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Abstract

Job finding and separation are not well studied in economies with high labor informality. In this paper we contribute to filling the gap in the literature of labor turnover, proposing a methodology to estimate both indicators in an economy with high informality. To this end we estimate indicators of job finding and separation rates for Peru's developing economy, in which labor informality stands at 70 percent. We find that, on average, these indicators in the formal sector are similar to those estimated in developed economies; however, in the informal sector the calculated indicators are approximately two times higher than those of the formal sector. The two indicators show considerable heterogeneity in the informal sector according to several observable categories; in addition, the separation rate is countercyclical and the finding rate is procyclical, this cyclicality being greater in the formal sector.

JEL Classification: E24, E26, J63, J64, O17.
Keywords: job creation, job destruction, informality, job duration, business cycle.

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1 Introduction

The job finding rate characterizes the proportion of unemployed people who get jobs within a month. Similarly, the job separation rate represents workers who leave employment as a proportion of the total stock of employees. These indicators mainly capture the inflows and outflows of the labor market, and thus represent the short-term dynamics of employment and unemployment in this market. These indicators are widely used in developed economies;[1] however, estimates for developing economies are scarce.[2] Therefore, we believe that the results of this study are very useful in providing statistics that enable a better diagnosis of the labor market in economies with high informality, as well as serving as an input in general equilibrium models that include labor market dynamics in informal economies-such as those developed by Pissarides (2000) (hereafter, DMP) for formal economies.

Informality can be defined as the collection of firms, workers, and activities that operate outside the legal and regulatory systems. The phenomenon is widespread in most developing countries, where the informal sector typically produces about 35 percent of gross domestic product and employs 70 percent of the labor force (Loayza, 2016). In the case of Peru, the rate of informality is around 70 percent based on six indicators: workers whose earnings from their main job fall below the minimum hourly wage; workers who are not affiliated with any type of pension scheme; workers whose employers do not keep accounts; workers whose employers do not constitute a legal entity; workers whose positions are not subject to any form of employment contract; and workers who whose pay is not subject to any deductions (Céspedes, 2013b).

The job finding and separation rates are fundamental aspects of any contemporary analysis of the labor market, and are characterized by the use of search and matching models (*à-la* DMP). These two indicators capture the propagation mechanism shocks in the decisions that workers make, which is absent in traditional analysis of the labor market (labor supply and demand). Thus, for example, positive shocks facing the economy can be reflected in a greater demand for workers among firms, and so workers find better job offers and their probability of being hired increases. In turn, the separation rate indicator captures decisions to leave (change) jobs for better offers in a context of productivity growth, and can also capture an employer's decision to lay off workers in a context of

[1] For estimations in developed economies see Shimer (2005a,b, 2012); Mazumder (2007); Fujita and Ramey (2009); Bjelland et al. (2011); Campoleti (2011); Elsby et al. (2013), Elsby et al. (2009); Nakamura et al. (2019); among others.

[2] Studies on transitions between labor categories in developing economies are diverse, although most of this literature uses low frequency transitions-quarterly and yearly due to data restrictions-to characterize these probabilities (see Bosch and Maloney, 2008; Bosch and Julen, 2012).

recession and/or a fall in productivity. In both cases, the indicator reflects the adjustment in the labor market at the worker level due to the shocks this market faces.

As such, we contribute to the literature of the job finding and separation rates in the following ways. First, we propose a method to estimate the two indicators based on the available data, extending the estimation methods used for developed economies proposed in Shimer (2012). Second, we estimate the economic cyclical properties of the two indicators. The relevant literature suggests that the job finding rate in developed economies is strongly procyclical while the separation rate is slightly countercyclical; the latter result contradicts some previous evidence, especially that referring to the separation rate, which is considered to be acyclical in the USA (Shimer, 2005b).[3] We believe that the study of the cyclicality of the two indicators in developing and highly informal economies has been sparsely studied. Third, we study the dynamic determinants of the two indicators. We provide some statistics to identify the effects of employment and unemployment composition on job finding and separation rates, an area where the literature has again paid little attention when it comes to developing economies.

The key point of dynamic determinants is to evaluate the contribution of various demographic and/or labor groups in the evolution of both indicators. In the context of the Peruvian economy, evaluating these hypotheses empirically is relevant because an episode of persistent economic growth was reported during the study period, and it is important to determine whether this persistent growth manifested itself in a homogeneous evolution of the two indicators according to groups and/or labor categories (real hypothesis), or whether a particular demographic group contributed to a greater extent in the evolution of each of the two indicators (composition hypothesis).

Thus, in this paper we estimate these two indicators for Metropolitan Lima in Peru.[4] What is more, we argue that the characteristics of the Peruvian labor market, the method of estimation and the sources of information used make these indicators very useful guidelines for the analysis of similar economies with high labor informality. We find that the job finding rate within a month is 44 percent, and the separation rate is 7.7 percent. We also find that the finding and separation rates in the formal sector are broadly similar to those reported in developed economies.

The presence of the informal sector, which predominates in developing economies,

[3]The discrepancy is attributed to the estimation method for this indicator. Shimer (2012) suggests that its estimation method better captures the regularities of the job finding rate.

[4]For the case of Peru, as with other developing countries, we have found no published studies on the characteristics of these variables. The closest papers study the dynamics of the Peruvian labor market by emphasizing the transitions between different labor categories (employment, unemployment and inactivity); see for example Chacaltana (2000), Diaz and Maruyama (2000) and Rodríguez and Rodríguez (2012).

makes the separation and finding rates high since these rates in the informal sector are approximately two times the corresponding rates of the formal sector. The job finding rate is procyclical, while the separation rate is countercyclical. There is no significant change in the composition of the unemployment rate, according to which the evolution of the job finding rate is similar across categories (gender, age, education, etc.). In the case of the separation rate, we find that the change in the composition of the employed population (including age, informality) has an influence on the separation rate, although this effect is important after 2008 in the case of the change of the composition of employment between the formal and the informal sector.

The remainder of this paper is organized as follows. Section 2 presents the proposed methodology for estimating the job separation and finding rates. Section 3 discusses the sources of information. Section 4 analyzes the characteristics of the job finding and separation rates in different job dimensions. Finally, section 5 summarizes the main results and discusses the policy implications of this paper.

2 Estimation method

2.1 Job finding rate

The job finding rate is estimated using a procedure similar to that proposed by Shimer (2012). The methodology involves estimating this indicator based on the monthly flows, or transitions, observed in the labor market between different categories of employment, unemployment and inactivity. Formally, let u_t denote the stock of unemployed persons in the period t, and u_{t+1} the stock of unemployed in the period $t+1$. Likewise, u^s_{t+1} denotes the number of short-term unemployed persons in the period $t+1$. These three variables are related, together with the probability of leaving unemployment between the period t and $t+1$ (f^0_t), by the following equation:

$$u_{t+1} = (1 - f^0_t)u_t + u^s_{t+1}. \tag{1}$$

This equation indicates that the number of unemployed persons in the period $t+1$ (u_{t+1}) is equal to the number of unemployed persons in the previous period who do not leave the unemployment category ($(1-f^0_t)u_t$), plus the number of new unemployed persons in the period $t+1$. This last term is measured by the number of short-term unemployed persons in the period $t+1$ (u^s_{t+1}). Thus, from equation (1), the probability of leaving unemployment (f^0_t) is given by:

$$f_t^0 = 1 - \frac{(u_{t+1} - u_{t+1}^s)}{u_t}. \tag{2}$$

The unemployed can leave unemployment and move into the categories of employment or inactivity; in this case the distinction is important because Peru's is an economy where mobility to and from inactivity is significant (Chacaltana, 2000). Thus, the rate at which the unemployed find employment (f_t) is calculated as the proportion of unemployed persons leaving unemployment (f_t^0) times the proportion of the employed, which we denote by γ_t.[5] Thus, the job finding rate f_t is estimated using the following expression:[6]

$$f_t = f_t^0 \times \gamma_t. \tag{3}$$

2.2 Job separation rate

The job separation rate is estimated following a procedure similar to that used estimate the job finding rate. In this case, the number of employees in the period $t+1$ (e_{t+1}) is made up of the number of employees in the previous period who were not separated from their employment ($(1 - s_t)e_t$) plus those (new) employees who got a job during the past month (e_{t+1}^s). Thus, the separation rate is calculated using the following formula:

$$s_t = 1 - \frac{e_{t+1} - e_{t+1}^s}{e_t}. \tag{4}$$

Note that in this equation, as in the definition of the job finding rate, short-term employment is made up of those who found employment during the month regardless of whether they came from unemployment, inactivity or another job. The same logic applies to the short-term unemployed. The peculiarity of our estimate is that both the job separation and finding rates are not explicitly related in the equations for estimating both indicators, unlike the methodologies used in Shimer (2005a, 2012).[7] In the Peruvian labor market context, there is a considerable labor market dynamic of movements between

[5]The term f_t^0 is called the probability (or rate) of job finding in Shimer (2005a) and, in general, in the literature on the labor market in developed economies where inactivity is not quantitatively important. In this paper, the job finding rate would be overestimated if the population moving from unemployment to inactivity were not considered; note that this overestimation could be significant, as shown in Figure 2.

[6]Céspedes (2013b) reports the estimator of Shimer (2012), f_t^0, for the Peruvian economy without discerning the flows of unemployment towards inactivity.

[7]In Shimer (2012) the short-term employment is equal to the number of unemployed persons who found employment. Thus, the equation that defines the number of employees in $t+1$ is $e_{t+1} = (1-s_t)e_t + u_{t+1}f_t$, where f_t is the job finding rate (computed using the equation described above), and s_t is calculated from equation (4). Note that this definition only considers the unemployed population who find employment between two consecutive periods, not the inactive persons who go into unemployment.

inactivity and employment without passing through unemployment (Chacaltana, 2000); thus, the methods described by Shimer (2005a, 2012)[8] could bias the estimates of the separation rate, as shown later in Figure 5.

2.3 Decomposition of job finding and separation rates

This subsection describes the procedure of Shimer (2012). The method consists, first, of calculating the two indicators for each of the n categories that we consider. These variables are denoted by f_{it} and s_{it}, where i denotes the category and t the period. The average job finding or separation rates is estimated as the weighted average of each of the categories. The weighting varies according to the indicator; the weighting for the separation rate is the number of employees in each category (e_{it}), and for the finding rate it is the number of unemployed persons in each category (u_{it}). The formulas are as follows:

$$f_t = \frac{\sum_i u_{it} f_{it}}{\sum_i u_{it}}, \tag{5}$$

$$s_t = \frac{\sum_i e_{it} s_{it}}{\sum_i e_{it}}. \tag{6}$$

The decomposition involves estimating the job finding rate (separation rate) for each period by isolating the effect of changes in the composition of the unemployed population (employee); that is, a job finding rate (separation rate) is generated, keeping the structure of the unemployed (employed) population constant. By construction, the finding (separation) rate built in this way contains only the real effect. If u_i (e_i) denotes the average number of unemployed (employed) in category i with $u_i = \frac{\sum_t u_{it}}{T}$ ($e_i = \frac{\sum_t e_{it}}{T}$), then the job finding (separation) rate that isolates the effect of changes in composition of the unemployed (employed) population is denoted by f_t^{real} (s_t^{real})

$$f_t^{real} = \frac{\sum_i u_i f_{it}}{\sum_i u_i}, \tag{7}$$

$$s_t^{real} = \frac{\sum_i e_i s_{it}}{\sum_i e_i}. \tag{8}$$

[8] Shimer (2005a) estimates the separation rate using the short-term unemployment. The number of short-term unemployed in the period $t+1$ (u^s_{t+1}) is considered to be equal to the number of employees who lose employment in the period t ($s_t e_t$) minus those who found employment in the month under consideration, which is assumed to be half of those who sought employment ($\frac{s_t e_t f_t}{2}$). Thus, the separation rate is estimated from the following equation $u_{t+1} = s_t e_t (1 - \frac{f_t}{2})$. Note that in this case the job separation rate always ends in unemployment or employment, ruling out the possibility of inactivity.

In order to measure the importance of the composition of unemployment (employment) for the finding (separation) rate, we use the following procedure. In this case, the job finding (separation) rate remains constant at its average value for each category i as $f_i = \frac{\sum_t f_{it}}{T}$ ($s_i = \frac{\sum_t s_{it}}{T}$), and the composition of the unemployed (employed) population is allowed to change. Thus, the job finding (separation) rate that captures the effect of changes in the composition of unemployment (employment) results from the following equations:

$$f_t^{comp} = \frac{\sum_i u_{it} f_i}{\sum_i u_{it}}, \tag{9}$$

$$s_t^{comp} = \frac{\sum_i e_{it} s_i}{\sum_i e_{it}}. \tag{10}$$

3 Data

We take our data from the Peruvian National Statistics Institute's Permanent Employment Survey (PES), a monthly survey designed to track employment in Metropolitan Lima. This survey began in 2001 with a monthly sample size of 500 people, rising to approximately 5,600 people per month by 2019. The study period is January 2002 to December 2019. The survey has a quarterly rotating panel design so that a percentage of workers surveyed in a given month are re-interviewed three months later. Approximately 30 percent of respondents correspond to this sample.

The data needed to estimate these monthly indicators are the number of unemployed persons in consecutive periods, the number of new or short-term unemployed (persons who were looking for employment during the last month), and the number of unemployed persons who are moving towards employment or towards inactivity in consecutive periods. The PES enables estimation of the number of employed persons, the number of unemployed persons, the number of inactive persons and the number of short-term employed and unemployed persons.

The incomplete duration of unemployment is estimated from direct survey records where each unemployed person reports the number of weeks they are unemployed (incomplete duration of unemployment). Thus, short-term unemployment corresponds to those who report being unemployed for less than one month (four weeks). On the other hand, the number of short-term jobs is estimated using the reports of the reference week, or day on which the interview was conducted, and the day from which her or she is employed. Both variables are part of the survey questionnaire, and short-term employment is estimated as those jobs that last less than one month in the reference period.[9]

The following imputation process was carried out to estimate the start of employment in cases of non-response of either the start day, month or year of employment. For periods where only the month is reported and not the day, it is assumed that the start day was at the beginning of the corresponding month. For cases where only the year is reported, it is assumed that employment began at the beginning of that year. When the imputation period changes in the middle of the corresponding month or year, the results do not change significantly. In December 2006, the survey does not report any indicators that identify the start of employment, which is why for this month the average of the adjacent months was assigned as an estimator of the number of short-term jobs. The imputation exercise is mostly carried out for medium or long-term jobs, because the probability of forgetting the exact start date of employment is greater when the employment is long-term (several years). Thus, estimates of short-term jobs (less than one month) are not very sensitive to the imputation process.

The number of unemployed people moving to employment and inactivity is estimated from the PES quarterly sample panel. The ideal indicator should be estimated from the monthly sample panel; however, since this type of information is not available, γ_t is estimated with the PES quarterly panel sample, and these values are subsequently applied to the data for each month. Note that the PES quarterly transitions estimated are stable over time.

The descriptive statistics of the variables are shown in Table 1. The evolution of these variables during the period of study is illustrated in Figure 1. In the sample, the employment rate is 92.3 percent and the number of unemployed persons is approximately 7.7 percent of the economically active population (EAP). The accuracy of the indicators is reasonable as the coefficients of variability are less than five percent. Likewise, it is estimated that approximately 5.6 percent of the EAP are short-term unemployed, while short-term employment is equivalent to 7.1 percent of the EAP.

This highlights that a high proportion (73 percent) of workers are unemployed for short periods, while a smaller proportion report having periods of incomplete unemployment of more than one month. This evidence is consistent with the hypothesis that unemployment in Peru is short-lived (Chacaltana, 2000; Diaz and Maruyama, 2000; Belapatiño et

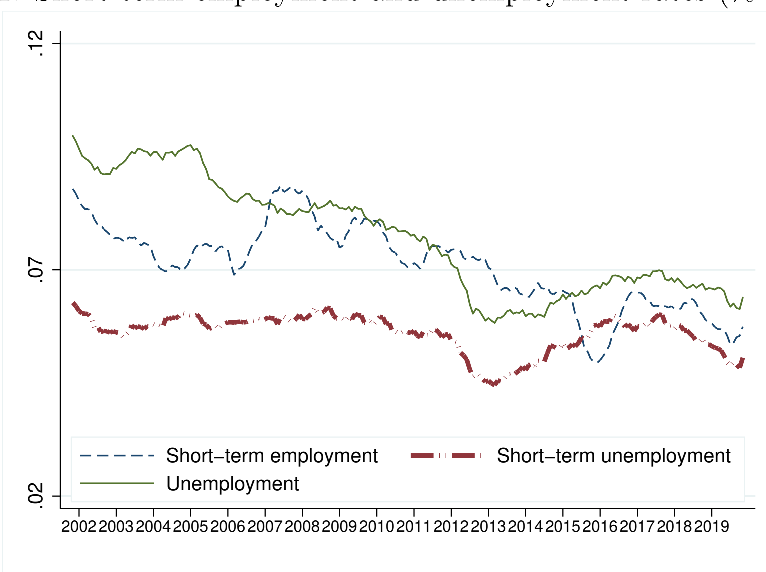
[9] In the PES, the declaration of the day from which employment begins has measurement errors, especially in the years 2001-2003, which mark the beginning of this survey. Thus, for example, in 2001 the non-response rate to this question is high. The greatest omission in these periods was recorded on the start day of employment and to a lesser extent in the start month. The start year of employment has a low non-response rate. However, the quality of the survey in terms of the start date of employment is improving to the point where the response rate of these three variables (start day, month and year of employment) covers almost the entire sample in recent years.

Table 1: Descriptive statistics

	Months	Mean	Median	St. Dev.	Min.	Max.
Unemployment rate	217	0.077	0.078	0.012	0.058	0.100
Short-term unemployment rate	217	0.056	0.057	0.004	0.045	0.063
Short-term employment rate	217	0.071	0.072	0.009	0.049	0.089
Job finding rate	216	0.436	0.437	0.063	0.267	0.555
Formal	217	0.154	0.139	0.094	0.041	0.301
Informal	217	0.282	0.283	0.005	0.201	0.390
Job separation rate	216	0.076	0.075	0.028	0.011	0.148
Formal	216	0.041	0.042	0.011	0.014	0.061
Informal	216	0.106	0.106	0.014	0.072	0.145

Note: The short-term employment and unemployment rates are measured relative to the active population.
Source: PES.

Figure 1: Short-term employment and unemployment rates (% of EAP)



Note: Seasonally adjusted series.
Source: PES.

al., 2014). Finally, when considering the sample size, the accuracy of the estimates of incomplete duration of unemployment and employment is slightly lower than the estimates of the unemployment and employment rates.

4 Results

4.1 Job finding rate

The job finding rate is estimated at 0.44 on average between 2002 and 2019, which implies that around 44 percent of unemployed persons find work within a month. This indicator has shown an upward trend during the study period, with an average annual growth rate of 2.1 percent (see Figure 2).[10] In addition, the indicator is heterogenous according to age ranges, education level and type of unemployed (unemployed with experience "old unemployed" and those without experience "new unemployed"); while according to gender there are no major differences in the average (see Figure 3).

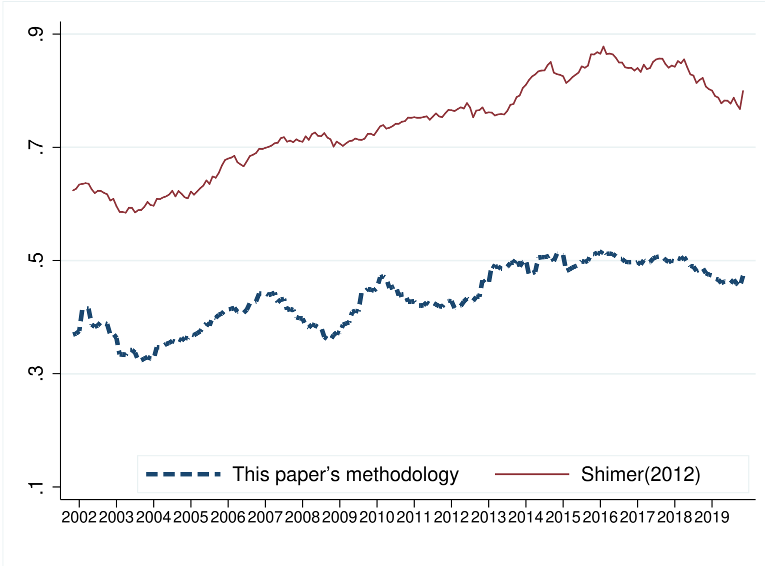
Unemployed, younger and less educated workers find employment more easily, while for educated and older workers it is more difficult get work within a month. These results are consistent with the existence of higher reserve salaries for older and educated workers (who generally have more experience), but longer duration of unemployment due to the greater effort involved in the search for jobs with greater return. Likewise, household heads post a lower job finding rate compared to other household members, which is consistent with the greater search effort and longer duration of unemployment involved in finding better jobs.

In general, those with prior work experience find jobs at a rate close to the average; while those without experience, who (probably) have lower reserve salaries in relative terms, accept job offers more frequently. However, the gap in the job finding rate between the unemployed with experience and those without experience has been smaller in recent periods; the job finding rate for the unemployed with experience increased at an annual rate of 2.2 percent, a value higher than that of those without experience. This evidence is consistent with the hypothesis that workers with prior work experience are in increasing demand on the market and so receive the best job offers. The context of persistent economic growth in Peru over the last two decades, with the consequent greater demand for skilled labor, is consistent with these results.

The evolution of job finding may be influenced by several variables, which may be aggregates such as economic activity, or specific characteristics of certain population groups. There are two hypotheses that can partially explain the evolution of the later indicator. The first is the heterogeneity hypothesis, which refers to the preponderance of a certain category in the evolution of the job finding rate, where a certain population group con-

[10] The average annual growth rate of this indicator is positive in several categories (education, age, gender, etc.). The annual average growth rates are estimated using the annualized coefficient of the regression of the log of the seasonally adjusted separation rate in relation to the monthly trend.

Figure 2: Job finding rate



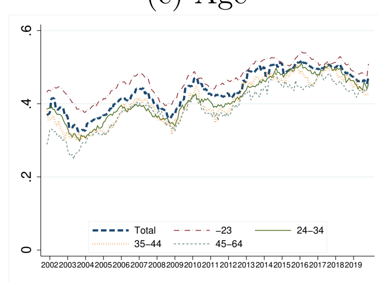
Note: f_t is estimated by using the method described in this paper and f_t^0 is estimated following Shimer (2012).
Source: PES.

Figure 3: Job finding rate by categories

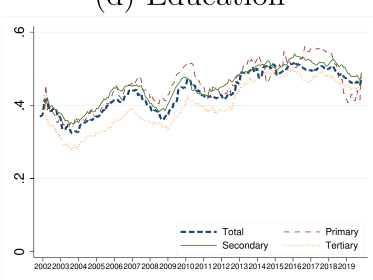
(a) Gender

(b) Household head

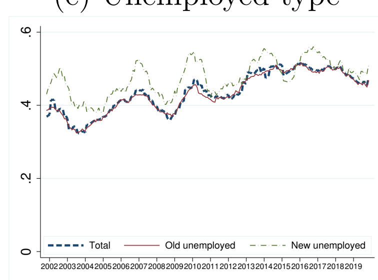
(c) Age



(d) Education



(e) Unemployed type

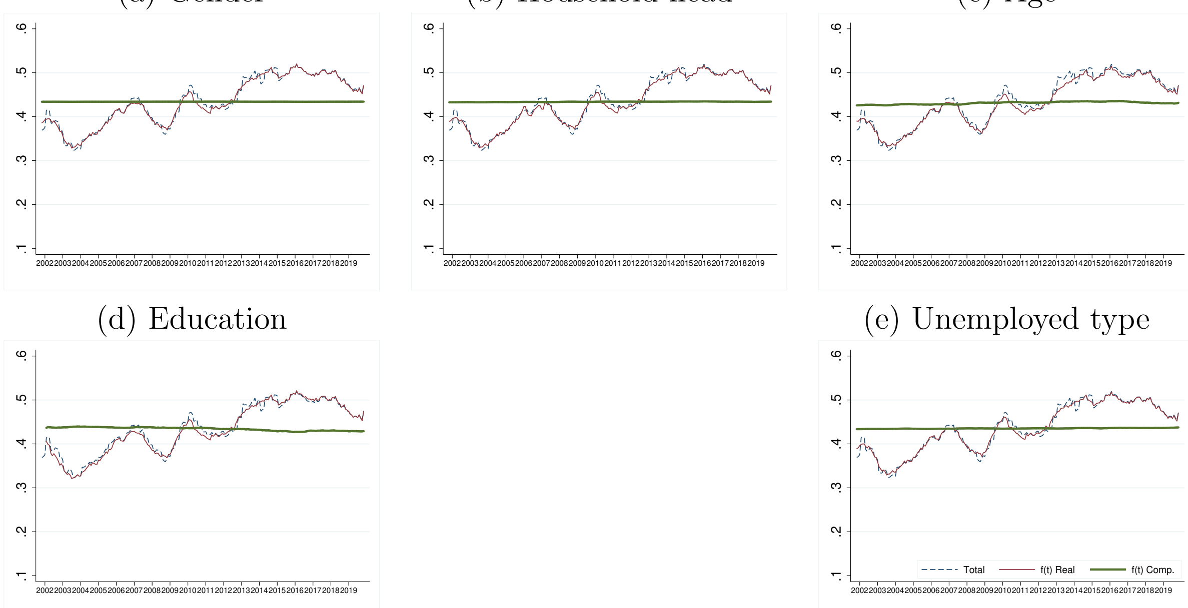


Source: PES.

tributes more to job finding, leaving the other groups less represented. The alternative hypothesis is the real hypothesis, which suggests that the composition of the unemployed who find employment is similar over time, and the finding rate trend in each of the categories is similar. Note that the two hypotheses may be complementary and both could explain the evolution of the job finding rate.

Both hypotheses are evaluated by decomposing the evolution of the job finding rate. Note that implementing the decomposition requires reliable estimators of the job finding rate and the unemployed population in each category and period. Thus, we consider the following categories: gender, age, household head, type of unemployed (unemployed with experience and those without experience) and education level. Figures 3 and 4 illustrate the estimates of job finding rate by categories and the results of decomposition, respectively. Each of the subfigures in Figure 4 shows three series: the average separation rate, the effect of changes in the composition of unemployment, and the real effect.

Figure 4: Decomposition of the job finding rate



(a) Gender (b) Household head (c) Age (d) Education (e) Unemployed type

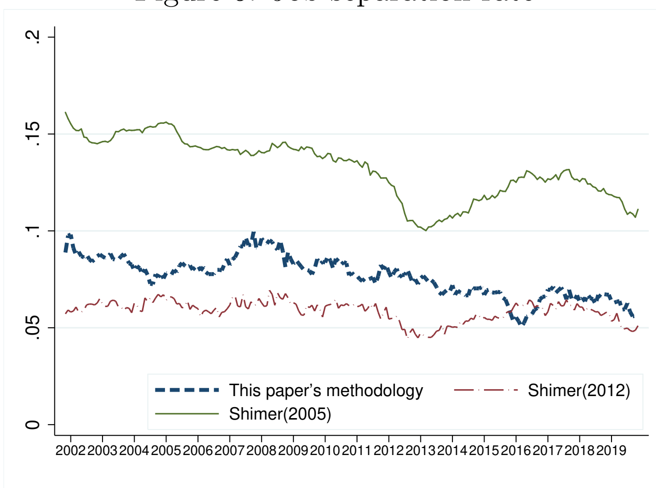
Source: PES.

Overall, the variability in the job finding rate is mainly explained by the real effect in all categories, the effect of changes in the composition of unemployment being almost nil. In other words, f_t^{comp} is almost a constant in all categories of Figure 4, while f_t^{real} has a behavior close to f_t for the entire sample. A feature that stands out is that the effect of the composition of unemployment by age ranges and/or education level begins to be important from 2008; a tentative explanation could be related to the relative importance of youth unemployment in comparison with unemployment among the oldest population in this period.

4.2 Job separation rate

The separation rate is 0.08 on average between 2002 and 2019 (see Figure 5). During this period, this indicator has shown a downward trend with an average annual growth rate of -2.2. This indicator is heterogeneous since there is considerable variability between different categories; for example, the separation rate is higher among young people (0.16 on average among young people below 23 years of age), among those who work at a firm with less than ten workers (0.9 on average), and among those working in the construction and manufacturing sectors. Likewise, the higher separation rate in the construction sector is likely related to the typical short-term employment contracts in this sector.

Figure 5: Job separation rate

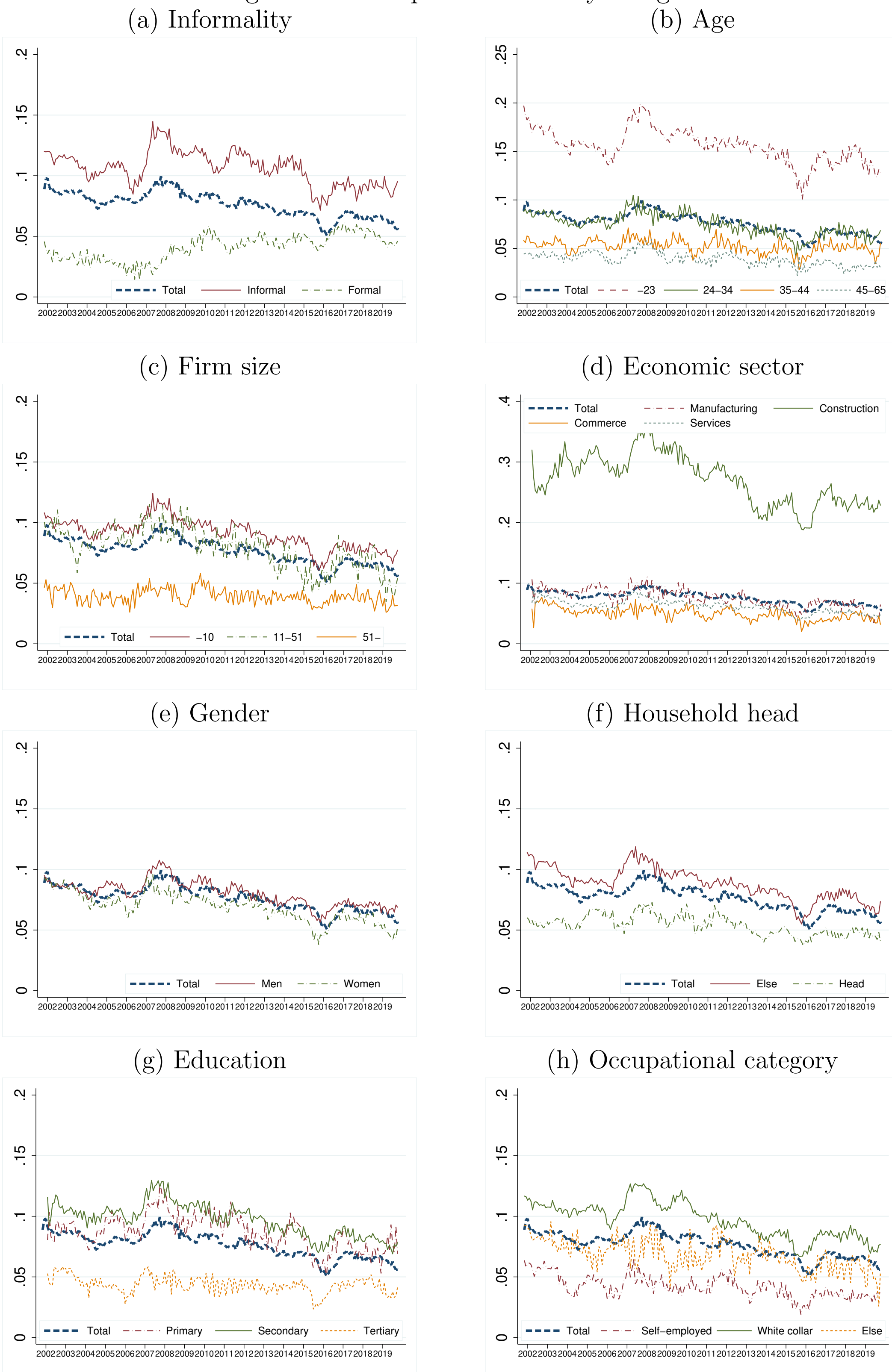


Note: S_t is estimated by using the method described in this paper. The other calculations follow Shimer (2005b) and Shimer (2012), respectively.
Source: PES.

This highlights the decreasing trend that this indicator has shown not only at the aggregate level but also in each of the categories studied, as illustrated in the group of subfigures in Figure 6. When we estimate the average annual growth rate between 2002 and 2019, we find that the separation rate has been reduced to a higher rate among formal jobs, in larger firms, etc. (see Figure 6 for more categories).

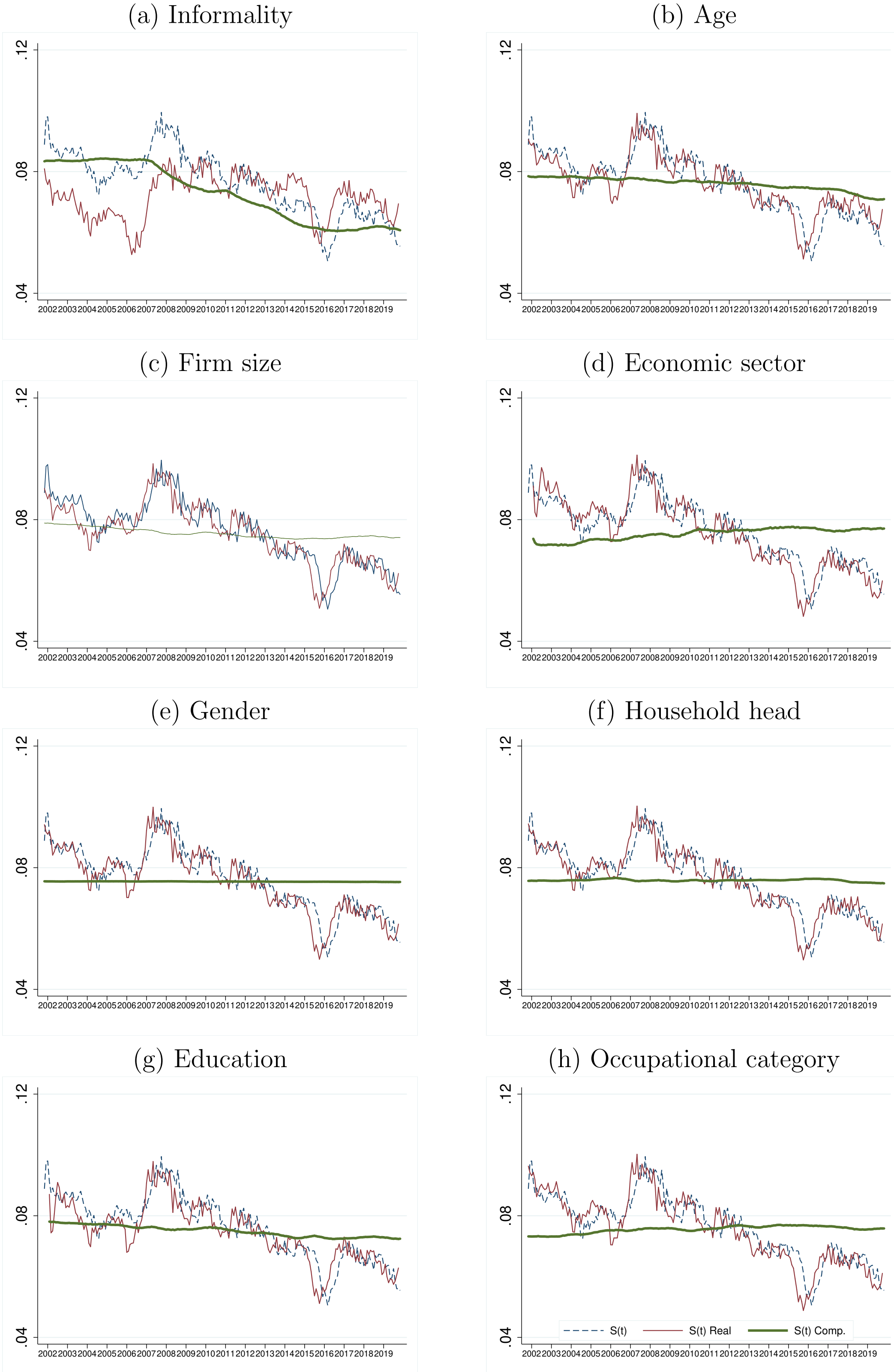
What type of jobs are the most frequently destroyed? Has the economic growth in Peru over the last fifteen years, which has led to the creation (and/or destruction) of jobs in a specific sector, been heterogeneous? Or has the growth been homogeneous, with no significant preponderance of any particular sector or labor category? These questions can be analyzed using the decomposition of the evolution of the separation rate, for which we follow a similar procedure in order to decompose the job finding rate.

Figure 6: Job separation rate by categories



Source: PES.

Figure 7: Decomposition of the job separation rate



Source: PES.

We find that heterogeneity makes an important contribution to the evolution of the separation rate. Figure 7 suggests that the component associated with changes in the composition of employees is important. Higher growth of those employed in the manufacturing and construction sectors is reported, significant growth in formal jobs is recorded, and employment according to demographic characteristics of workers has not changed significantly (age ranges, gender, household members). According to firm size, employment in firms with more than ten workers has shown greater dynamism.

These trends are persistent throughout the period of study, so these persistent changes are expected to affect the evolution of the separation rate. Figure 7 shows that the component associated with the composition of employment has changed throughout the span period, the change being noticeable at the end of the decade. While the contribution could still be small, it could be significant when registered in most of the categories considered.

4.3 Cyclical features

The aggregate relationship between the business cycle and the job finding and/or separation rates can be determined by comparing the cross correlations of the seasonally adjusted series, or using the cyclical component of the series in relation to a long-term trend. When we use seasonally adjusted series, the correlation of the job finding rate with the gross domestic product (GDP) is 0.96, while the correlation of the job separation rate and the GDP is -0.75[11] (see Figure 8).

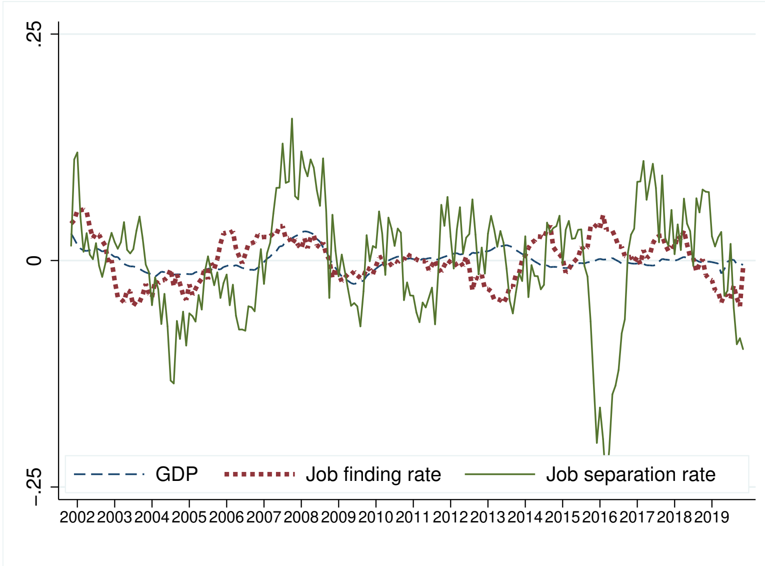
This high correlation is mostly shown in the short-term trend of each of these variables and suggests that periods of economic growth have been related to a high job finding rate, and a lower relationship with the job separation rate. These results are consistent with the existence of jobs that last longer in periods of economic expansion and episodes of unemployment of shorter duration. Estimates of complete and incomplete duration of employment and unemployment, and their evolution over a similar period, are consistent with the latter hypothesis (see Belapatiño et al., 2014).

On the other hand, when we use an estimator of the volatility of each of these variables,[12] we find that the volatility of the job separation rate is greater than that of the

[11] All correlations of the variables studied, as well as the standard errors, are estimated using the series in logarithm. The measure of volatility is the standard deviation of the cycle component of each indicator.

[12] The cyclical component is estimated by the HP filter on monthly seasonally adjusted series in the period 2002-2019. During this period there was only one episode of recession, and several episodes of economic slowdown. Thus, estimates of the cyclical component of the variables are referential because there are no long series of labor market variables available, which means identifying periods of booms and recessions is not possible. Strictly speaking, by estimating the cycle for a series with few recessions, we analyze basically the volatility of the variables around the short-term trend (unless the short-term

Figure 8: Cycle: gaps relative to the HP trend



Source: PES.

job finding rate (see Figure 8). The standard error of the finding and separation rates are 2.4 and 6.4 percent, respectively. Likewise, both indicators have a greater volatility to GDP volatility, which suggests the existence of considerable labor market volatility in relation to aggregate economic volatility.

4.4 The role of labor informality

Labor informality significantly affects the estimates of the job separation and finding rates. In the case of the job separation rate, informal workers are separated from their jobs at a rate of 11 percent per month, and formal workers at a rate of 4 percent. Given that the average job separation rate is 7.7 percent, the informal sector makes a significant contribution to estimating the separation rate (see Figure 9). The results also highlight that the estimate of the formal sector separation rate is similar to those estimated for developed economies; in the United States, for example, this indicator is in the range of 2-3 percent range per month (see Shimer, 2005b).

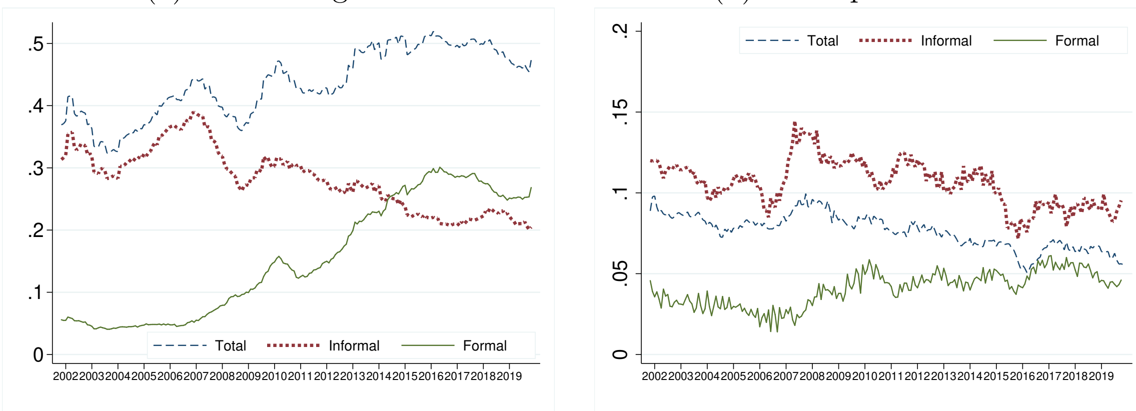
In the case of the job finding rate,[13] the informal sector also makes a large contribu-

trend coincides with the long-term trend). For this reason, the analysis of the cyclical component of the job separation and finding rates refer mainly to the volatility of each of these variables.

[13]The job finding rate in the formal and informal sectors is estimated as follows. The sector in which the unemployed who find work in the period following the period under consideration is estimated. These workers are identified by short-term jobs that come only from unemployment, this is excluding those that come from inactivity. The informality rate of these new employees makes it possible to identify the proportion of unemployed people who find employment in the informal sector. The job finding rate in

Figure 9: Job finding and separation rates by informality

(a) Job finding rate (b) Job separation rate



Source: PES.

tion. Unemployed persons find formal work at an average rate of 15.7 percent per month, while informal jobs are found at an average rate of 28.2 percent. In other words, finding employment in the informal sector is on average around two times easier than finding employment in the formal sector[14] (see Figure 9). By comparison, the United States reports an average estimate between 40-45 percent-a value that is higher than the estimated average values for the formal sector of the Peruvian economy.

The significant contribution of the informal sector to the job separation and finding rates suggests that the dynamics of the Peruvian labor market are largely influenced by the dynamics of this sector. However, this result will have been weakening recently, as the evidence suggests a growth in the contribution of the formal sector. To reinforce this observation the formal job finding rate has been growing since 2007, while in the informal sector this indicator reported a slightly positive annual average growth rate over a similar period. These results are also consistent with the declining trend in the informality rate in Metropolitan Lima (-2.2 percent annual growth during the 2000s).[15] (See Figure 10).

Finally, we report evidence that suggests that changes in the informality rate occurred due to changes in the informality rate for new jobs, understood as those jobs that last at least one month. Thus, although there is a preponderance of informality among recent jobs (30 percent of recent jobs are formal), we find that the proportion of formal jobs created has been increasing considerably between 2011 and 2017, as shown in Figure 10.

the informal (formal) sector is estimated by multiplying the job finding rate by the proportion of informal (formal) jobs among new jobs.

[14]This indicator was 3.6 times before 2015, which implies that the gap in the job finding rate between the formal and informal sector has been closing in recent years.

[15]Similar results are found in this period at the national level, for several definitions of labor informality, with data from the National Household Survey.

Figure 10: Labor informality rate in Metropolitan Lima

Source: PES.

5 Conclusion

In this paper we study the job separation and finding rates in Metropolitan Lima in Peru, a city that is characterized by high labor informality. Studies of these two indicators in developing economies are scarce, so we consider that the stylized facts found in this paper could be useful in understanding the short-term dynamics of labor markets in developing economies. We find the separation rate to be approximately 7.7 percent, while the job finding rate is approximately 44 percent. When we estimate these indicators for the formal sector, the average values are similar to those estimated for developed economies.

The job separation rate is countercyclical, while the job finding rate is procyclical. We also find that the composition of the evolution of unemployed persons did not change substantially during the period of study. However, in the case of the separation rate, the labor force displayed a slight preponderance for formality and jobs in smaller firms, and changes in the composition of the workforce will have influenced the evolution of the job separation rate.

Labor informality exhibited a downward trend until 2017. The contribution of the composition of new jobs is important in this regard: the informality rate of short-term jobs decreased at a faster rate than the labor market average. The separation rate in the informal sector is 2.6 times higher than the separation rate in the formal sector, while the job finding rate in the informal sector is 1.8 times higher than in the formal sector. These indicators are directly related to the dynamics of the labor market and point to a considerable contribution by the informal sector to the dynamics of the Peruvian labor market.

A first application of the results is to support the development of macroeconomic models for developing economies that explicitly include labor informality. Since informality exists in high proportion in such economies, measures of efficiency of the effects of government intervention, or the effects of different economic shocks generally, may not be fully captured in models that ignore informality. There are macro model proposals with labor informality in a monetary policy framework for Peru (Castillo and Montoro, 2012); a model that links informality, regulations, migration, and economic growth (Loayza, 2016); an equilibrium matching model (Yassin and Langot, 2018); and a small open business cycle model with an informal sector (Leyva and Urrutia, 2018). The structural model that serves as a theoretical framework for this paper (see Céspedes, 2013a), or some extension of this, can be used as a starting point for assessing the potential effects of the tax system on labor informality-an important topic for future research.

References

Belapatiño, V., N. Céspedes and A. Gutierrez (2014). "La duración del desempleo en Lima Metropolitana". *Revista Estudios Económicos*, 27(1), 67-80.

Bjelland, M., B. Fallick, J. Haltiwanger, and M. Erika (2011). "Employer-to-employer flows in the United States: estimates using linked employer-employee data". *Journal of Business and Economic Statistics*, 29(4), 493-505.

Bosch, M. and W. William (2008). "Cyclical movements in unemployment and informality in developing countries". IZA Discussion Papers 3514, Institute for the Study of Labor (IZA).

Bosch, M. and E. Julen (2012). "Job creation and job destruction in the presence of informal markets". *Journal of Development Economics*, 98(2), 270-286.

Campoleti, M. (2011). "The ins and outs of unemployment in Canada, 1976-2008". *Canadian Journal of Economics*, 44(4), 1331-1349.

Castillo, P. and C. Montoro (2012). "Inflation dynamics in the presence of informal labour markets". BIS Working Papers 372, Bank for International Settlements.

Céspedes, N. (2013a). "Creación y destrucción de empleos en economías informales". Cuadernos de investigación 19, Universidad San Martín de Porres.

Céspedes, N. (2013b). "La probabilidad de creación de empleos en el Perú". *Revista Moneda* 152(1), 40-43.

Chacaltana, J. (2000). *Un análisis dinámico del desempleo en el Perú*. Fondo de Investigaciones del Programa MECOVI-Perú. Lima. INEI. 2000.

Diaz, J. and Maruyama (2000). "La dinámica del desempleo urbano en el Perú: tiempo de búsqueda y rotación laboral". GRADE, Lima.

Elsby, M.W., B. Hobijn and A.S. Ahin (2013). "Unemployment dynamics in the OECD". *Review of Economics and Statistics*, 95(2), 530-548.

Elsby, M.W., R. Michaels, and G. Solon (2009). "The ins and outs of cyclical unemployment". *American Economic Journal: Macroeconomics*, 1(1), 84-110.

Fujita, S. and G. Ramey (2009). "The cyclicality of separation and job finding rates". *International Economic Review*, 50(2), 415-430.

Leyva, G. and C. Urrutia (2018). "Informality, labor regulation, and the business cycle". Working paper 2018-19, Bank of Mexico.

Loayza, N.V. (2016). "Informality in the process of development and growth". *The World Economy*, 39(12), 1856-1916.

Mazumder, B. (2007). "New evidence on labor market dynamics over the business cycle". *Economic Perspectives*, 31, 36.

Nakamura, A., E. Nakamura, K. Phong and Jon Steinsson (2019). "Worker reallocation over the business cycle: evidence from Canada". University of Alberta, mimeo.

Pissarides, C. (2000). *Equilibrium unemployment theory.* 2nd Edition, MIT Press, edition 1, volume 1.

Rodríguez, J. and G. Rodríguez (2012). "Explaining the transition probabilities in the Peruvian labor market", Documentos de Trabajo 2012-334, Pontificia Universidad Católica del Perú.

Shimer, R. (2005a). "The cyclical behavior of equilibrium unemployment and vacancies". *American Economic Review*, 95(1), 25-49.

Shimer, R. (2005b) ."The cyclicality of hires, separations, and job-to-job transitions". *Federal Reserve Bank of St. Louis Review*, 87(4), 493-507.

Shimer, R. (2012). "Reassessing the ins and outs of unemployment". *Review of Economic Dynamics*, 15(2), 127-148.

Yassin, S. and F. Langot (2018). "Informality, public employment and employment protection in developing countries". *Journal of Comparative Economics*, 46(1), 326-348.