter when informality is included in the model. This flattening implies that the responsiveness of inflation to unemployment is diminishing (monetary policy shocks have smaller real effects). In other words, when a central bank tightens policy to reduce inflation, the adjustment in prices occurs more slowly and with smaller changes in unemployment because part of the adjustment happens in the informal sector. For policymakers, this result suggests that the traditional Phillips curve framework may overstate the power of interest rate adjustments to influence inflation in economies with pervasive informality.

We also argue that informality acts as a structural shock absorber, but at a cost. Our results highlight a dual role for informality. On the one hand, it provides flexibility to firms and workers by facilitating rapid labor reallocation during downturns or policy tightening.

This reduces the amplitude of unemployment cycles and helps maintain output stability. On the other hand, it weakens the transmission of stabilization policies and perpetuates a segmented labor market, where a large share of workers remains outside social protection systems. Hence, informality can be interpreted as a stabilizer with structural costs: it cushions the economy against short-term shocks but hinders long-term efficiency and productivity growth.

Finally, we also find that the evolution of the NAIRU-E reveals important structural changes after 2017 and especially following the COVID-19 pandemic. While formal employment contracted sharply in 2020, informality expanded, keeping overall labor participation relatively stable. The estimated NAIRU-E declined during this period, indicating that informal employment absorbed the shock, preventing inflation from accelerating despite the economic contraction. This reinforces our argument that ignoring informality can lead to misinterpreting cyclical adjustments as structural unemployment and thus to an incorrect reading of inflation pressures.

From a policy standpoint, the findings imply that standard NAIRU-based assessments may systematically overestimate inflation risks in economies with large informal sectors. For a central bank (and similar institutions), this means that using formal unemployment alone could suggest a tighter labor market than exists, prompting unnecessarily restrictive policy. Conversely, relying on an extended unemployment concept provides a more nuanced measure of slack and can improve the calibration of policy responses—especially in periods of structural change, such as labor market reform or external shocks.

Our results also contribute to the literature in line with labor market heterogeneity and informality that are integral to a modern view of inflation dynamics in emerging economies. By embedding informality directly into the state-space estimation of the NAIRU, we aim to bridge the gap between developing-country realities and standard models. We show empirically that the NAIRU is not a fixed or purely formal-sector concept, but rather a system-wide measure of labor slack that must account for informal labor absorption.

Future work could extend our framework by incorporating wage inflation and productivity data to strengthen the identification of the Phillips curve; estimating sector-specific NAIRUs to capture differential price-setting behavior; and testing for nonlinearities or regime changes to better model crises like COVID-19 or sharp disinflation episodes.

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APPENDIX

The steps to estimate the bivariate unobserved components model with bounds, as in Chan et al. (2016), are outlined as follows:[6]

i. Initializing the model using the priors previously stated.

ii. Setting the number of estimations to $J = 50\ 000$ and starting with $j = 1$.

iii. Deriving the conditional posterior distribution $p(\tau^{\pi}|y, \tau^{u}, \rho^{\pi}, \lambda, h, \Phi)$, where the presence of bounds and inequalities in (8) leads to a non-standard conditional

[6] The base code for the procedure is available at: https://joshuachan.org/code/code_biUC_bounded.html

distribution. Thus, the sampling of τ^{π} is approximated via an independence-chain Metropolis-Hastings (MH) step, where candidate estimates are obtained as in Chan and Jeliazkov (2009), and then subjected to an Acceptance-Rejection Metropolis Hastings (AR-MH) step.

iv. Obtaining the conditional posterior distribution $p(\tau^{u}|y,\tau^{\pi},\rho^{\pi},\lambda,h,\Phi)$ via AR-MH (in the same way as in step iii).

v. Calculating the conditional posterior distribution $p(\rho^{\pi}|y,\tau^{\pi},\rho^{\pi},\lambda,h,\Phi)$ using the posterior distribution algorithm for trend inflation and the NAIRU.

vi. Obtaining the conditional posterior distribution $p(\lambda|y,\tau^{\pi},\tau^{u},\rho^{\pi},h,\Phi)$ using the posterior distribution algorithm.

vii. Calculating the conditional posterior distribution $p(h|y,\tau^{\pi},\tau^{u},\rho^{\pi},\lambda,\Phi)$ using the algorithm proposed by Chan and Strachan (2012).

viii. Obtaining the conditional posterior distribution $p(\Phi|y,\tau^{\pi},\tau^{u},\rho^{\pi},\lambda,h) = p(\sigma_u^2|y,\tau^{\pi},\tau^{u},\rho^{\pi},\lambda,h) \ldots p\left(\sigma_\lambda^2|y,\tau^{\pi},\tau^{u},\rho^{\pi},\lambda,h\right)$, where $p(\sigma_u^2|y,\tau^{\pi},\tau^{u},\rho^{\pi},\lambda,h)$ and $p(\sigma_h^2|y,\tau^{\pi},\tau^{u},\rho^{\pi},\lambda,h)$ are standard Inverse-Gamma densities, while the rest follow non-standard densities, leading to the implementation of a MH step with a proposed Inverse-Gamma density.

ix. If $j < J$, set $j + 1$ and return to step iii; otherwise, proceed to the next step.

x. Performing a burn-in of the initial 5 000 estimations to minimize the initial value effect.