The Ins and Outs of Unemployment in a Dual Labor Market

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Resumo

Este artigo estende o modelo tradicional de fluxos de entrada e saída do desemprego para incorporar dois tipos de emprego. Um modelo de quatro estados é apresentado e aplicado ao Brasil, onde a informalidade é marcante no mercado de trabalho. Os resultados indicam que a abordagem tradicional com três estados (desemprego, emprego e inatividade) é insuficiente para o entendimento completo da dinâmica do mercado de trabalho observada na última década, já que ele superestima a contribuição da probabilidade de saído do emprego para a queda do desemprego. Ao separar o emprego formal do informal, os resultados mostram que os principais fatores associados à queda na taxa de desemprego entre 2003 e 2014 foram (em ordem de importância): (i) a queda na taxa de participação que ocorreu por conta de uma menor taxa de entrada na PEA; (ii) o aumento da probabilidade de entrada no emprego formal e (iii) a queda na probabilidade de entrada no desemprego observada pelos trabalhadores com carteira assinada.

Abstract

This paper extends the traditional literature on flows into and out of unemployment by accounting for two different types of employment. We develop a four-state model and apply it to Brazil, where formal and informal work are both relevant in the labor market. Our findings suggest that the standard three-state approach is insufficient for a full understanding of the labor market dynamics witnessed in the past decade, since it overstates the contribution of the employment exit rate to the change in unemployment. When disentangling formal and informal work, we find that the main drivers of the decline in the unemployment rate between 2003 and 2014 were (in order of relevance): (i) the decline in the participation rate that happened due to a decrease in the entries into the workforce (from inactivity); (ii) the increase in the formal job finding rate and (iii) the decline in the inflow from formal employment into unemployment.

Keywords: unemployment, employment flows, transition rates, participation rate.

JEL Classification: J6, E24, E32

1. Introduction

What drives the unemployment dynamics: inflows or outflows? Many authors raised this question in the past decade, and still no consensus has emerged: answers change according to the countries where the analysis is made and also depend on the methodology adopted in each study. Understanding the unemployment rate dynamics is extremely relevant for macroeconomic and labor market policies, since the absence or presence of cyclicality in separations/admissions should drive employment protection policies and researchers' attention.

While Hall (2005) and Shimer (2007 and 2012) found that in the US outflows dominates the unemployment rate's dynamics, Fujita and Ramey (2009) and Elsby et al. (2009) have argued the opposite. Petrongolo and Pissarides (2008) found that in the UK and in Spain the inflow rate explains roughly half of the changes in unemployment dynamics, whereas in France the outflows are more relevant. Smith (2011) contributed by developing a slightly different framework that accounts for deviations in the equilibrium unemployment rate. We make a different, but in our view also relevant contributions to the theory developed by these authors.

The contributions of this paper are twofold. First, we extend the traditional framework that calculates the relative importance of changes in inflow and outflow rates to equilibrium unemployment dynamics by incorporating a second employment status. This is particularly relevant for economies with large informal sectors, but even in the developed world this might be useful. Particularly after the Great Recession, structural changes in the labor markets are occurring throughout the world, with increases in the share of part time work and contingent work. Attachment to employment or the labor force might be different depending on the type of employment relationship, and thus accounting for these two different states might be relevant.

Second, we investigate three relevant changes in the Brazilian labor market that occurred in the past decade: the decline of roughly seven percentage points in the unemployment rate (see Figure 1), the increase of more than 10 p.p. in the share of formal employment from and the decline of roughly 1.5 p.p since 2012 in the share of the working age population that engages in the labor market (the participation rate).

Menezes Filho et al. (2014) documented that the separation rate declined and the job finding rate increased in Brazil in recent years and that both movements contributed to the decline in the unemployment rate, but they argue that the latter explained almost entirely the unemployment variation between 2002 and 2009. Silva and Pires (2014), using the standard framework to assess which flows are more relevant to explain the unemployment dynamics in Brazil, find the opposite and argue that more than 80% of the unemployment rate variation is explained by changes in the separation rate (inflows). Attuy (2012) find similar results, even though his focus is on the relationship between unemployment, transitions and the business cycle. However, the last two papers do not pay proper attention to movements in and out of the labor force, even if their modeling strategy allows for it; also, there seems to be a confusion in both papers regarding what they are actually measuring. The authors sometimes refer to the contributions of changes in the transitions rates' volatility to the unemployment rate's volatility as if they were contributions of changes in the level of each rate to the level of unemployment.

Figure 1 - Unemployment and participation rates in Brazil
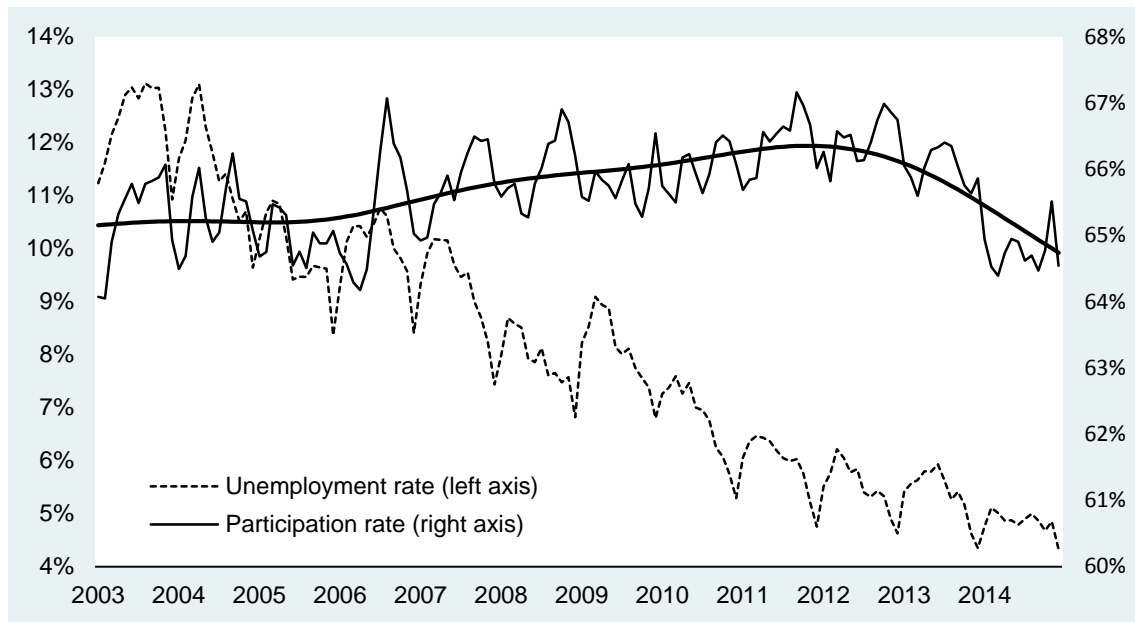
Note: Unemployment and participation rate are calculated based on PME (IBGE) data for individuals aged 15 years of age or more. Thick lines depict each series' HP filtered trend, using a smoothing parameter of 14,400.

Still, our findings show that in the traditional three state world, indeed it was the decline of the inflows into unemployment that explain almost half of the decline in unemployment in Brazil between 2003 and 2014. However, when disentangling informal and formal employment (and thus allowing for a fourth state in the labor market), the most relevant change was the decline in the likelihood of entering the workforce. If analyzing employment types separately, the outflows of unemployment into formal employment explained slightly more than the inflows (i.e. formal job finding rates dominate), whereas regarding informal employment and unemployment, inflows and outflows almost offset each other. It seems relevant, thus, to account for different labor market statuses in this type of analysis.

This paper is organized as follows. Section 2 describes the data used throughout this paper. Section 3 describes the standard three-state model used in the literature to assess changes in the unemployment rate and describe the results of such model when applied to the Brazilian case. Section 4 extends this model to account for two different employment types and shows how results change with this improvement. Section 5 concludes.

2. Data

This paper uses the *Pesquisa Mensal de Emprego* (Monthly Employment Survey, henceforth PME), a monthly rotating panel of households in six major metropolitan areas in Brazil (São Paulo, Rio de Janeiro, Belo Horizonte, Salvador, Porto Alegre and Recife) surveyed by IBGE (Brazilian Institute of Geography and Statistics). The six regions represent roughly 25% of the country's population, providing a reach set of information on employment in Metropolitan Areas in Brazil. The paper covers the period from January, 2003 to December,

2014[3]. The survey investigates schooling, labor force status, demographic attributes, and labor income of each dweller aged 10 or more that lives on the surveyed households. This yields approximately 100,000 individuals from 35,000 households every month. We restrain our sample to individuals aged between 15 and 70 years.

The rotating scheme is as follows. Each household is surveyed during the first four consecutive months. After this initial period, the household leaves the sample for eight months and then returns to the panel and is interviewed again for another four consecutive months. After the eighth interview the household is permanently excluded from the sample. Households are divided into 4 rotating groups in order to ensure that 75% of the sample is repeated in two consecutive months.

Shimer (2012) argues that using survey data to measure the transition rates might yield biased estimates due to time aggregation. In fact, several countries carry labor force surveys on a quarterly basis, and both Shimer (2012) and Gomes (2015) show that quarterly data underestimate the probability of transiting between states, because some individuals can move more than once during this relatively long time span. Shimer (2012) proposes a method to recover the instantaneous transitions, which he used in his study of the US case. However, Petrongolo and Pissarides (2008) argue and Gomes (2015) shows that for monthly surveys, time aggregation does not influence their results, whereas calculations based on quarterly surveys are quite significantly affected. Based on Petrolongo ans Pissarides, we have used discrete monthly transitions rates to obtain the results described later in this paper.

One important caveat of PME survey is that it does not identify individuals directly. Only their households are identified, making it difficult to match each person over time. Also important to highlight is the fact that in each household only one individual answers the questions for all members in each round. Thus, attrition and reporting errors occur with a high frequency. For instance, it is common to have more than two years of difference in age or schooling in two consecutive months for the same individual. We follow the matching algorithm proposed by Ribas and Soares (2008), which corrects for misinformation on individuals' characteristics and reduces attrition. After pairing each individuals and restraining the sample to the working age population (between 15 and 70 years of age), our database contains 11,623,365 observations.

Because we are interested in transition rates, we only keep the observations for which we have information for two consecutive months. To avoid attrition bias (which still remains even after pairing individuals as shown by Ribas and Soares, 2008) we only use the first four months of each household's interviews. For instance, for any given individual, if s/he participated in all four interviews, she will contribute with three observations: the pairs of interviews (1, 2), (2,3) and (3,4). If there was attrition and she did not complete the four first interviews, we will have less contributions. We then pool all pairs of information into one single dataset and discard individuals with missing employment status information on one of both sequential periods. This leaves us with 5,505,985 observations in the dataset.

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[3] We will focus on transition rates between employment statuses considering two consecutive months. Thus, to assess the period from January, 2003 to December, 2014 we used observations since December, 2002.

For the objective of this paper, we must also examine carefully the impact of response errors. To put it shortly, response errors occur whenever the interviewed member of the household misreports the labor status of any of the other inhabitants of the household (see Zylberstajn, 2015; Abowd and Zellner, 1985; Smith, 2011; Gomes, 2015). As Smith (2011) and Gomes (2015) point out, this error can be particularly relevant for our study, since they create spurious transitions. In our case, the most relevant cases of misreporting are answers regarding to formal and informal work and out of labor force and unemployed status. For instance, it is common to find in the data individuals who are reported as informal workers in a given month, than in formal employment in the subsequent month and back to informal in the next period, but on the same time with long employment spells recorded in every interview (and thus with an inconsistent employment history). Because of the way formal employment is defined (the employer must sign each workers *carteira de trabalho*; if she does not sign, than the job relation is considered informal), the interviewed member might not have perfect information on the member of interest's *carteira* status (remember that in each round the respondent might change) and be confused or mistaken when answering the survey. Thus, the likelihood of misreporting formal/informal employment might be high. The same holds for every other employment status, including unemployment and non-participation.

We follow the correction algorithm proposed by Zylberstajn (2015) to address the misreporting issue. By adopting this procedure, we corrected 7.92% of individuals' labor status (a total of 435,785 observations). This apparently small share of response error actually decreased average transitions significantly, and has caused a decrease of approximately 1 percentage point in the average unemployment rate for 2003:01 to 2014:12 (see Table 1 and Table 2). Smith (2011), also faces a similar pattern depending on the method adopted for the correction. We refer the reader to Zylberstajn (2015) for details on the correction procedure. Whenever we present results throughout the paper, we will always show the results for both the corrected and original data. Often, the results do not change significantly. What is most important is that there is a substantial commonality across the corrected and original series.

We are interested in the information on each individual's employment status. Originally, we would observe in the data seven possible classifications: out of the labor force (OLF), unemployed, unpaid worker, self-employed, employer, informal employee and formal employee. We grouped the categories by reclassifying the unpaid workers as OLF, self-employed and informal employees as informal employment and employers and formal employees as formal employment. This is important for the four-state model we describe in section 4, which accounts for OLF, unemployment and formal and informal employment only.

An interesting test is to compare the average transition rates for Brazil with those reported by Gomes (2015) for the US, based on CPS data. Results for the transitions involving employment (E, considering both formal and informal as one status), unemployment (U) and inactivity (I) are shown in Table 2. It is interesting to note that after correcting for response error we have obtained smaller values and volatilities for the transition probabilities (as would be expected), and the US serves as a good benchmark (remember that there is no response error correction in the US estimates).

Table 1 – Labor status distribution after correcting for response error

	Original		Corrected	
	Obs.	*%*	*Obs.*	*%*
Out of labor force	1,915,093	34.8%	1,946,637	35.4%
Unemployed	318,034	5.8%	268,896	4.9%
Self employed	620,677	11.3%	624,815	11.4%
Employer	146,252	2.7%	139,505	2.5%
Informal employment	624,317	11.3%	594,005	10.8%
Formal employment	1,880,985	34.2%	1,931,500	35.1%
Total	**5,505,985**	**100.0%**	**5,505,985**	**100.0%**

Source: Author's calculations based on PME (IBGE) for the period 2003:01 to 2014:12.

Note: unpaid workers are considered out of the labor force, self-employed and informal employees are grouped into informal employment and employers and formal employees are grouped into formal employment.

**Table 2 – Level and volatility of transition probabilities**

Mean	US (CPS)	Brazil (original)	Brazil (corrected)
E → U	0.015	0.012	0.008
E → I	0.029	0.040	0.015
U → E	0.260	0.162	0.122
U → I	0.221	0.294	0.121
I → E	0.046	0.059	0.028
I → U	0.026	0.042	0.018
Volatility			
E → U	0.0025	0.0042	0.0027
E → I	0.0026	0.0038	0.0015
U → E	0.0405	0.0184	0.0198
U → I	0.0240	0.0311	0.0176
I → E	0.0040	0.0057	0.0027
I → U	0.0035	0.0118	0.0050

Note: Average transition rates and standard deviation from 2003:1 to 2014:12 for Brazil. Correction for response errors follow the algorithm proposed in Zylberstajn (2015). For the US, transitions rates and standard deviation from 1976:2 to 2011:6.

Sources: Author's calculations based on PME (IBGE) for the Brazilian data and Gomes (2015) for the US.

Figure 2 displays the observed separation and finding rates and the transition rates into and out of inactivity. The top left panel shows that the transition rate U→I has been rising since 2005, while the job finding rate has risen between 2006 and 2012, and declined afterwards. Other important trends are the continuous decline in the separation rates (i.e. the transitions E→U and E→I) and the sharp fall in the transitions rates I→U during the entire analyzed period. Finally, the decline in transitions from inactivity into employment after 2012 is also worth noting. We can state that 2012 seems to be a turning point in the movements of some relevant transition rates.

Figure 2 – Monthly transition rates: unemployment, employment and inactivity
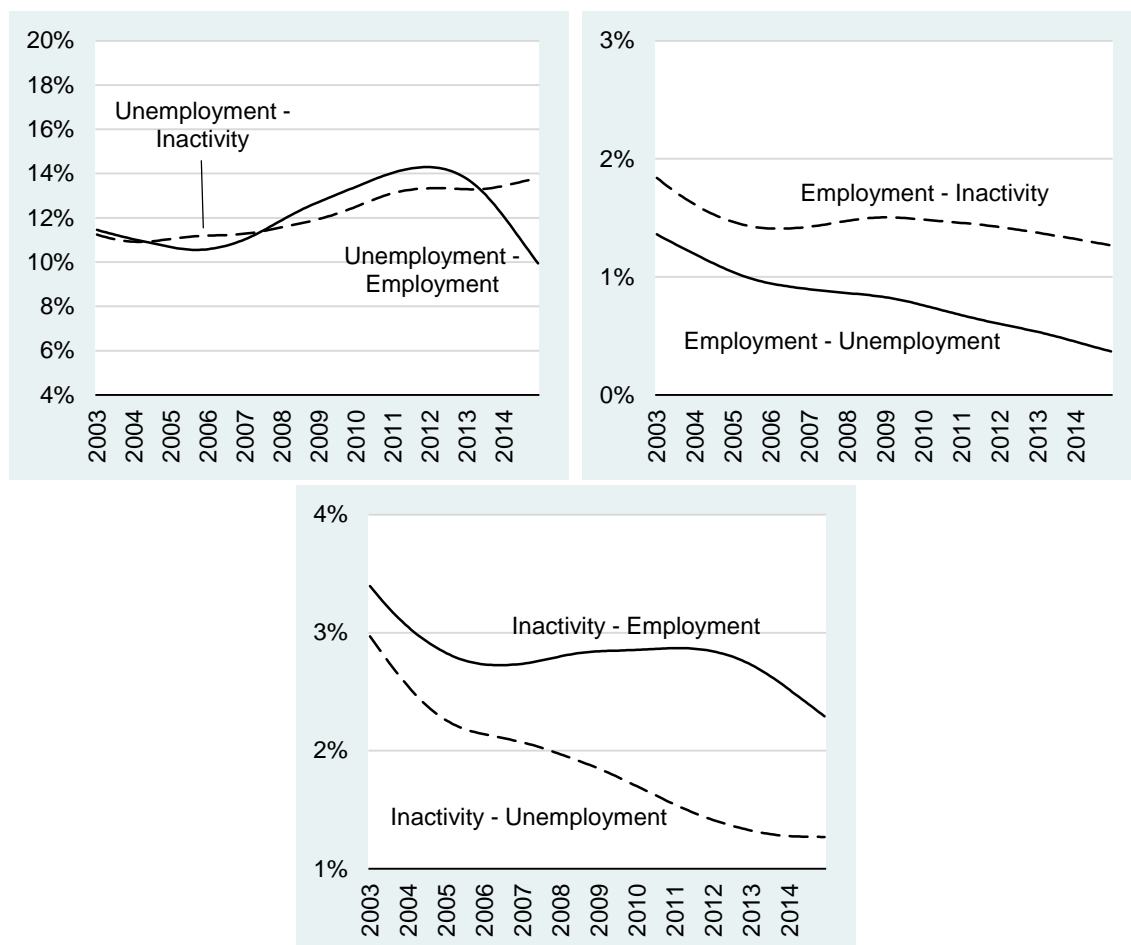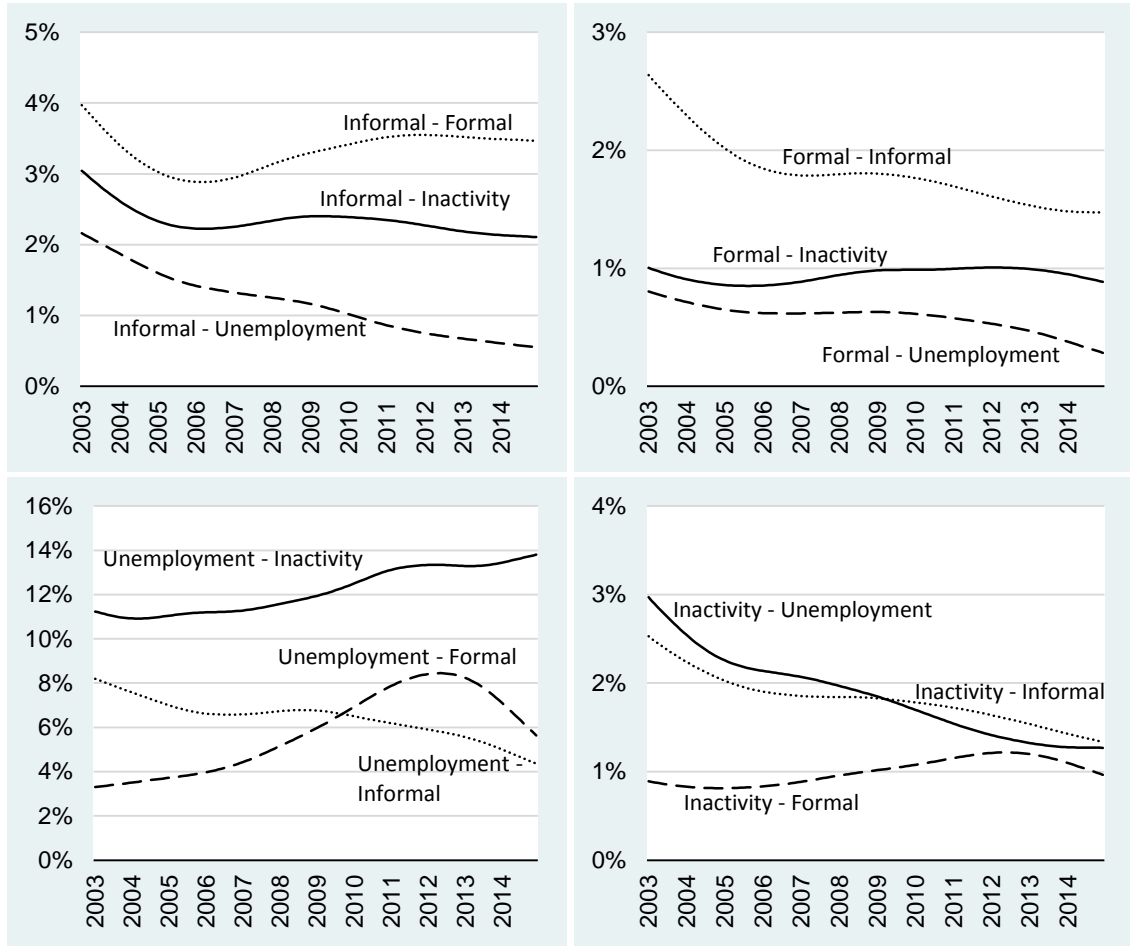

Note: The six monthly transition rates are derived from PME (IBGE) and smoothed using an HP filter with parameter 14.400. Response errors are corrected using the algorithm proposed in Zylberstajn (2015).

One important feature of developing economies is the presence of a large informal sector in the labor market. As Figure 3 shows, transitions into and out of formal employment have evolved in remarkably different paths when compared to transitions into and out of informal employment. If we followed the standard methodology of the literature and focused only on the traditional three states (considering employment as a whole), the relevant interactions between formality and informality would be missed.

Figure 3 breaks down the same transitions shown in Figure 2, but it considers formal and informal employment as two different states (we consider self-employment as informal and employers as formal employment). For instance, the transition U→E has two distinct dynamics when the formal-informal dichotomy is considered (bottom left panel). The difference may be observed comparing top left panel of Figure 3. The informal job finding rate has been falling since 2006 and is still following this trend, whereas the formal job finding rate rose sharply since 2006 but since 2012 is rising by a smaller pace. Similar patterns are exhibited by other transitions: formal and informal employment have trailed opposing paths in the last decade. This is particularly relevant because, as we will show, the formalization of the labor market accounts for a large share of the decline in the unemployment rate.

Figure 3 – Monthly transition rates: unemployment, formal/informal employment and inactivity

Note: The six monthly transition rates are derived from PME (IBGE) and smoothed using an HP filter with parameter 14.400.

3. Using flows to assess unemployment dynamics

We begin describing a two-state model of employment status exactly as Petrongolo and Pissarides (2008) and Smith (2011). At any time t individuals can either be employed (E_t) or unemployed (U_t). The unemployment rate is, by definition, $u_t = U_t / (U_t + E_t)$ and evolves according to:

$$\dot{u}_t = s_t e_t - f_t u_t = s_t(1 - u_t) - f_t u_t \tag{1}$$

where e_t is the employment rate, f_t is the job finding rate and s_t is the separation rate at time t (or, respectively, the instantaneous time unemployment outflow and inflow rates). In steady state $\dot{u}_t = 0$, so the unemployment rate can be expressed as:

$$u_t = \frac{s_t}{s_t + f_t} \tag{2}$$

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The advantage of using this expression to calculate the unemployment rate is that one can decompose changes in the unemployment rate according to changes in the inflow or outflow rates.

In order to account for inactivity, we continue to follow both Petrongolo and Pissarides (2008), Smith (2011) and also Shimer (2012). In a three-state world where individuals can also be out of the labor force (I), the dynamics of each state can be described by the following equations:

$$\dot{U}_t = \lambda_t^{EU} E_t + \lambda_t^{IU} I_t - (\lambda_t^{UE} + \lambda_t^{UI}) U_t \tag{3}$$

$$\dot{E}_t = \lambda_t^{UE} U_t + \lambda_t^{IE} I_t - (\lambda_t^{EU} + \lambda_t^{EI}) E_t \tag{4}$$

$$\dot{I}_t = \lambda_t^{UI} U_t + \lambda_t^{EI} E_t - (\lambda_t^{IU} + \lambda_t^{IE}) I_t \tag{5}$$

where λ_t^{AB} describes the transition rate at time t between states A and B.

In steady state, $\dot{U}_t = \dot{E}_t = 0$, so we can rearrange (3) and (4) and express U_t as a function of N_t and the transition probabilities:

$$(\lambda_t^{IE} \lambda_t^{UE} + \lambda_t^{IE} \lambda_t^{UI} + \lambda_t^{IU} \lambda_t^{UE}) U_t = (\lambda_t^{IU} \lambda_t^{EI} + \lambda_t^{IU} \lambda_t^{EI} + \lambda_t^{IE} \lambda_t^{EU}) E_t \tag{6}$$

Recalling that $u_t = U_t / (U_t + E_t)$, we can express the steady state unemployment rate only in terms of the six transitions rates:

$$u_t = \frac{\lambda_t^{EU} + \dfrac{\lambda_t^{IU}}{\lambda_t^{IU} + \lambda_t^{IE}} \lambda_t^{EI}}{\lambda_t^{EU} + \dfrac{\lambda_t^{IU}}{\lambda_t^{IU} + \lambda_t^{IE}} \lambda_t^{EI} + \lambda_t^{UE} + \dfrac{\lambda_t^{IE}}{\lambda_t^{IU} + \lambda_t^{IE}} \lambda_t^{UI}} \tag{7}$$

The expression above is essentially similar to equation (2). The numerator accounts for the separation rates from employment to unemployment and to inactivity, but the latter needs to be 'rescaled' in order to have its impact in the unemployment rate appropriately measured. The same rationale applies to the finding rate, which now should be thought of as the share of unemployed that leaves unemployment (either to employment or to inactivity).

Using the measures of the transition rates described in the previous section, we are now able to construct a series for the steady state unemployment rate, as depicted in Figure 4. The adopted method replicates well the actual unemployment rate: the correlation between the actual and the steady state unemployment rates is 0.965.

Figure 4 – Unemployment rate
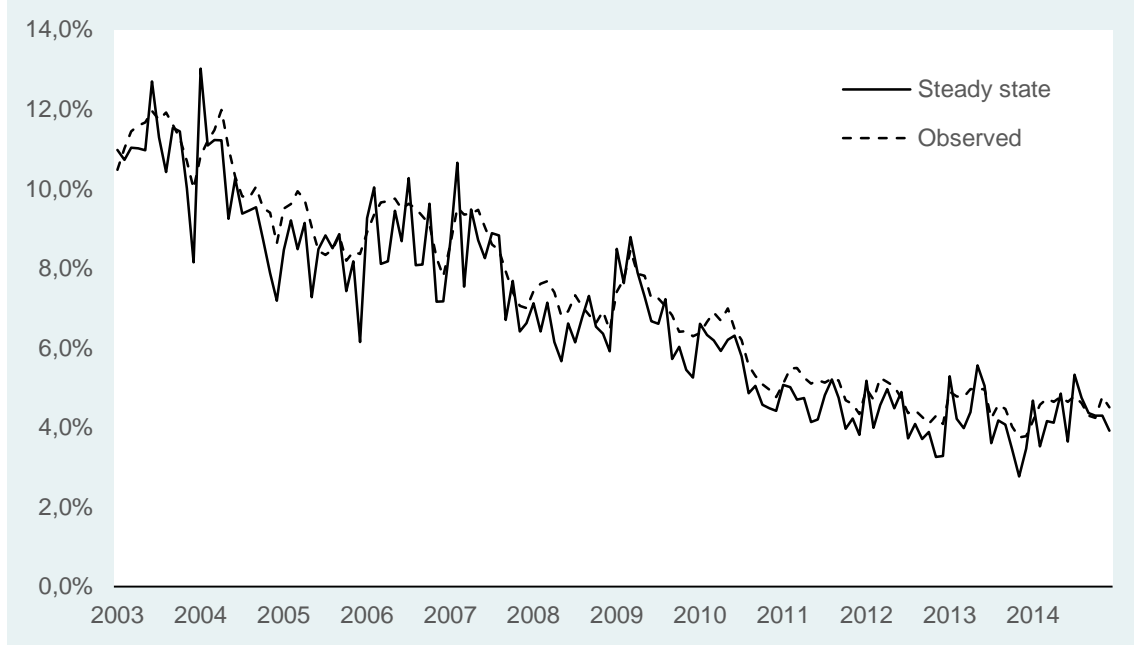
Note: Steady state unemployment is calculated according to Eq. (7) using the six monthly transition rates derived from PME (IBGE) data and corrected for response error as described in Zylberstajn (2015).
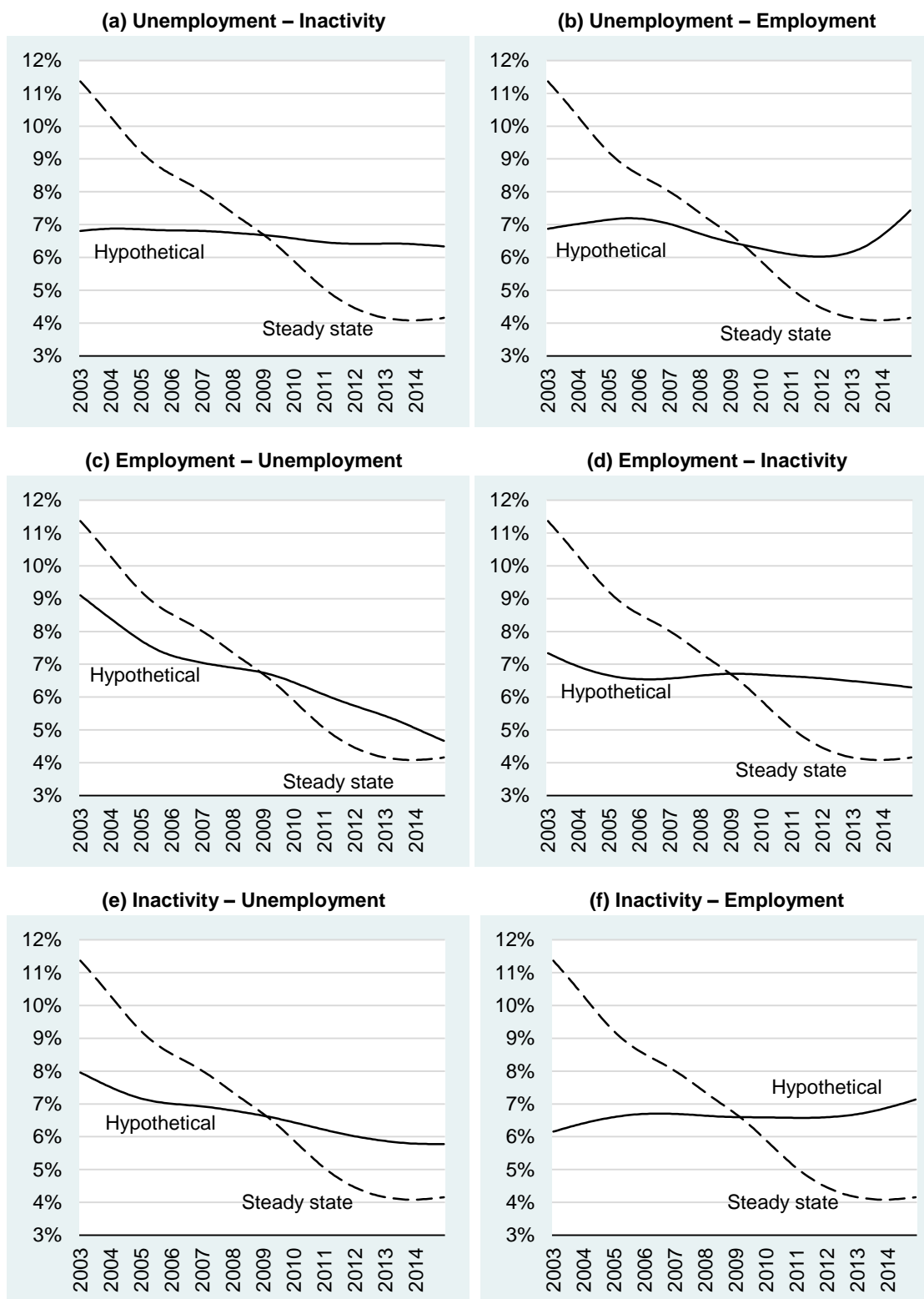
We follow Shimer (2012) to measure the contribution of the changes in each of the transition rates to the change in the unemployment rate. The method is simple: first, we construct the hypothetical unemployment rate using equation (7) holding every transition rate constant (and equal to their historical average), allowing only the transition of interest to change. For instance, the hypothetical unemployment rate had only the transition E→U changed is given by:

$$u_t^{EU} = \frac{\bar{\lambda}^{EU} + \frac{\bar{\lambda}^{IU}}{\bar{\lambda}^{IU} + \bar{\lambda}^{IE}}\bar{\lambda}^{EI}}{\lambda_t^{EU} + \frac{\bar{\lambda}^{IU}}{\bar{\lambda}^{IU} + \bar{\lambda}^{IE}}\bar{\lambda}^{EI} + \bar{\lambda}^{UE} + \frac{\bar{\lambda}^{IE}}{\bar{\lambda}^{IU} + \bar{\lambda}^{IE}}\bar{\lambda}^{UI}} \tag{8}$$

where $\bar{\lambda}^{AB}$ is the average transition rate A→B between January 2003 and December 2014. We do this for every transition rate between the three states u_t^{EU}, u_t^{EI}, u_t^{UE}, u_t^{UI}, u_t^{IE}, u_t^{IU}. This exercise yields the series shown in Figure 5.

Clearly, the main drivers of the decline in unemployment in the past decade were the decline in the E→U (panel c) and in the I→U (panel e) movements. On the other hand, it is worth noting that the job finding rate (U→E and I→E transitions, panels b and f) have both recently contributed to an increase in unemployment, even though this contribution has been offset by the movements in the other transition probabilities and we have not seen unemployment rise (at least not until the end of 2014).

Figure 5 – Contribution of fluctuations in transition rates to the unemployment rate

(a) Unemployment – Inactivity

(b) Unemployment – Employment

(c) Employment – Unemployment

(d) Employment – Inactivity

(e) Inactivity – Unemployment

(f) Inactivity – Employment

Note: Each panel show the steady state unemployment rate (dashed line) and the hypothetical unemployment if there were only fluctuations in each subtitled transition rate (all others are held constant and equal to their 2003-2014 average). All calculations are based on PME (IBGE) data. Transitions rates are smoothed using an HP filter with parameter 14.400.

Next, we calculate the contribution of each transition rate as $\beta_{AB} = \frac{cov(u_t^{AB}, u_t)}{var(u_t)}$, where u_t is defined in equation (7) and u_t^{AB} is defined in equation (8). Notice that β_{AB} is the coefficient of the regression of the hypothetical unemployment on the steady state unemployment rate[4]. The results of this decomposition are shown in Table 3[5].

The first column of the table below shows each β for the entire period (2003-2014), without any correction to the data. The second column shows the results after correcting for response bias and will be the subject of our analysis. The results confirm what we described based on the visual inspection we had done when analyzing Figure 5: transitions from employment into unemployment (inflows) contributed to roughly 48% of the decline in unemployment, whereas transitions from inactivity into unemployment accounted for approximately 27%. The third most relevant transition was U→E, which contributed to 13% to the change in the unemployment rate, but this contribution was partially offset by the I→E movements (-5%). Results do not change significantly if we don't correct for response bias, except for the contribution of I→U, which is higher in the original (uncorrected) data. We argue that this result is both expected and imprecise, because a share of these transitions are spurious.

Table 3 – Decomposition of the change in the unemployment rate

Transition	2003-2014 (Original)	2003-2014 (Corrected)
E → U	0,412	0.481
E → I	0,061	0.065
U → I	0,093	0.080
U → E	0,058	0.126
I → U	0,447	0.266
I → E	-0,076	-0.048

Note: Each row shows the covariance of u_t^{AB} and u_t divided by the variance of u_t. All calculations are based on PME (IBGE) data. Transitions rates are smoothed using an HP filter with parameter 14.400. The first column shows the results for the original dataset, while second shows the results after correcting for response errors following the algorithm described in Zylberstajn (2015).

In short, the results for the three-state model highlight two key factors that explain the decline in the unemployment rate between 2003 and 2014 in Brazil. First, contrary to what Shimer (2012) documented for the US, the 'ins win' in Brazil: inflows into unemployment were more relevant to explain the unemployment rate movements in the past decade than the outflows (given by job finding rates). Given that in this period there was a significant decline in unemployment, an appropriate expression for this phenomenon would be *employment hoarding*, a situation where workers are less likely to move into

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[4] This is not an exact decomposition; the sum of all betas for the entire period 2003:1 – 2014:12 is 0.970.

[5] Other authors, such as Petrongolo and Pissarides (2008), adopt a slightly different approach. They decompose Δu_t into Δs_t and Δf_t and only then apply the beta approach to the Δ series. This method does not measure the contribution of each of the transitions to Δu_t; rather, it yields the contribution of each of the transition rates variation to the unemployment rate **volatility**. Even though they clarify what they are measuring, other papers that followed (such as X and Y) seem to miss the difference.

unemployment. It is worth mentioning that employment hoarding is different from job hoarding: an increase in the attachment to employment does not (necessarily) mean that the attachment to the same job increased (in fact, as Chapter 2 shows, job turnover increased dramatically, i.e. job-to-job transitions increased). It means only that workers are less prone to return to the condition of being unemployed.

Second, the *decrease in the participation rate* that happened through *less frequent movements into the workforce*, also played a key role in the unemployment rate movement. These two phenomena are perhaps two sides of the same coin: if there are less persons entering the workforce, those who want to work will be more likely to be employed, or perhaps if workers have increased their attachment to employment, there is less room for new entrants (we cannot establish any causality).

4. Accounting for informality

We now propose a model with for states. In this specific application, we consider state 0 (N_0) to be formal employment and state 1 (N_1) to be the informal sector, while unemployment (U) and inactivity (I) are the other possible positions. It is worth mentioning that in advanced economies the differentiation might also be useful in other labor market dimensions, such as part-time and contingent work.

The procedure is the same as before. Unemployment, formal and informal employment and inactivity evolve according to:

$$\dot{U}_t = \lambda_t^{0U}E_t^0 + \lambda_t^{1U}E_t^1 + \lambda_t^{IU}I_t - (\lambda_t^{U0} + \lambda_t^{U1} + \lambda_t^{UI})U_t \tag{9}$$

$$\dot{E}_t^0 = \lambda_t^{U0}U_t + \lambda_t^{I0}I_t + \lambda_t^{10}E_t^1 - (\lambda_t^{0U} + \lambda_t^{0I} + \lambda_t^{01})E_t^0 \tag{10}$$

$$\dot{E}_t^1 = \lambda_t^{U1}U_t + \lambda_t^{I1}I_t + \lambda_t^{01}E_t^0 - (\lambda_t^{1U} + \lambda_t^{1I} + \lambda_t^{10})E_t^1 \tag{11}$$

$$\dot{I}_t = \lambda_t^{UI}U + \lambda_t^{0I}E_t^0 + \lambda_t^{1I}E_t^1 - (\lambda_t^{IU} + \lambda_t^{I0} + \lambda_t^{I1})I_t \tag{12}$$

In steady state, the flows in and out each type of employment are equal, as are the flows in and out of unemployment: $\dot{U}_t = \dot{E}_t^0 = \dot{E}_t^1 = 0$. Similarly to the case of three states, by manipulating (9), (10) and (11) we get:

$$(\lambda_t^{I0}(\lambda_t^{U0} + \lambda_t^{U1} + \lambda_t^{UI}) + \lambda_t^{IU}\lambda_t^{U0})U_t = (\lambda_t^{IU}(\lambda_t^{01} + \lambda_t^{0U} + \lambda_t^{0I}))E_t^0 + (\lambda_t^{I0}\lambda_t^{1U} - \lambda_t^{IU}\lambda_t^{10})E_t^1 \tag{13}$$

$$(\lambda_t^{I1}(\lambda_t^{U0} + \lambda_t^{U1} + \lambda_t^{UI}) + \lambda_t^{IU}\lambda_t^{U1})U_t = (\lambda_t^{IU}(\lambda_t^{10} + \lambda_t^{1U} + \lambda_t^{1I}))E_t^1 + (\lambda_t^{I1}\lambda_t^{0U} - \lambda_t^{IU}\lambda_t^{01})E_t^0 \tag{14}$$

The equations above are similar with each other and are also the four-state equivalent to equation (6). Because of the notation burden, we rewrite them simply as:

$$\tilde{f}U = \tilde{s}_0 E^0 + \tilde{s}_1 E^1 \tag{15}$$

$$\hat{f}U = \hat{s}_1 E^1 + \hat{s}_0 E^0 \tag{16}$$

where the subscript t is omitted, f refers to job finding rates and s refers to separation rates. Manipulating them the equations again we obtain the unemployment rate only in terms of the twelve transition rates at time t:

$$u = \frac{\tilde{s}_0 \left(\dfrac{\tilde{f}\hat{s}_1 - \hat{f}\tilde{s}_1}{\hat{f}\tilde{s}_0 - \widetilde{f\tilde{s}_0}} \right) + \tilde{s}_1}{\tilde{s}_0 \left(\dfrac{\tilde{f}\hat{s}_1 - \hat{f}\tilde{s}_1}{\hat{f}\tilde{s}_0 - \widetilde{f\tilde{s}_0}} \right) + \tilde{s}_1 + \tilde{f} \left(1 + \left(\dfrac{\tilde{f}\hat{s}_1 - \hat{f}\tilde{s}_1}{\hat{f}\tilde{s}_0 - \widetilde{f\tilde{s}_0}} \right) \right)} \tag{17}$$

which is the four-state model equivalent to equations (2) and (7).

Figure 6 – Unemployment rate
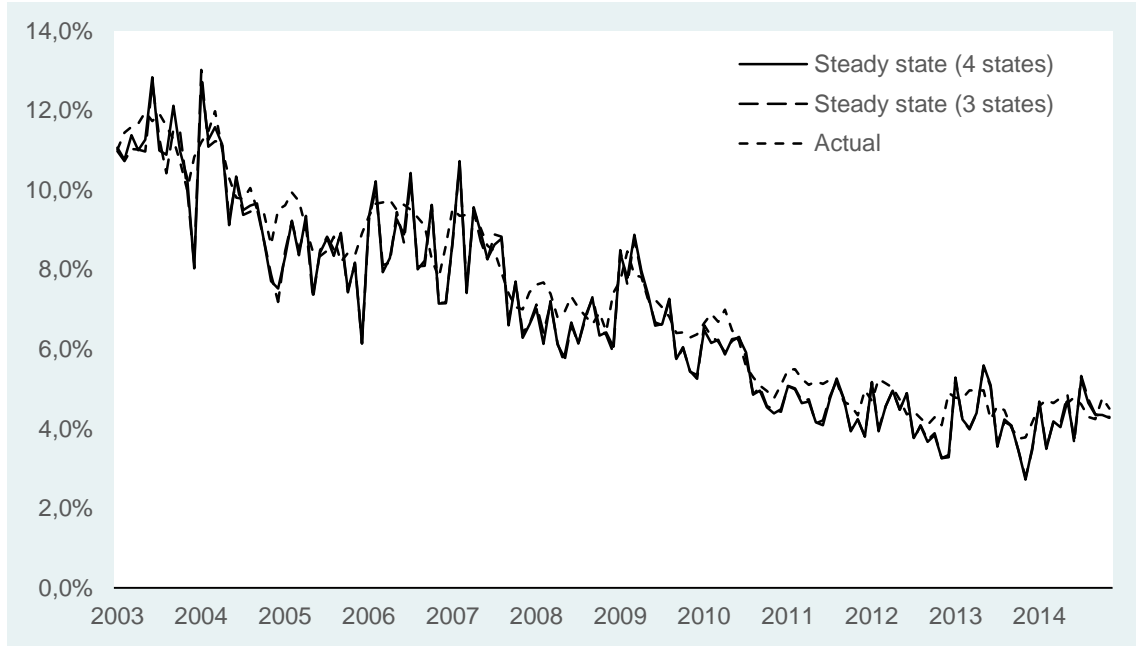
Note: Steady state unemployment is calculated according to Eq. (7) for the 3-state model and Eq. (17) for the 4 state-model, using the monthly transition rates derived from PME (IBGE) data after correcting for response bias. The correlation between both steady state series is 0.999.

Once again we follow Shimer (2012) and replicate the procedure from the previous section to measure the contribution of the changes in each of the transition rates to the change in the unemployment rate. We now have twelve hypothetical unemployment rates: u_t^{0U}, u_t^{0I}, u_t^{01}, u_t^{1U}, u_t^{1I}, u_t^{10}, u_t^{U0}, u_t^{U1}, u_t^{UI}, u_t^{I0}, u_t^{I1} and u_t^{IU}, where we remind that 0 refers to formal employment and 1 refers to informal employment. The series are shown in Figure 7.

In Section 3, our results showed that the transitions from unemployment into employment contributed little to the change in the unemployment rate (roughly 13%), i.e. the job finding rate did not play a key role to explain the decline in unemployment. Moreover, the key

conclusion was that the inflow into unemployment from employment was the most relevant factor for the decline in the unemployment rate.

With the four-state model, however, we conclude differently as Figure 7 and Table 4 show. First, the transition that contributed the most to the change in the unemployment rate is I→U, suggesting that the participation rate played a key role in the unemployment rate dynamics. The second most relevant contribution comes from U→Formal, i.e. the formal job finding rate. Remember that in the previous section the (aggregate) job finding was not especially relevant, but this was actually the aggregation of three different and large effects: First, the U→Formal movements accounted for 26% of the change in the unemployment rate, and this was because the formal job finding rate increased between January/2003 (3.6%) and December/2014 (5.7%). Second, U→Informal contributed with -20% to the decline in unemployment, meaning that unemployment would have risen by a significant amount due to the decline in the informal job finding rate. Third, we have the 15% contribution to the decline in the unemployment rate from the transition Formal→Informal.

The reduction in the Formal→Informal transition probabilities and its contribution to the unemployment reduction is a second-order effect, but with a high magnitude. The smaller frequency at which a worker moves from formal to informal employment itself plays a key role in the unemployment dynamics, possibly because once remaining formal, the likelihood of becoming unemployed is much smaller (see Figure 3).
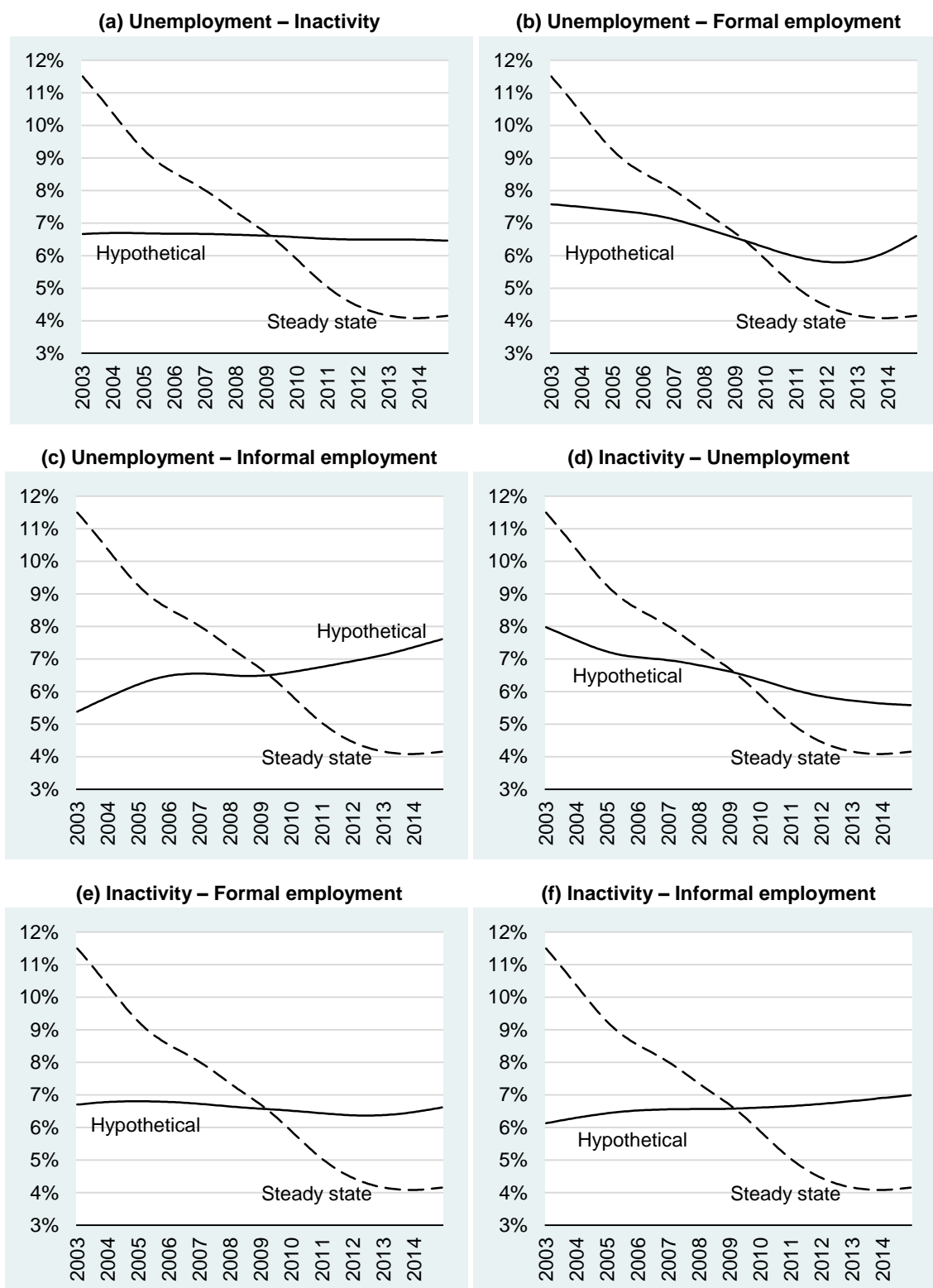
Our methodology does not allow to assess any causality, but these results indicate that either unemployment fell because of the formalization that took place in the Brazilian labor market, or conversely, the decline in unemployment induced the increase in the formal share of the market. In any case, we can establish a strong correlation between formalization and the reduction in the unemployment rate, which by itself is relevant for policy-makers. Further research is necessary to clarify the mechanics behind this phenomenon.

It is also worth pointing out that while Formal→U and U→Formal both contributed positively to the decline in unemployment, the respective movements from and into informal jobs have opposite signs. That is, in the formal sector it became both more likely to find a job *and* to remain in employment, whereas in the informal sector it is now less likely to find a job, but those that have one are more likely to keep it[6].

We can therefore summarize the forces that led to changes in the Brazilian unemployment rate between 2003 and 2014 in three main factors: (a) *Employment hoarding*, with 43% (the sum of Informal→U, Informal→I, Formal→U and Formal→I); (b) *Participation effect* which involves all transitions from and into inactivity but is well represented by the sum of I→U and U→I contributions (both accounting to roughly 36%); and finally (c) *Formal job finding rate* was very relevant with a total contribution of 32% (the sum of Informal→Formal, U→Formal and I→Formal).
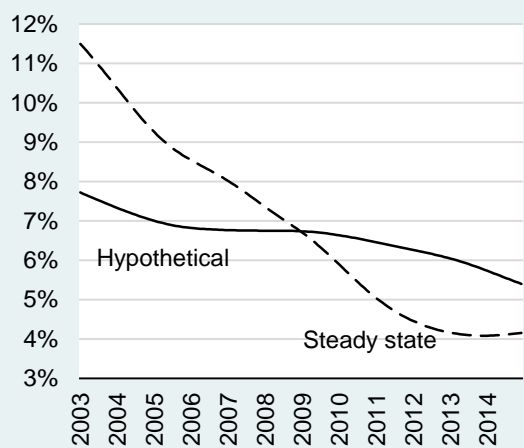
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[6] We loosely interpret here the informal job exit rate as separation rates. It is worth pointing out that we do not consider job-to-job flows, so using the term separation rate is imprecise. Still, the literature employs such terms and we follow the same standard.

Figure 7 – Accounting for informality to assess the contribution of fluctuations in transition rates to the unemployment rate
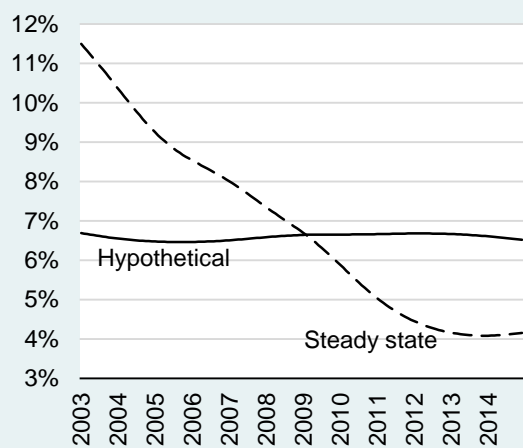

(a) Unemployment – Inactivity

(b) Unemployment – Formal employment

(c) Unemployment – Informal employment

(d) Inactivity – Unemployment

(e) Inactivity – Formal employment

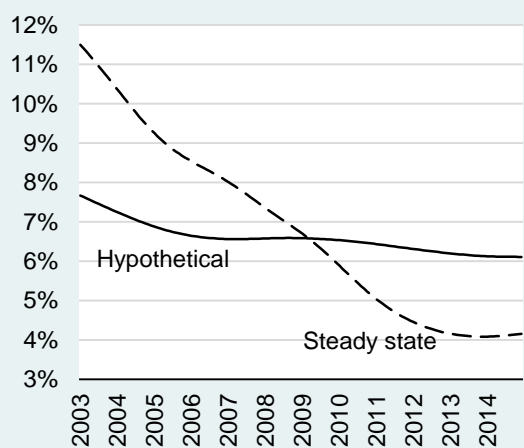(f) Inactivity – Informal employment

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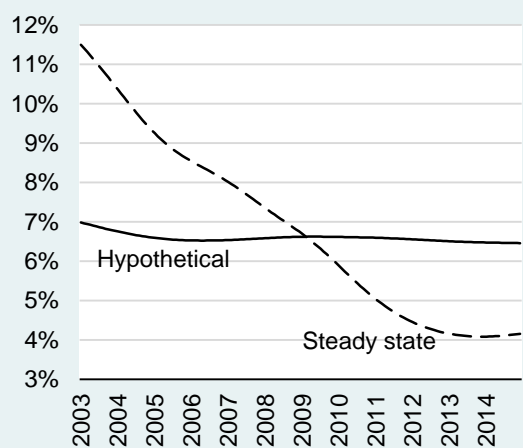**(g) Formal employment – Unemployment**

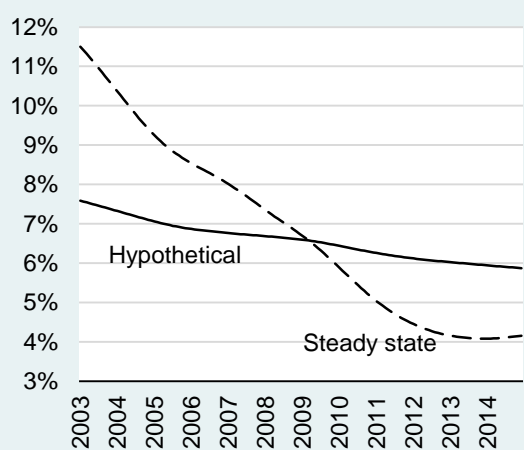**(h) Formal employment – Inactivity**

(i) Formal employment – Informal employment
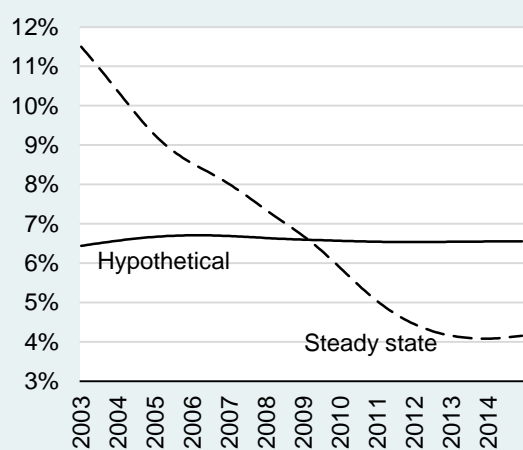

(j) Informal employment – Inactivity

(k) Informal employment – Unemployment

(l) Informal employment – Formal employment

Note: Each panel show the steady state unemployment rate (dashed line) and the hypothetical unemployment if there were only fluctuations in each subtitled transition rate (all others are held constant and equal to their 2003-2014 average). All calculations are based on PME (IBGE) data. Transitions rates are smoothed using an HP filter with parameter 14.400.

Table 4 – Accounting for informality in the decomposition of the change in the unemployment rate

Transition	2003-2014 (Original)	2003-2014 (Corrected)
Informal → U	0,211	0.205
Informal → I	0,018	0.032
Informal → Formal	0,015	0.011
Formal → U	0,139	0.211
Formal → I	-0,035	-0.018
Formal → Informal	0,278	0.152
U → I	0,035	0.034
U → Formal	0,198	0.258
U → Informal	-0,317	-0.201
I → U	0,454	0.300
I → Formal	0,091	0.060
I → Informal	-0,103	-0.081

Note: Each row shows the covariance of u_t^{AB} and u_t divided by the variance of u_t. All calculations are based on PME (IBGE) data. Transitions rates are smoothed using an HP filter with parameter 14.400. Both Informal and formal refer to types of employment. The first column shows the results for the original dataset, while second shows the results after correcting for response errors as described in Zylberstajn (2015).

Notice that the magnitude of the contributions of the inflows from formal employment is similar to the ones from the outflows. Thus, we can conclude that both inflows and outflows are relevant to the changes in the unemployment rate. However, differently from what the three-state model analysis indicated, the single most important contribution does not come from the inflows from employment, but rather from inflows from inactivity.

5. Conclusion

This paper measures both formal and informal job finding rates, employment exit rates, and inactivity's inflow and outflow rates in Brazil from 2003 to 2014. Throughout this period, the decline in the entrance of inactive persons in the workforce and the formalization of the labor market were the main drivers of the decline in the unemployment rate. We found that in particular the reduction of inflows into unemployment were determinant for this trend.

The main contribution of this paper is the extension of the tradition three-state model used to study inflows and outflows contributions to changes in the unemployment rate. We included a fourth state in the model, allowing the separation of employment into two different forms. For instance, in developed countries, employment could be classified as full-time or part-time/contingent work. In the developing world, a useful classification is between formal and informal work.

In Brazil, we showed that formal and informal employment followed different paths and that not accounting for this fact leads to incomplete conclusions: when looking at employment as a whole, the most relevant flow that led the decline in unemployment was the employment exit rate; however, we show that the formal job finding rate increased

substantially, while the corresponding informal rate contributed negatively to the drop in the unemployment rate. At the same time, both formal and informal employment exit rates decreased, contributing further to the reduction of the unemployment rate. In sum, while in the three-state approach, the job finding rate did not contribute much to explain the variation in the unemployment rate, we have shown that the dynamics are much more complex (as revealed with the four-state approach).

We must consider, however, that these findings do not allow to establish any causality, and we do not present any theoretical framework to help us do that. Also, we need to take into account that the data is available in Brazil for a short period of time (less than 15 years), and given that this period was particularly positive for the labor market, results should not be generalized without caution. Still, the evidence we presented helps to understand the key movements in the Brazilian labor market during the past decade.

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