DISCUSSION PAPER

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CONTENTS

ABSTRACT

We implement decompositions of cyclical unemployment in a large developing country using the conventional 3-states and a 4-states representation of the labor market, where in the latter we subdivide the employment state into formal and informal forms of employment. This allows a richer analysis of the dynamics of unemployment that unveils the role played by the inflows and outflows from and into the formal and informal sectors. Results for the 3-states representation show that job separation play a much larger role than job finding, a result that differs from what is found for the U.S. The 4-states decomposition unveils that the contribution of the flow from informality to unemployment is larger than that of the flow from formal jobs. This evinces that job separations from the informal sector do play a role in explaining variations in the unemployment rate along the cycle. Opposite results are revealed for the job finding rate, where the formal sector displays a much larger contribution than the informal sector. We also compare the model performance of the 3- and 4-states representations and show that for many indicators the latter is superior to the former.

Keywords: unemployment dynamics; variance decomposition; informality.

1 INTRODUCTION

Unemployment dynamics in developed countries has been extensively discussed with an ongoing debate on the importance of the ins and outs of unemployment (Petrongolo and Pissarides, 2008; Fujita and Ramey, 2009; Elsby, Michaels and Solon, 2009; Shimer, 2012; Ahn and Hamilton, 2020). The analysis is typically conducted considering three states in the labor market (unemployment, employment, and inactivity), which is a reasonable partition for most OECD countries. However, one should expect that cyclical unemployment in developing countries is influenced by a prominent feature that characterizes those countries, a large informal sector.[1]

The influence of informality on unemployment is recognized in the theoretical literature, which has proposed various direct and indirect connections between the informal sector and unemployment. This includes dual labor market models in which informality in simply a state that workers pass while waiting for a formal job position (Fields, 2005 and the references therein), search models that have incorporated the informal sector (e.g., Albrecht, Navarro and Vroman, 2009; Haanwinckel and Soares, 2021), and arguments that informality is not disguised unemployment but rather a voluntary employment decision of workers (e.g. Perry et al., 2007). Despite these theoretical efforts, there is still little evidence that investigates the role played by informality in explaining cyclical unemployment in developing countries.[2]

To fill part of this gap, in this paper we implement decompositions of cyclical unemployment in a large developing country using the conventional 3-states and a 4-states representation of the labor market, where in latter we subdivide the employment state into formal and informal forms of employment. This allows a richer analysis of the dynamics of unemployment that unveils the role played by the inflows and outflows from and into the formal and informal sectors, as well as the contributions of the reallocation of workers between these two sectors.

To accomplish that we use distinct decomposition methods. The first is based on the widely used steady-state decomposition (Shimer, 2012), where steady-state unemployment is taken as a surrogate for actual unemployment. This decomposition has been criticized on the grounds that, apart from the U.S., steady-state unemployment is not a good proxy for actual unemployment in various countries (Smith, 2011; Elsby, Hobijn and

1. According to ILO (2018), the share of informal employment was around 60% in developing and emerging countries and 54% in Latin America.

2. One exception is Corseuil and Foguel (2012) that adapt the job ladder model proposed by Moscarini and Postel-Vinay (2009) and discuss how formal and informal jobs interact in an expansionary phase of the business cycle.

Sahin, 2013; Moreira, Foguel and Corseuil, 2021). We thus apply a modification of the steady-state decomposition that allows assessing the contributions of the flows to the variance of current unemployment while at the same time gauging the contribution of the error of using steady-state unemployment instead of current unemployment (Corseuil, Foguel and Moreira, 2021). For robustness, we also present results for a decomposition that gauges the contributions of flows for different time horizons of the projected unemployment rate, where the steady state is just a special case. The use of different decomposition methods distinguishes our work from Bosch and Maloney (2008) and Zylberman and Souza (2015), which also incorporate informality in the cyclical analysis of unemployment but only considering the steady-state framework.[3]

Using some easily implemented indicators, we also evaluate whether decompositions based on the 4-states representation displays a better performance than its 3-states counterpart. We believe implementing this assessment can be important for both developing and developed countries, the latter group when there is concern that part-time or temporary work can be relevant to explain the dynamics of unemployment.

We use data for Brazil for the period between 2003 and 2016 from the Monthly Employment Survey (Pesquisa Mensal de Emprego – PME), a survey whose sampling scheme is similar to that of the Current Population Survey (CPS) in the U.S. We construct gross flow data across the labor market states and apply usual filters in the literature (Shimer, 2012) to obtain cyclical variations in the series that enter the decompositions.

Results for the 3-states representation show that job separation play a much larger role than job finding, a result that differs from what is found for the U.S. The 4-states decomposition unveils that the contribution of the flow from informality to unemployment is larger than that of the flow from formal jobs. This evinces that job separations from the informal sector do play a role in explaining variations in the unemployment rate along the cycle. Opposite results are revealed for the job finding rate, where the formal sector displays a much larger contribution than the informal sector. In fact, outflows from unemployment to informality displays a negative contribution, suggesting that the contribution of the job finding rate would be higher if the informal sector behaved like the formal sector.

As shown by Moreira, Foguel and Corseuil (2021) variance decompositions analogous to the one performed using the steady state proxy for unemployment can also be performed with alternative proxies based on projected unemployment rates.

3. Our period of analysis is also different from these studies, especially Bosch and Maloney (2008), which covers data from the 1980's and 1990's.

We use these alternative variance decomposition exercises to attest the robustness of the results mentioned above.

The comparison between the performance of the 3- and 4-states representations of the labor market shows that the proxy error of using steady-state unemployment as a surrogate for observed unemployment is larger for the former than for the latter context. Robustness checks confirm that this is also the case for various time horizons of the projected unemployment rate.

The rest of the paper is organized as follows. In the second section, we present the decomposition methods we employ and in the third section we describe the data we use. Decomposition results and the comparison between the performance of the 3- and 4-states representations are presented in section four. Section five presents robustness checks for the main findings of the paper. Section six concludes the paper.

2 METHODS

The standard framework to evaluate the contribution of each flow between labor market states is built upon a Markovian representation of the labor market with few states, usually three (unemployment, u_t; employment, e_t; and inactivity, i_t). Such framework is based on a labor market representation that contains two components: i) a state probability vector, which for the standard three states representation can be represented as $p_t = (u_t, e_t, i_t)'$; and ii) a transition matrix, π_t, whose columns add up to one and in which a typical element $\pi_t(i, j)$ represents the probability of transitioning from state *i* to state *j* from period $t-1$ to period t. Assuming a population of working age that is constant over time, the transition matrix π_t relates the vectors p_t and p_{t-1} in a Markovian sense as follows.

$$p_t = \pi_t p_{t-1}. \quad (1)$$

The endpoint of the framework is a variance decomposition exercise that linearly decomposes the variance of unemployment rate according to factors driven by each of the flows between any two different labor market states.[4]

Moreira, Foguel and Corseuil (2021) show how to perform such calculations based on matrix algebra (section 2.2 and appendix A there). Their procedure elucidates that it is trivial to accommodate any number of states, in particular the four states representation analyzed here in which the employment state becomes two different states: the formal state (f_t) and the informal state (n_t).

4. In terms of the Markovian model, each factor is driven by an off-diagonal component of the transition matrix.

2.1 Variance decomposition using steady-state unemployment as a proxy

The most influential specifications within the Markovian framework described above (Shimer 2012; Petrongolo and Pissarides, 2008; Fujita and Ramey, 2009) use the steady-state unemployment rate (u_t^*) as a proxy for the current unemployment rate (u_t). This is very convenient since the steady-state unemployment rate can be expressed as a function only of the current labor market flows. On such representation, one can apply a standard first order expansion around its sample average. After such linearization procedure, the steady-state unemployment rate can be expressed as follows.[5]

$$u_t^* \cong \kappa^* + \sum_{i \neq j} u_{ijt}^*, \tag{2}$$

in which κ^* is a constant and each u_{ijt}^* on the right hand side of (2) represents a transformation of the steady-state unemployment rate when all components of π_t are held fixed, except the correspondent off-diagonal element "*i,j*".

Expression (2) is the basis for the following variance decomposition of the steady-state unemployment rate.

$$\frac{V(u_t^*)}{V(u_t^*)} = 1 \cong \sum_{i \neq j} \frac{cov\langle u_t^*, u_{ijt}^* \rangle}{V(u_t^*)} = \sum_{i \neq j} \beta_{ij}^*, \tag{3}$$

in which β_{ij}^* captures the contribution of the transition between state i to state $j \neq i$ to explain the variance of steady-state unemployment rate. This contribution can be estimated by regressing the time series of each u_{ijt}^* against the time series of the steady-state unemployment rate.

2.2 Variance decomposition for the current unemployment rate

Using the steady-state unemployment rate as a proxy for the actual rate is a reasonable approach for the case of the U.S., a country known for its flexible labor market. However, there are concerns in the literature about the adequacy of the steady-state rate as a proxy for the current rate for countries that do not exhibit such flexibility (e.g., Smith, 2011; Elsby, Hobij and Sahin, 2013; Moreira, Foguel and Corseuil, 2021). Indeed, as shown in the literature the steady-state rate is not a good approximation for the current rate in various countries – including Brazil –, which renders decomposition results that are less informative.

5. See Moreira, Foguel and Corseuil (2021) for more details.

As proposed by Moreira, Foguel and Corseuil (2021), Shimer (2012)'s framework can be easily modified to compute a decomposition of the current unemployment rate based on the same components used to explain steady-state unemployment. Adding u_t on both sides of expression (2), it can be rewritten as described in the following.

$$u_t \cong \kappa^* + \sum_{i \neq j} u^*_{ijt} + (u_t - u^*_t), \tag{4}$$

in which the last term in the right-hand side captures the deviation between the current and the steady-state unemployment rates. Expression (5) spells out the associated variance decomposition.

$$\frac{V(u_t)}{V(u_t)} = 1 \cong \left\{ \sum_{i \neq j} \frac{cov\langle u_t, u^*_{ijt} \rangle}{V(u_t)} \right\} + \frac{cov\langle u_t, (u_t - u^*_t) \rangle}{V(u_t)} = \sum_{i \neq j} \gamma^*_{ij} + \gamma^*_p. \tag{5}$$

Note that, differently from β^*_{ij} in expression (2), γ^*_{ij} measures the relative importance of each labor market flow to the variance of the current unemployment rate. In other words, differently from Shimer (2012)'s method, which relies on the empirical correlation between u^*_t and u_t to decompose the variance of the steady-state unemployment, expression (5) offers a decomposition of the variance of the current rate relying on the empirical correlation between u_t and the factors that explain u^*_t. The last term in the right-hand side, γ^*_p, is an additional term that captures the contribution of the steady-state approximation error to the decomposition of variance of the actual rate. We will explore this term in section 4. As before, all γ^*_{ij} and γ^*_p can be estimated by running simple linear regression models.

3 DATA

Data come from the Monthly Employment Survey (Pesquisa Mensal de Emprego – PME), which was implemented by the Brazilian Institute of Geography and Statistics (Instituto Brasileiro de Geografia e Estatística – IBGE, the Brazilian Census Bureau) in the six major metropolitan areas in Brazil, where around 40% of population in the country lives. PME's sampling design is similar to that of the Current Population Survey (CPS) in the U.S.: it follows a 4–8–4 rotation scheme so that households are surveyed for four consecutive months, leave the sample for eight months, and are re-interviewed for four additional months.

We use PME to compute monthly gross flows across labor market states for the period from February 2003 to January 2016. For the 3-states representation, the labor market states are inactivity (i), unemployment (u), employment (e), and for the 4-states context, the employment state is subdivided into formal (f) and informal (n) states. Formal workers are those that have a signed labor contract and informal workers are those that are self-employed or work as salaried workers without a signed contract.

To implement the decompositions, the monthly gross flow data were subjected to some filters. First, the monthly series were seasonally adjusted using the U.S. Census Bureau's X13 software. Second, we compute quarterly averages of the resulting monthly series to mitigate high-frequency fluctuations that likely reflect measurement error. Finally, we detrend the quarterly data through the HP filter with the same smoothing parameter used by Shimer (2012), 10^5.

4 RESULTS

4.1 *Decompositions for the steady-state and the observed rates of unemployment*

Table 1 reports the contributions of the various flow rates for both the 3- and the 4-states representations of the labor market. Results are displayed for each representation for the steady-state and the observed unemployment rates. For the 3-state representation, the states are employment (e), unemployment (u), and inactivity (i); for the 4-states representation, the employment state is subdivided into formal (f) and informal (n) states. Following Bosch and Maloney (2008), flows rates are grouped in terms job separation, job finding, job reallocation between formal and informal jobs (4-states), exit from employment to inactivity, and between unemployment and inactivity.

TABLE 1
Contributions of flows rates to the variance of the cyclical unemployment rate by number of states in the labor market and type of unemployment

Flow rates	3-States			4-States		
		Steady-state unemp. rate	Observed unemp. rate		Steady-state unemp. rate	Observed unemp. rate
Job separation	-	-	-	-	0.38	0.37
	e->u	0.36	0.46	f->u	0.17	0.15
				n->u	0.21	0.22
Job finding	-	0.07	0.12	-	0.12	0.19
	u->e	0.04	0.08	u->f	0.13	0.18
				u->n	-0.04	-0.03
	i->e	0.03	0.04	i->f	0.04	0.05
				i->n	-0.01	-0.01
Job reallocation	-	-	-	-	0.02	0.03
	-	-	-	n->f	-0.01	0.00
	-	-	-	f->n	0.03	0.03
Exit labor force	-	-	-	-	0.12	0.14
	e->i	0.12	0.13	f->i	0.05	0.07
				n->i	0.07	0.07
Unemployment-inactivity	-	0.38	0.48	-	0.30	0.33
	i->u	0.35	0.39	i->u	0.29	0.27
	u->i	0.03	0.09	u->i	0.01	0.06

Authors' elaboration.
Obs.: The labor market states are: employment (e), unemployment (u), inactivity (i), formal employment (f), and informal employment (n). See section 2 for the decomposition methods for the steady state and the observed rates of unemployment.

Several results emerge from table 1. Looking first at the results for the 3-state representation, the job separation rate is the single most important contributor to cyclical unemployment. This is observed for both the decompositions of the steady-state (0.36) and the observed (0.46) rates. The job finding rate contributes much less to the steady-state (0.07) and the observed (0.12) variance of unemployment. This result shows that the pattern of the ins and outs of cyclical unemployment in Brazil is different from that of the U.S., where the job finding rate tends to play a larger role than the job separation rate (Fujita and Ramey, 2009; Elsby, Michaels and Solon, 2009; Shimer, 2012). More consistent with the evidence for the U.S. is the relevant contribution of the flow from inactivity to unemployment (0.35 and 0.39 for the steady-state and the observed rates of unemployment respectively). This shows that the fluidity between these two non-employment states is an important driver of cyclical changes in the unemployment rate.

While the 3-state representation allows comparisons with advanced economies, it can potentially hide the relative importance of formal and informal forms of employment to the dynamics of unemployment in developing countries. The 4-states representation reveals that the contribution of job separations to cyclical unemployment can be more attributable to movements from informality to unemployment (n->u) than correspondent movements from formality (f->u). The contribution of the flow from informality to unemployment amounts to 21% (22%) of the steady-state (observed) unemployment variance, while the contribution from the formal sector to unemployment corresponds to 17% (15%) of the steady state (observed) unemployment variance. This result, which is in line with the Zylberstajn and Souza (2015) and Bosch and Maloney (2008), reveals that the informal sector tends to play an important role in explaining entry into unemployment along the economic cycle.

In contrast, the incorporation of the formal-informal distinction into the job finding rate shows that the formal sector is much more important than the informal sector for the outflow from unemployment (and inactivity). In fact, the contribution of outflows to informality is even negative, showing that reductions in the unemployment rate does not happen because of increases in the flow from unemployment into informal jobs. The much larger role associated with exits to formal jobs suggests that were that sector the dominant sector in Brazil, the results might not be so different from those found for the U.S. economy (Bosch and Maloney, 2008).

It is also interesting to compare the relative contribution of the flows into and out of unemployment associated with the formal and informal forms of employment. On the one hand, flows involving the formal sector and unemployment are of similar magnitude in both directions: the contributions from formal sector into unemployment explains 17% (15%) of steady-state (observed) unemployment variance, while the contributions for the reverse flow explains 13% (18%) of the same variance. On the other hand, flows involving the informal sector and unemployment contributes in very uneven way. As mentioned, the flow from informal sector to unemployment contributes significantly to unemployment variance, explaining over 20% for both the steady state or the observed unemployment variance. In contrast, the contribution of the reverse flow is roughly null (even negative).

These patterns are consistent with predictions made by papers analyzing the effects of lay-off costs on labor adjustment. Studies like Bentolila and Bertola (1990), Hopenhayn and Rogerson (1993), and Ljungkvist (2002) claim that higher lay-off costs tend to balance labor adjustments to negative shocks between the margins of hiring and separation; in the absence of such costs, adjustments would be largely driven by the separation margin . These predictions match our results as lay-off costs tend to be negligible in the informal sector but can reach significant levels (depending on workers tenure and wage) in the formal sector.[6]

Interestingly, job reallocation between the formal and informal sectors does not contribute substantially to the dynamics of unemployment. This is somewhat surprising since one would expect that movements between the two sectors would display a larger contribution to explain changes in the unemployment rate. This is particularly so for movements from the formal to the informal sector, which is a state that could absorb workers that would otherwise flow into unemployment following negative shocks.

Exit from employment to inactivity does not display a very large role and the state from which it originates (formal or informal) has a similar contribution. Like in the 3-state decomposition, the flows between inactivity and unemployment also present a substantial contribution in the 4-state decomposition (0.29 and 0.27 for the steady-state and the observed rates respectively).

4.2 Comparing the 3- and 4-states representations of the labor market

In this subsection, we compare whether a representation of the labor market with four states seems more appropriate than the more conventional representation with three states. We use two different criteria to make the comparison. The first criterion is related to the adequacy of the steady-state unemployment rate as a proxy for the actual unemployment rate. This criterion, referred to as “proxy error” in the first column of table 2, can be readily accessed by one of the regression coefficients, denoted as γ_p^* in expression (5). By this criterion, the use of the steady-state approximation delivers a much larger error (in module) for the 3-states than for the 4-states representation of the labor market. Indeed, the proxy error for the former amounts to -26%, which is almost twice the magnitude for the latter representation, -14%.

6. Kugler and Pica (2008) also provide empirical evidence corroborating labor adjustments more uniformly distributed among the margins of hiring and separations; analyzing an increase in layoff cost that took effect in Italy only for small firms (under 15 employees).

The second criterion is related to the linear approximation that is used in the steady-state decompositions. Specifically, we compare the sum across the contributions of all flows to the unitary value. This is referred to as "linearization error" and is presented in the last column of table 2. One can see that the linear approximation for the steady-state decomposition induces the same magnitude of error for both representations of the labor market: the sum of the contributions of all 6 flows in the 3-states representation is 0.94 which is the same as the sum of the contributions of all 12 flows in the 4-states representation.

In sum, the 4-states representation of the labor market does seem to bring an advantage relatively to the 3-states representation, as the steady-state proxy seems to be superior in the former context and the linearization approximation is equally adequate for both representations.

TABLE 2
Adequacy of the 3- and the 4-states representations to unemployment variance decompositions

	Proxy error	Linearization error
Representation	γ_p^*	$\left(1-\sum_{i\neq j}\beta_{ij}^*\right)$
3 states	-0.26	0.06
4 states	-0.14	0.06

Authors' elaboration.
Obs.: The linearization error refers to the difference between the unitary value and the sum of contributions of all flows. The proxy error refers to the contribution of the difference between the current unemployment rate and the steady-state rate. The coefficients in the table appear in the formulas for the steady state and the current unemployment rate decompositions (section 2). In the 3-state representation, the labor market states are: employment, unemployment, and inactivity, whereas in the 4-states representation, the employment state is subdivided into formal and informal states.

5 ROBUSTNESS TO ALTERNATIVE PROXIES FOR UNEMPLOYMENT RATE

As mentioned in section 2.2, the use of the steady state approximation is pointed as a concern for the accuracy of unemployment variance decompositions for many other countries apart from U.S. We have already presented results for an alternative decomposition for the observed rate of unemployment, but it seems appropriate to check the robustness of our main results to the use of alternative proxies of the unemployment rate. In this section, we employ the methodology proposed by Moreira, Foguel and Corseuil (2021) which allows implementing the decomposition for different time horizons for the unemployment rate and which can be applied for both the three and four states representations considered in this paper.

5.1 The extended unemployment variance decomposition framework

Moreira, Foguel and Corseuil (2021) departure from the same Markovian representation of the labor market as in expression (1) and demonstrate that a variance decomposition can be performed for any chosen projected unemployment rate, denoted $u_{t+h}, h = 1,2, \ldots$.

Analogous to the steady-state context, the contribution of each component to the variance of u_{t+h} can be calculated from:

$$\frac{V(u_{t+h})}{V(u_{t+h})} = 1 \cong \frac{cov\langle u_{t+h}, u_{0t+h}\rangle}{V(u_{t+h})} + \sum_{i \neq j} \frac{cov\langle u_{t+h}, u_{ijt+h}\rangle}{V(u_{t+h})} = \beta_0^h + \sum_{i \neq j} \beta_{ij}^h, \quad (6)$$

in which β_{ij}^h denote the contribution of the transition from state i to state $j \neq i$ for time horizons $h = 1,2, \ldots$. In fact, the variance decomposition for the steady-state unemployment rate corresponds to the case when $h \to \infty$.

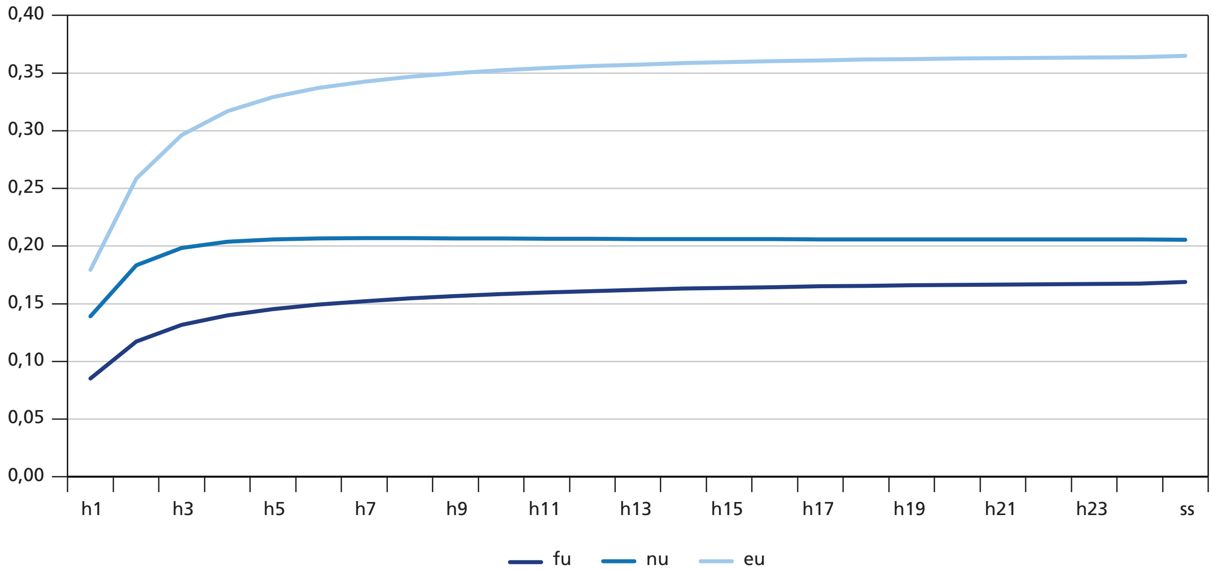
β_0^h captures the contribution of the initial conditions and the higher this statistic the less informative is the model with respect to the contribution of the relevant flows to the variance of unemployment.

In what follows we will show that all qualitative results highlighted in the previous section are robust to variance decompositions based on projected unemployment rates for various distinct time horizons.

5.2 Robustness relative to contributions of key flows

We start from the main results presented in section 4.1 . There we first pointed to the more prominent role of informality to job separation to explain cyclical unemployment variance. Figure 1 confirms this result showing that for all time horizons the contribution of separation rate (e->u) comes mainly from inflows from informality (n->u) than from formality (f->u).

FIGURE 1
Contribution of entry to unemployment (u) from formal (f) and informal (n) jobs

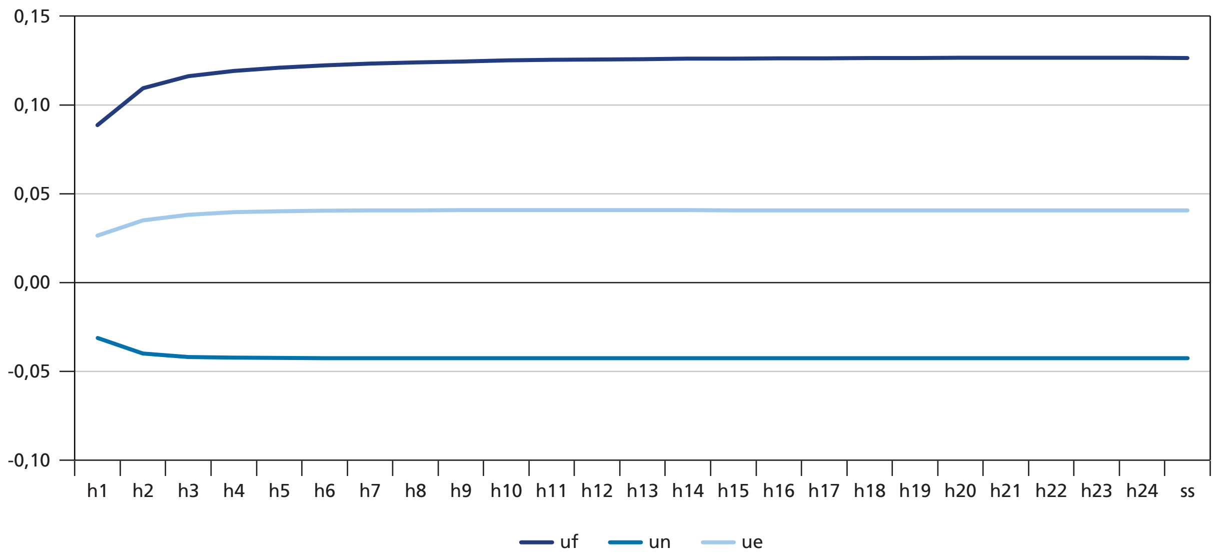


Authors' elaboration.
Obs.: The horizontal axis represents quarters, and the last point corresponds to the steady state. The results are based on the decomposition put forward by Moreira, Foguel and Corseuil (2021).

We also pointed in section 4.1 to the more prominent role of formal jobs in job finding to explain cyclical variations in unemployment. Figure 2 confirms this result also holds for all time horizons, as it shows that the contribution of the flow from unemployment to formal jobs (u->f) is more relevant than the contribution of the flow from unemployment to informality (u->n). It is also noticeable that the contribution of the latter flow is negative throughout all time horizons.

FIGURE 2

Contribution of exit from unemployment (u) to formal (f) and informal (n) jobs



Authors' elaboration.

Obs.: The horizontal axis represents quarters, and the last point corresponds to the steady state. The results are based on the decomposition put forward by Moreira, Foguel and Corseuil (2021).

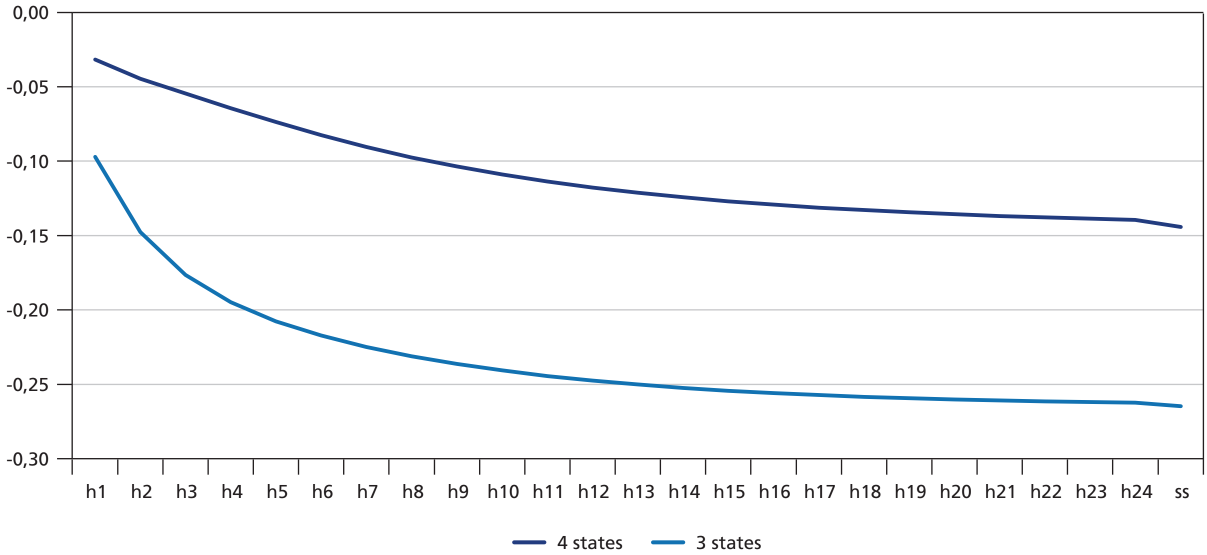
5.3 Reviewing the comparisons between 3- and 4-states representations of the labor market

Variance decompositions based on alternative proxies for the unemployment can also be useful to check the robustness of the result that the 4-states representation of the labor market seems superior to the 3-states representation for decompositions of cyclical unemployment. This result was based on a smaller contribution of the proxy error to decompose the variance of the observed unemployment rate when the 4-states representation was used (table 2).

Figure 3 evinces the robustness of this result as it shows that the contribution of the proxy error is much lower for any projection horizon for the 4 states than for 3 states representation of the labor market.[7]

7. For this calculation we rely on (observed) unemployment variance decompositions analogous to the one described in expression (5); replacing components defined using steady state unemployment by components defined using projected unemployment.

FIGURE 3
Contribution of the proxy error

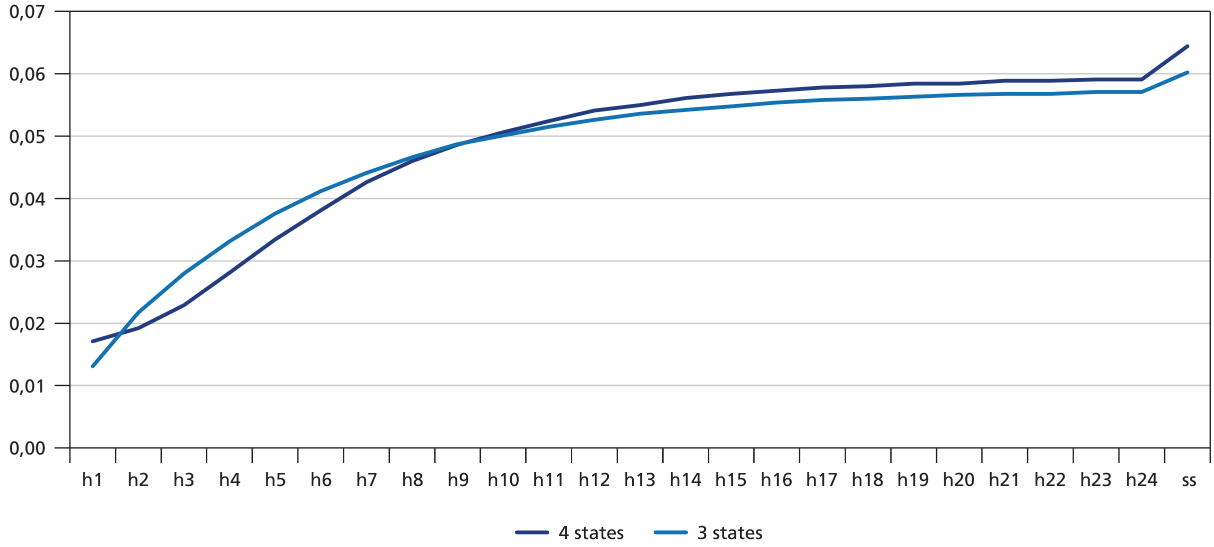


Authors' elaboration.
Obs.: The horizontal axis represents quarters, and the last point corresponds to the steady state. The results are based on the decomposition put forward by Moreira, Foguel and Corseuil (2021).

The other statistics we used to compare the 4-states and the 3states representations was the contribution of the linearization error. This is the difference between the unitary value and sum of all contributions of labor market flows to the variance of the steady-state unemployment rate. The result presented in the second column of table 2 shows very similar values of this statistics for both representations. Figure 4 confirms that the linearization error is very similar for the 3- and 4-states representations not only for the steady-state proxy of unemployment, but also for proxies based on projections for almost all time horizons. The exception is for the period between the 3rd and 7th quarters, for which the 4-states representation presents slightly smaller errors than its 3-states counterpart.

FIGURE 4

Linearization error for the 3- and 4-state representations



Authors' elaboration.

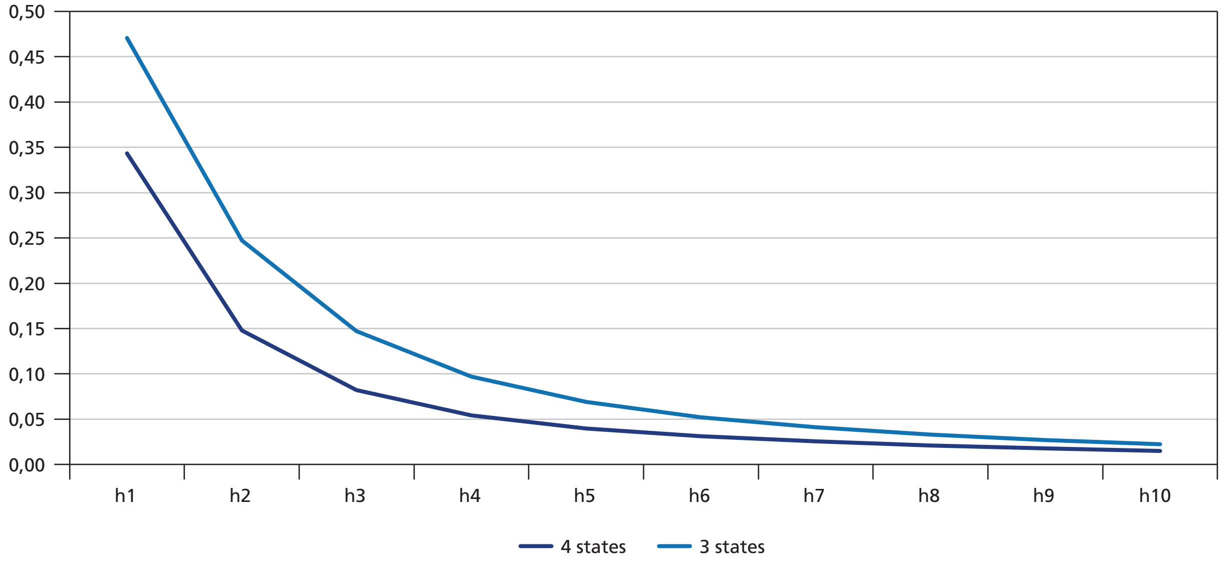
Obs.: The horizontal axis represents quarters, and the last point corresponds to the steady state. The results are based on the decomposition put forward by Moreira, Foguel and Corseuil (2021).

This analysis can be expanded adding an additional statistic to compare the adequacy of the 3- and 4-states contexts. As we mentioned before, β_0^h in expression (6) captures the contribution of the initial conditions and the higher this statistic the less informative is the model with respect to the contribution of the relevant flows to the variance of unemployment. When contrasting the 3- and 4-states representations, we can also compare the relative importance of the initial conditions between the two representations, which is illustrated in figure 5 below.

The pattern reported in figure 5 shows that the contribution of the initial conditions is always higher in the 3-states representation than in the 4-states representation.[8] In other words, the relative contribution of the relevant labor market flows is lower for the 3-states representation than for its 4-states counterpart. This implies that variance decompositions of a wide range of proxies for unemployment are less informative when such decompositions are based on the former than in the latter representation.

8. We limit the horizontal axis up to 10 quarters, as the contributions remain virtually null for larger projection horizons.

FIGURE 5
Contribution of the initial condition to the variance of projected unemployment rate



Authors' elaboration.
Obs.: The horizontal axis represents quarters, and the last point corresponds to the steady state. The results are based on the decomposition put forward by Moreira, Foguel and Corseuil (2021).

In sum, we have shown in this subsection that, while the linearization error is similar between the 3- and the 4-states representations for various time horizons (including the steady-state), other statistics such as the proxy error and the importance of otherwise uninformative initial conditions evince that the 4-states context is more appropriate than the 3-states context to perform variance decompositions of several projections of the unemployment rate. Thus, separating the employment state into formal and informal states seems to bring a gain in terms of accuracy for decompositions of cyclical unemployment.

6 CONCLUSION

In this paper, we have conducted several decompositions of cyclical unemployment departing from the usual three states representation of the labor market (employment, unemployment, and inactivity) by partitioning the employment state into formal and informal states. This new setup is particularly relevant for developing countries where informality is an important feature of labor markets and therefore has potential implications for the dynamics of unemployment. Our data are for Brazil, a large developing country for which one can construct labor market flows for an extensive period. Methodologically we implement the standard steady-state decomposition used in the literature as well as a decomposition for the variance of the actual unemployment rate. For robustness, we also conduct decompositions for projections of the unemployment rate over a large range of time horizons.

The first contribution of the paper was to show that the relative contribution of the flows between employment and unemployment depends on whether one is considering formal or informal forms of employment. While informal employment drives the contribution of job separations to unemployment variance, formal employment dominates the contribution of job finding to unemployment variance. This distinction was completely hidden in the three states representation and confirms the importance of a finer treatment of the employment state to unveil the dynamics of unemployment in a richer way.

The second contribution of the paper was to provide evidence that the four states representation performs better than the three states one to model unemployment dynamics. This was evinced through easily implemented indicators of model performance and was also shown to be robust to projections of the unemployment rate over various time horizons (including the steady-state one). Thus, the gain in information with a finer treatment of the employment state does not come at the cost of any loss in model performance.

One should have in mind that a four states representation can be used to accomplish any partition of employment in two groups, including alternatives suitable labor markets of developed countries. For instance, one may think in jobs with lower and higher adjustment costs such as temporary or part-time jobs, which are forms of employment that have gained in importance in developed countries in the last years.

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