



UNEMPLOYMENT DYNAMICS IN CHILE: 1960-2015*

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I. INTRODUCTION

The labor market has always been an area of critical importance for economists. From a microeconomic perspective, since labor income is generally the single most important source of risk for households, an individual's labor market status is probably what most closely determines individual welfare. From a macroeconomic perspective, labor markets are relevant for fluctuations in the business cycle, as well as for long-run macroeconomic outcomes. Regarding the former, individuals' decisions in the labor market are a critical propagation mechanism for different business cycle shocks. With respect to the latter, economies that in the long-run are unable to reduce unemployment after structural reform are more likely to face increasing social pressure and demands.

During the last few years a number of articles have focused on the behavior of labor market flows.¹ Unfortunately, limited data has confined these studies strictly to advanced economies. This work tries to narrow the gap with emerging economies by analyzing the “ins and outs” of unemployment in the labor market of Chile's Greater Santiago between 1962 and 2015.

The study of the evolution of the Chilean labor market is particularly interesting because, in contrast with most advanced economies, the Chilean economy has undergone major changes during the past fifty years. In fact, Chile has transited from being one of the most regulated and least productive economies in the world during the 1960s, to becoming one of the most dynamic emerging economies during the 1990s.² This transition was driven primarily by several waves of pro-market reforms, privatization programs, deep financial reform, social security privatization, and a trade liberalization process, all of which had an important impact on the level of competition within the Chilean economy. Labor market regulation also suffered significant changes in both directions throughout the

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1 See Shimer (2012); Elsby et al. (2013); Fujita and Ramey (2009). A summary of the literature with a special emphasis on search models is in Rogerson and Shimer (2010).

2 According to Gallego and Loayza (2002), Chile's economic growth rate in 1985-2002 was among the four highest in the world. Moreover, according to the same source, the change in the growth rate per capita between 1985 and 2002 was actually the highest in the world.

last fifty years that either increased or decreased labor market flexibility.³ From an international comparative perspective, the Chilean labor market is currently considered a fairly regulated labor market mainly due to an increasing, yet limited, tenure-based severance pay policy.⁴

To review the evolution of the Chilean labor market throughout the last fifty years, we rely on the University of Chile's employment survey (EOD for its name in Spanish) of Greater Santiago.⁵ Throughout the paper, we refer to labor market flows calculated for the Metropolitan Region with Chile's nationwide labor market. Following Shimer (2012) and others, our analysis is based on the use of time-series methods to calculate labor market transition hazard rates considering short-run and long-run unemployment stocks.

Our results show that the average monthly job finding rate throughout the studied period was 24.6%, while the average monthly job separation rate was 2.4%. In a cross-country comparison, these numbers indicate that in spite of relatively stringent labor legislation, the Chilean labor market appears to be as dynamic as the average Anglo-Saxon country's, yet considerably less so than the labor market of the United States.⁶ Additionally, we determine that from a historical perspective, the finding rate has been more important than the separation rate in contributing to changes in the unemployment rate. In the last few years the finding rate has been increasingly important in explaining fluctuations in unemployment. This behavior is similar to that of advanced economies, where despite sharp increases in the separation rate being responsible for increasing unemployment in the short term, the slow gradual recovery of the outflow rate has been increasingly important in explaining unemployment variability (see Elsbey et al., 2013; Fujita and Ramey, 2009; Hall, 2006; Shimer, 2012).

Interestingly, in spite of becoming a more flexible economy, at least in terms of labor market dynamics, the trend unemployment rate is roughly the same as it was fifty years ago, before the implementation of structural reforms. We discuss this phenomenon by analyzing the low frequency behavior of separation and finding rates and show that both these hazard rates have increased significantly over time, rendering a trend unemployment rate not very different from that of the 1960s.⁷ Albeit with significant variation, the separation rate more than doubled between 1962-71 and the past decade 1986-2015 from 1.5% to 3.1%, while the finding rate rose from 24.3% to 33.4%. Of note, these increases occurred in the

³ For a broader discussion on changes to labor market regulation in Chile see Edwards and Edwards (2000) and Montenegro and Pages (2004) among others.

⁴ According to the World Bank's *Doing Business 2017 Report*, Chile has the highest severance payment for the dismissal of a worker with ten years of tenure among OECD economies with 43.3 salary weeks.

⁵ For further information on the survey, see the Data section.

⁶ Our results are consistent with the results obtained by Jones and Naudon (2009) using data from another employment survey in Chile, further discussed in detail in section 5.1.1 and illustrated in panel B of table 1. The fact that the labor market in Chile is relatively flexible is also found in Albagli et al. (2005). See sub-section V.1 of this paper for further discussion.

⁷ As is further discussed in section 4.2, this increasing unemployment trend has also occurred in a number of advanced economies. Particularly, Rogerson and Shimer (2010) argue that movements in unemployment trends are very persistent.



context of significant changes in the economy's trend growth, with increases in the trend finding rate associated with periods of higher trend growth, and the trend separation rate increasing throughout. Greater trend hazard rates also occur in the context of ongoing sectoral reallocation towards services from manufacturing and important changes to labor market legislation, that sometimes strengthened and other times weakened labor market institutions. In addition, our results may be at least partly driven by changes in the composition of the labor force, including the ongoing increase in female labor force participation, the decline in youth participation, greater participation of individuals over 55 years of age, and the gradual aging of population.

The paper is structured as follows. The next section briefly places this document in the context of related literature. In section III, we describe the employment survey data. In section IV we detail the methods and procedures we used to build our hazard rates. In section V we present our results from a high and low frequency perspective, compare our results to other economies, and use our results to estimate how changes in hazard rates have affected changes in the unemployment rate. In section VI we discuss our results in the context of greater macro trends that may drive our results, and propose further areas of related research. The final section presents our main conclusions.

II. RELATED LITERATURE

From a thematic standpoint, this work draws from labor market flow research pioneered by Diamond-Mortensen-Pissarides. In terms of methodology, this work builds on contributions from Shimer (2012), as well as Elsby et al. (2013).

Regarding previous efforts at analyzing the dynamics of the Chilean labor market, this work is related to several other works. At least in terms of data and time-span, this work is probably most closely related to Lima and Paredes (2007), since they also estimate quarterly transition probabilities for Chile's labor market between a similar time-span (1962-2007), yet do so by applying a different methodology.

In their analysis of the ins and outs of unemployment, Jones and Naudon (2009) use data from the National Employment Survey (ENE) for 1997-2009 to determine that Chile's labor market dynamics are similar to those of Australia and New Zealand, and furthermore conclude that the rate of job separation is critical to explain the variance as well as the unemployment rate during the last decade. García and Naudon (2012) build on Jones and Naudon (2009) and adjust their results for time aggregation bias. More recently, Marcel and Naudon (2016) continue to build on earlier work through 2016 with the same employment survey and disaggregate transition rates across age groups and genders. More recently Castex et al. (2014) estimate transition probabilities for salaried workers across geographic locations and sectors for the Chilean economy using unemployment insurance data. Bravo et al. (2005) also employ the ENE dataset between 1996 and 2004 to construct a panel of matched people between different periods to demonstrate that unemployment is strongly related with the behavior of job-to-job transition rates. In the Results section we compare our results to these studies.

Due to the nature of this work, it is also related to a number of documents that have associated changes in labor market legislation with subsequent impacts on labor market dynamics. Montenegro and Pagés (2004) take advantage of the lengthy span of the EOD survey and examine the impact of labor market regulations on the level and distribution of unemployment, concluding that employment security provisions and minimum wages in Chile have reduced the share of youth and unskilled employment, as well as affected their employment rates. Similarly, Edwards and Edwards (2000) use data from the EOD to analyze the impact of changes in regulation on the labor market during the last fifty years finding that reforms in the collective bargaining process performed in the early 1990s improved the flexibility of the labor market and significantly contributed to a decline in unemployment; at the same time they determine that the job security reforms, also performed in the nineties, did not have a significant effect on the long-run natural rate of unemployment. More recently, Cowan et al. (2004) use ENE data to analyze the impacts of changes in the minimum wage on the wage distribution of employment as well as the slow recovery and persistence of unemployment after the Asian crisis.

III. THE DATA

Our analysis is based on data from the University of Chile's employment survey (EOD), a questionnaire carried out on a quarterly basis since 1960 that tracks the labor market status in the Metropolitan Region of Santiago, an area that includes close to 35% of the country's population, corresponding to 40% of the economy's labor force that accounts for approximately 40% of the economy's GDP.⁸

One of the main advantages of the EOD survey is that it has maintained a constant structure throughout, as well as a consistent set of variables since its implementation, which facilitates time series analysis. Throughout, the EOD has interviewed between 2,300 and 3,500 households per survey, accounting for approximately 10,000–16,000 observations, of which 3,300 to 5,400 individuals have been active labor force participants at the time the survey was completed. As mentioned above, the sample is representative of the population of Greater Santiago as a whole and is updated accordingly after every census taking into consideration changes in demographic patterns as well as the city's limits.

The EOD has been performed quarterly since 1960; however, the complete set of micro-data from the survey is only digitally available since 1960 for June.⁹ Fortunately, quarterly aggregate labor market data from the survey since 1960 has been made available separately (Central Bank of Chile, 2001). As will be described in the next section, to calculate the hazard rates we need data on short-term unemployed, total unemployed, and employed. The micro-data for June

⁸ The first survey was originally carried out in October 1956 and has been performed quarterly since 1960.

⁹ Micro-data for other quarters is digitally available starting in 1980 (March) and 1997 (September and December).



collects information on the duration of the unemployment spell, with which we can calculate short-term unemployment, defined as being unemployed for less than 14 weeks. Since the question regarding the duration of the unemployment spell was introduced in 1962, we perform our analysis starting that year. In addition to the short-term unemployment data from June, we use the aggregate labor market data from the June and March surveys. To be clear, if survey data were available for all quarters stretching back to 1962, we would be able to estimate four hazard rates (for a given duration) each year, that is one hazard rate corresponding to each survey. However, since only June data is available, we are constrained to estimate one hazard rate per year.¹⁰ One relevant caveat regarding our use of March and June data is that seasonal effects result in these months having greater unemployment rates than September and December.

It is important to mention that the main employment survey used to study the Chilean labor market is the National Employment Survey (ENE), carried out by the National Statistics Institute (INE) since 1986. In practice, both questionnaires present important methodological differences that have an impact over the measurement of unemployment.¹¹ We take advantage of the EOD's consistent structure to analyze Chile's labor market dynamics from a historical perspective.

IV. METHODOLOGY

We conduct our analysis using EOD data and restricting our sample to the working age population, explicitly individuals between 15 and 64 years of age. Our unemployment rate estimates are derived from EOD data, and as a result may differ significantly with ENE unemployment rates used in other studies.

In order to calculate the ins and outs of unemployment in the Chilean labor market, more specifically, the job separation rate at which an employed worker becomes unemployed during the current quarter, denoted by s_t , as well as the job finding rate that an unemployed worker finds a job, denoted by f_t , we resort to the method pioneered by Shimer (2012) and subsequently adjusted by Elsby et al. (2013).

Assuming a fixed and homogenous labor force,¹² Shimer develops original measures to calculate the job finding and separation probabilities, and estimates these transition probabilities using monthly labor market data publicly available from the United States. Since monthly data for Chile is not available, we apply Elsby et al.'s extension to Shimer's method in our quarterly dataset in order to build a time series of monthly hazard rates into and out of unemployment with

¹⁰ Limitations to this approach are discussed in the end of the Methodology section.

¹¹ The ENE (now NENE) is the main source of labor market data in Chile. It aims at achieving a representative sample of Chile's entire labor market (not only the capital or Metropolitan area) by monthly surveying around 36,000 randomly selected households. For a detailed analysis of historic and methodological differences between the EOD and ENE see Bregger and Hoy (2006); and Bravo et al. (2003).

¹² As discussed in section VI, Chile's labor market has experienced a significant increase in participation as well as compositional changes which suggest the "fixed and homogenous" assumption is quite strong.

EOD data on an annual basis. To be clear, for every year we report a single monthly hazard rate, which is approximated from quarterly data.

Following Shimer, for $t \in 0, 1, 2, \dots$, the interval $[t, t+1)$ is referred to as the “period t .” $F_t \in [0, 1]$ refers to the job finding probability in the interval t , and $S_t \in [0, 1]$ is the job separation probability in t . Unemployed workers are assumed to find a job according to a Poisson process with arrival rate $f_t = -\log(1 - F_t) \geq 0$, while employed workers are separated from their job also according to a Poisson process with arrival rate $s_t = -\log(1 - S_t) \geq 0$.

Let $\tau \in [0, 1]$ be the time interval between measurement dates (quarters), and $e_{t+\tau}$ be equal to the stock of employed workers in $t+\tau$, $u_{t+\tau}$ equal to the stock of unemployed workers in $t+\tau$, and finally $u_t^s(\tau)$ be equal to the stock of short-term unemployed at time $t+\tau$ but were employed in $t' \in [t, t+\tau]$. For $\tau = 0$, $u_t^s(0) = 0$, and for convenience Shimer assumes the stock of short-term unemployed at the end of period t is $u_{t+1}^s \equiv u_t^s(1)$.

The procedure assumes unemployment and short-term unemployment evolve according to the following equations:

$$\dot{u}_{t+\tau} = e_{t+\tau}s_t - u_{t+\tau}f_t \quad (1)$$

$$\dot{u}_t(\tau) = e_{t+\tau}s_t - u_t^s(\tau)f_t \quad (2)$$

In (1), the stock of unemployed increases when employment separations occur and decreases when the unemployed find jobs. In (2) we can apply the same logic to short-term unemployment.

By subtracting (2) from (1), we eliminate $e_{t+\tau}s_t$ and obtain:

$$\dot{u}_{t+\tau} = \dot{u}_t(\tau) - (u_{t+\tau} - u_t^s(\tau))f_t \quad (3)$$

Since $u_t^s(0) = 0$, for a given initial value of u_t , we can solve for u_{t+1} , $u_{t+1}^s \equiv u_t^s(1)$,

$$u_{(t+1)} = (1 - F_t)u_t + u_{(t+1)}^s \quad (4)$$

The expression above states that the stock of unemployed next quarter is equal to the number of unemployed that had not exited the unemployment state prior to the start of the current quarter, and the stock of incoming short-term unemployed that were separated from employment during the quarter. In other words, $F_t u_t$ is the flow out of unemployment during the interval, and u_t^s is the stock of people that have been unemployed for less than one quarter. Reorganizing and solving for the job finding probability F_t we obtain

$$F_t = 1 - \frac{u_{t+1} - u_{t+1}^s}{u_t} \quad (5)$$

Assuming a constant hazard rate within the quarter, it is possible to calculate the corresponding monthly outflow hazard rate, the job finding rate f_t , as follows:

$$f_t = -\frac{\ln(1 - F_t)}{3} \quad (6)$$



where we divide the expression above by 3 to express the rate on a monthly basis in order to facilitate comparison with hazard rates in other studies. We solve for the monthly inflow hazard rate, the separation rate s_t , by solving equation (1):

$$u_{t+1} = \frac{(1 - e^{-f_t - s_t})}{f_t + s_t} s_t l_t + e^{-f_t - s_t} u_t, \quad (7)$$

where $l_t \equiv u_t + e_t$ is the labor force, assumed to be constant throughout the period t . In steady state, equation (7) is reduced to:

$$u_t^* = \frac{s_t}{s_t + f_t} \quad (8)$$

As demonstrated by Shimer (2012), these estimates are robust to temporal aggregation bias. As mentioned in the previous section, since aggregate unemployment data from the EOD is available for each quarter since 1960 and the unemployment spell duration data is available as of the second quarter of 1962, it is possible to calculate the hazard rate corresponding to one quarter, two quarters, three quarters and a year.

Considering that job finding rates measured at different durations (one quarter, two quarters, three quarters, and a year) may present similar trend behavior, yet differ in terms of range and variability, we test for duration dependence for the hazard rates within a given year. Formally, we test the hypothesis of duration dependence under the null hypothesis that finding rates are equal across different durations using the methodology applied by Elsby et al. (2013) and reject the null of no duration dependence. Our results yield evidence of negative duration dependence where the outflow hazard rate decreases with duration of the unemployment spell.¹³

This result is consistent with the findings of Elsby et al. (2013) for Anglo-Saxon and Nordic countries as well as for Japan. Although the test for duration dependence is different, our findings are also consistent with the results of Machin and Manning (1999) for Australia, the UK, and the U.S.

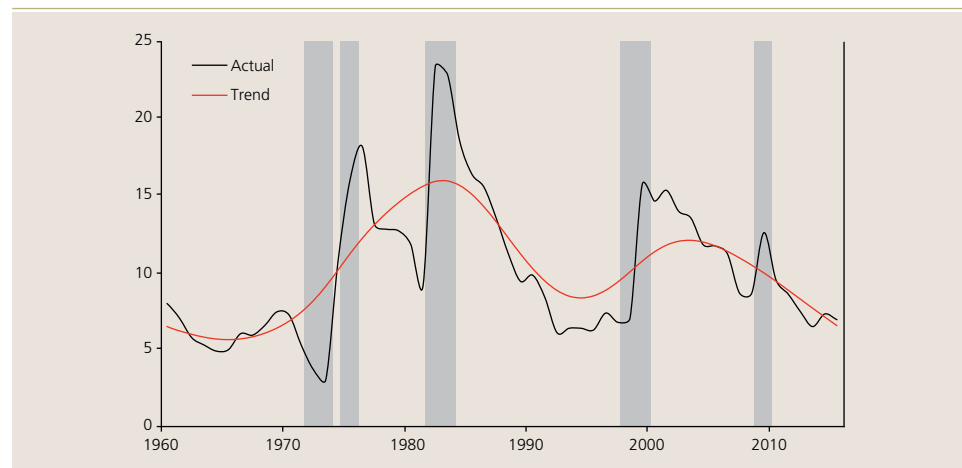
It is important to note certain caveats with our methodological approach. First, since we estimate a single *monthly* hazard rate for every year which is approximated from data from one quarter of the year, we are significantly smoothing out seasonal and cyclical properties of the time series. As mentioned in the Data section, because of seasonal effects March and June have higher unemployment rates relative to September and December. However, we do not think this is an issue since unemployment is not materially different between March and June, and thus we should not expect a positive seasonal impact on hazard rates calculated using data for these months.

¹³ One must be mindful that this duration dependence test does not account for compositional change in the unemployment pool. Duration dependence may arise from a real impact of unemployment duration on outflow rates and/or dynamic selection, where the negative correlation between duration and outflows is due to workers with high outflow rates exiting unemployment sooner than those with lower outflow rates.

About the cyclical properties of the hazard rates, we recognize that using an estimated hazard rate with data from three months of the year smooths out the cyclical behavior of the series. As a result we should interpret the high frequency behavior of the time series with care. This reservation is especially important when it comes to analyzing the importance of variations in outflow or inflow rates, specifically with respect to the timing of crises. As mentioned above, our data is for the second quarter, thus if a crisis hits the economy in this quarter we may see a high correlation between separation rates and unemployment, while the relation between the latter and the finding rate will be underestimated because this hazard rate tends to lag unemployment. It is also worth noting that we have implicitly assumed that transition probabilities do not change during the quarter, which we believe is a reasonable assumption at a quarter's duration, but not so for longer durations as evidenced by the results of our duration dependence test cited above. With these considerations in mind, we note that we are fundamentally interested in the long-run trend behavior of these series, and thus any cyclical properties lost during the elaboration of the time series should not appear as a major concern. Finally, implications of the constant labor force participation assumption are discussed in section VI.

Figure 1

Actual and Trend Unemployment Rate (percent)



Note: The figure plots both actual and trend time series of the unemployment rate for Chile's Greater Santiago calculated with EOD data. The trend was calculated using a Hodrick-Prescott filter with a smoothing parameter of 100. Gray bars represent years in which Chile's real output growth rate was negative: 1972-73, 1975, 1982-83, 1999, and 2009.



V. RESULTS

Since forces driving high- and low-frequency movements of separation and finding rates may vary, both theoretically and empirically, we present our results in two sub-sections. First we analyze the high-frequency movements of the hazard rates during the business cycle, paying specific attention to the behavior of inflows and outflows during crises. We compare our results with those obtained by other authors for Chile, and to place our results in a broader context, we also compare our results to those obtained for other economies. In the second sub-section, we analyze the evolution of low-frequency components with respect to the evolution of the unemployment trend and the long-run behavior of separation and finding rates.

1. Evolution of hazard rates

The estimated hazard rates are summarized in table 1, where the first row summarizes our results for the entire sample (1962-2015), and the latter two columns include data for smaller sub-sets to facilitate comparison with other studies. Focusing on the entire sample, the average unemployment rate throughout the last fifty years has been slightly above 10% and has presented a considerable degree of variability ranging from 3% to 23%. During the same period, the average monthly separation rate was 2.4%, with a minimum of 0.7% and a maximum of 3.8% throughout the whole time span. Meanwhile, the average finding rate was 24.6%, fluctuating between 7.2% and 43.6%. It must be noted that the large difference in the hazard rates is due to the fact that the job finding rate is calculated as a ratio to the unemployment pool and the separation rate is computed as a ratio to the employment pool. Since the size of the employment pool is much larger than the size of the unemployment pool, the separation rate is much lower than the job finding rate.

TABLE 1

Unemployment Rate and Monthly Hazard Rates

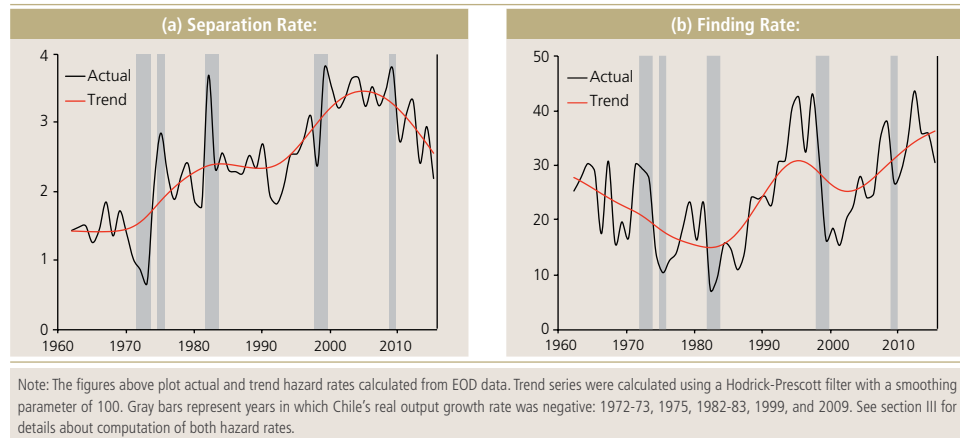
(percent)

| | Unemployment Rate | Separation Rate | Finding Rate |
|-----------|-------------------|-----------------|--------------|
| 1962-2015 | 10.2 | 2.4 | 24.6 |
| 1997-2009 | 11.6 | 3.4 | 26.4 |
| 2010-2015 | 7.7 | 2.8 | 34.9 |

Note: All are period averages expressed in percentage terms. Unemployment is calculated from EOD data. Monthly hazard rates are calculated according to the procedure described in the Methodology section.

Figure 2

Monthly Hazard Rates (percent)



Our calculations for the separation rate as well as the H-P filtered separation rate are both presented in figure 2.¹⁴ In analyzing the actual results of the separation rate, what comes to our attention are the drastic swings in the separation rate from year to year associated to economic downturns. In fact, the separation rate spikes during the economic recession periods of 1972-73, 1975, 1982-83, 1999, and 2009. In terms of the trend, notwithstanding significant variation throughout the period, the monthly separation rate more than doubles from close to 1.5% during the 1960s to a level above 3% towards 2010. In fact, figure 2 reveals a clearly positive trend in the separation rate starting in the early 1970s, when the separation rate hits its lowest value of 0.7% in 1973. Afterwards, albeit with considerable fluctuation, the separation rate spiked to 3.7% in 1982, dropping once again and regaining a positive trend to reach similar levels in 1999 and 2009.

Even though the separation rate tends to display a general positive trend throughout, it appears to have temporarily stabilized between 1985-1997, a period that is associated with the so called “golden years” of the Chilean economy. In fact, persistent improvements in total factor productivity during this period caused the economy to grow at an average rate of more than 7% per year.¹⁵ During this time the separation rate remained near those of the aftermath of the 1982-83 crisis; one possible explanation is the “creative destruction” process as firms gradually adjusted to the structural reforms.

Our results for the finding rates, both actual and H-P filtered, are presented in the right-hand panel of figure 2. During the first two decades of our sample, the finding rate appears to follow a downward trend dropping over five percentage

¹⁴ H-P filtered hazard rates were obtained using a smoothing parameter of 100.

¹⁵ For a discussion on the factors that drove growth during this period see Gallego and Loayza (2002) and Schmidt-Hebbel (2006).



points between the 1960s (with an average of 24.5%) and the 1970s (with an average of 19.7%). The reduction in the finding rate was further intensified by the international debt crisis of 1982, when it plummeted to single digits and reached its historical low of 7.2%; yet soon after it began a steady increase. During the late 1980s and the first half of the 1990s the finding rate increased consistently even surpassing 40% in 1994-1995. The average finding rate between 1985 and 1995 was 25.3%. The Asian crisis in 1999 had a significant impact on the probability of finding a job; actually, the finding rate reached a local minimum in 2002 at 16.3%. Henceforth, the finding rate regained another positive growth path, yet at a slower pace than in the previous decade. During the first decade of the new millennium, the average finding rate reached 26.4%, roughly four percentage points below the average finding rate of the “golden years.” In the aftermath of the 2009 recession, the finding rate reached a sample high of 44% in 2012, subsequently falling back to 30% in 2015.

Our results match prior studies of Chilean labor markets. Lima and Paredes (2007) use EOD data to calculate quarterly transition probabilities for Chile’s labor market considering three states within the labor force: employed, unemployed, and inactive. They compute the transition probabilities based on a stock-flow model of the labor market adapted from Haindl (1985). In spite of the differences in the methodology used to calculate the transition probabilities, our results are very similar. They find that, depending on the period analyzed, the *quarterly* probability of moving from employment to unemployment fluctuates between 2.5% and 6.6%, while the quarterly job finding probability ranges between 40% and 80%.¹⁶ Their data also reveals a positive trend for the transition probability from employment to unemployment, analogous to the results we obtain for the increasing trend in the separation rate. Like us, they cannot identify a clear trend with respect to the transition probability from unemployment to employment.

Particularly with respect to the behavior of the hazard rates during the 1982 crisis, our results are also consistent with the results from Gallego and Tessada (2012). In their study, the authors analyze the impact of sudden stops on labor market flows at a sectoral level for Chile, as well as Brazil, Colombia, and Mexico.¹⁷ Even though their results are economically significant between sectors, in general their evidence suggests that sudden stops are in fact associated with declines in job creation and significantly larger increases in job destruction.

Our results are also similar to those calculated by others with the National Employment Survey (ENE). To the best of our knowledge, the first study using the ENE dataset to compute labor market gross flows was Bravo et al. (2005); during the period 1996-2003, the authors report an average quarterly unemployment-employment probability of 35%, while the average quarterly employment-unemployment transition probability was close to 4%.

¹⁶ See table 2 in page 174 in Lima and Paredes (2007).

¹⁷ Once again, it must be noted that the authors calculate labor flows under a different methodology.

Several studies have continued to build on the work of Bravo et al. (2005) with the ENE dataset. First, Jones and Naudon (2009) construct *quarterly* transition probabilities considering three states in the labor market (employed, unemployed, and inactive) for 1997-2009 with ENE data. To facilitate comparison with their results, we report our results for the same period in the second row of table 1. First of all, we must adjust their results to a monthly basis, because they estimate quarterly flows.¹⁸ Accordingly, the estimated *monthly* employment-to-unemployment transition rate from Jones and Naudon (2009) is equal to 1.3%, considerably below our estimate of 3.4%. The estimated monthly unemployment-to-employment rate of 21% appears somewhat more in line with our estimate of 26%. García and Naudon (2012) estimate transition probabilities by extending the sample used by Jones and Naudon (2009) back to 1993 and correcting for aggregation bias, finding that the average monthly separation rate for the period 1993-2009 was 2.1% and the average monthly finding rate was 28.7%. Our monthly finding rate for the period 1993-2009 is the same (29%); however, our separation result is considerably greater at 3.2%. Finally, recently Marcel and Naudon (2016) further extended the ENE survey data with the new NENE data set through 2016, and found that the monthly separation rate for the 2010-2016 period was 1.9%, while the finding rate was 26%. Although our sample runs one year short, our hazard rate estimates for the 2010-2015 period are reported in the third row of table 1. Once again, our hazard rate estimates appear below those reported by the series of studies with ENE or NENE data, especially the separation rate. One possible explanation behind the large difference in the separation rate may be that the unemployment rate in the EOD survey tends to be above the ENE and NENE surveys.¹⁹

International comparison

We compare our results to those obtained for other OECD economies by Elsby et al. (2013) since their study is not only the most comprehensive but also has the same methodology (see also Rogerson and Shimer, 2010). Elsby et al. (2013) study the evolution of ins and outs for fourteen OECD economies. The comparison of transition probabilities across economies must be done with certain reservations, because definitions and procedures used in the elaboration of labor market statistics may differ across countries and, as a result, labor market statistics are not entirely comparable.²⁰ With this consideration in mind, the studied period varies across countries due to data availability, with initial years for the series ranging from 1968 to 1986 depending on the country, and all finalizing in 2007. The authors include Anglo-Saxon, Nordic and Continental European countries in

¹⁸ We compute the monthly hazard rate p using the following equation: $P = 1 - e^{-3p}$, where P is the quarterly probability and p is the monthly hazard rate.

¹⁹ The EOD survey shows a higher average unemployment rate than the ENE survey. For the 1986-2009 period, our EOD unemployment rate calculations have the average unemployment rate at 10.5%, while the average ENE unemployment rate for the same period is 8.5%.

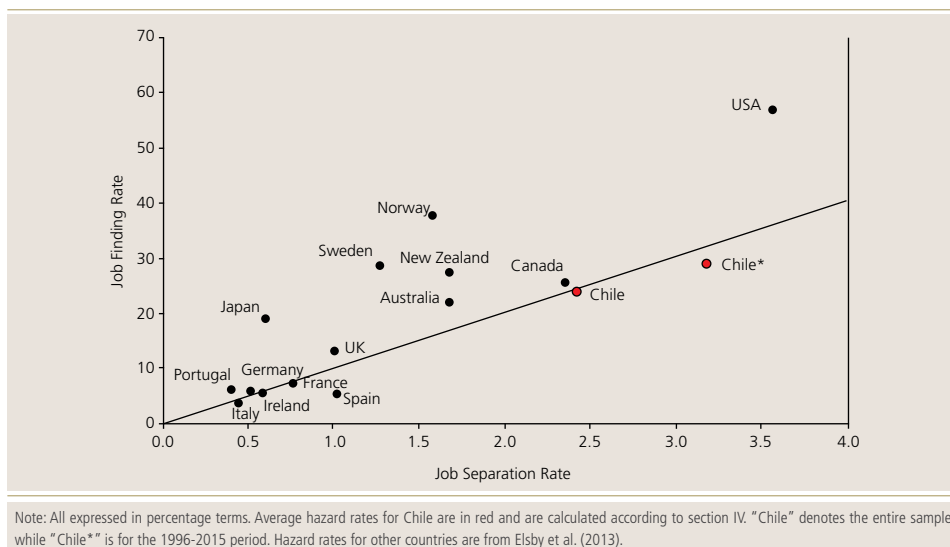
²⁰ Furthermore, in this context, it is important to insist that in our research we only consider two states: employed and unemployed. However, research in labor market dynamics generally also considers transition probabilities from and to inactivity.

their sample.²¹ Significant differences are observed in the labor market dynamics across these groups. In particular, the finding rate in Anglo-Saxon and Nordic economies throughout the sample is close to 30%, while it tends to lie below 7% for economies in Continental Europe. On the other hand, the separation rate for Anglo-Saxon and Nordic economies tends to lie above 1.5%, with Continental European economies displaying a considerably lower rate between 0.5 and 1%. They also show that the United States is by all means an outlier with separation rates above 3.5% and finding rates closer to 60%. These estimates and our results are presented in figure 3.

Chile ranks among the more dynamic labor markets in the sample, with average hazard rates that resemble those of Anglo-Saxon countries. This result may be surprising considering that conventional wisdom claims that the Chilean labor market tends to be among the less flexible. However this result does not contradict previous studies. For instance, as mentioned before, Jones and Naudon (2009) and Bravo et al. (2005) obtain similar average finding and separation rates using ENE data. Using a very different methodology and data, Albagli et al. (2005) reach the same conclusion; in particular, these authors analyze the dynamic response of unemployment in the presence of macroeconomic shocks identified with a structural VAR; their results show that Chile ranks third among all countries in their sample that includes (in ascending order of labor market flexibility): Korea, Hong Kong, Chile, Mexico, United States, Germany, Sweden, Spain and Colombia.

Figure 3

Average Monthly Hazard Rates across Countries



²¹ The Anglo-Saxon and Nordic countries group is composed of: Australia, Canada, New Zealand, Norway, Sweden, the United Kingdom and the United States, with the addition of Japan. Continental Europe includes France, Germany, Italy, Portugal and Spain, with the addition of Ireland.

An interesting insight of the analysis mentioned above is that even though the Chilean labor market appears relatively dynamic, the unemployment rate in Chile has been on average higher than in most of the countries analyzed by Elsby et al. (2013). In fact, for the sampled period the average unemployment rate in Chile was 10.4%, similar to the levels of Continental Europe and well above the 6% average unemployment rate of the Anglo Saxon and Nordic countries.

The obvious question then is why is the Chilean labor market more dynamic than Continental European labor markets, yet at the same time able to sustain similar levels of unemployment? The answer may also be in figure 3; here the solid black line represents combinations of hazard rates with the same steady-state unemployment rate as Chile for the period 1962-2015.²² The slope is evidently positive since, conditional on a given unemployment rate, a greater chance of losing a job must be associated with a greater chance of finding a new job. Countries with dots above the line represent economies with an average unemployment rate below 8.96%. This is true even for countries with labor markets that are less dynamic, such as Ireland and Germany. What seems critical to explain the level of unemployment in Chile is the fact that the separation rate is proportionally much larger than the finding rate. We explore the possible connection between the evolution of the hazard rates and changes in labor market legislation in more detail in sub-section V.2.

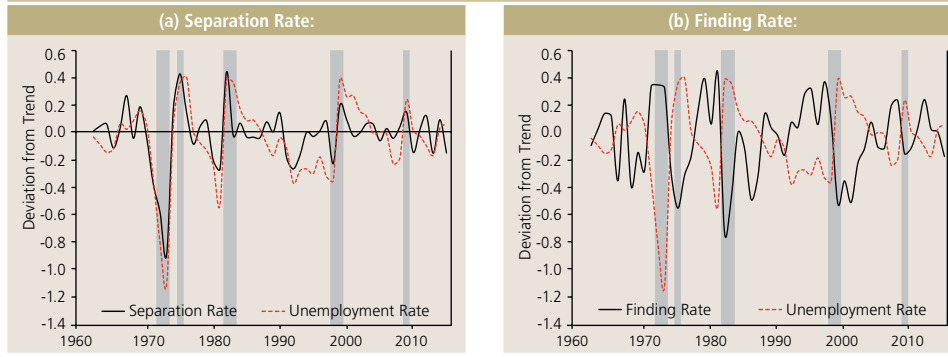
Variance decomposition

In this section we calculate the contribution of these hazard rates to the variation in the unemployment rate. First, we plot trend deviations of each hazard rate throughout the last fifty years with respect to the unemployment rate. The left hand panel of figure 4 shows the percentage deviation of the separation rate and the unemployment rate each with respect to their trend, obtained by applying an H-P filter with a smoothing parameter of 100 to each series. With the only exception of the 1972-73 recession, the separation rate increased during periods of economic slowdown, coupled with increases in the unemployment rate. If we refer to both figures 1 and 2, the data suggests that while the unemployment rate gradually returned to its trend, the separation rate did so faster. In terms of levels, figure 2 shows that only in the case of the recession of 1999, the separation rate did not return to earlier pre-crisis levels; our interpretation is that when the crisis hit, the separation rate was already following a positive trend, and as a result the relatively small decrease in the separation rate after the crisis must be seen as a return to the separation rate trend path.

²² *i.e.* all the combinations of s_t and f_t such that $s_t / (s_t + f_t) = 8.96\%$. The steady-state unemployment rate is, in general, very similar to the actual unemployment rate, and it has the advantage of establishing a direct connection between the unemployment rate and the inflows and outflows of unemployment.

Figure 4

Unemployment Rate and Hazard Rates: Deviations from Trend



Note: The figures above plot actual and trend hazard rates calculated from EOD data. Trend series were calculated using a Hodrick-Prescott filter with a smoothing parameter of 100. Gray bars represent years in which Chile's real output growth rate was negative: 1972-73, 1975, 1982-83, 1999, and 2009. See section III for details about computation of both hazard rates.

The deviation of the job finding rate with respect to its trend is shown on the right hand side of figure 4. With the sole exception of the 1972-1973 recession the finding rate has dramatically dropped during periods of economic slowdown, only to gradually recover its original value, mimicking the behavior of the unemployment rate. This behavior is particularly clear in the aftermaths of the crises of 1982, 1999 and 2009.

We now calculate the contribution of the hazard rates to the variation in the unemployment rate using the procedure in Shimer (2012) and Fujita and Ramey (2009). Following Shimer (2012), we quantify the contributions of hazard rates to overall unemployment variability according to equation (8), that is by approximating, using a log-linear approximation of the changes in the unemployment rate as follows:

$$\hat{u}_t^* \approx \underbrace{\frac{(1 - u_t^*) \hat{s}_t}{C_s}}_{\hat{C}_s} - \underbrace{\frac{(1 - u_t^*) \hat{f}_t}{C_f}}_{\hat{C}_f}, \quad (9)$$

where $\hat{x} = \ln(x_t / \bar{x}_t)$ for some reference value x_t and trend value \bar{x}_t .

We clarify that in this context, we calculate the trend value of the unemployment rate $\bar{u}_t \cong \frac{\bar{s}_t}{\bar{s}_t + \bar{f}_t} \equiv \bar{u}_t^*$ where \bar{s}_t and \bar{f}_t are the H-P filtered values of the separation and finding rate respectively. The expression above decomposes deviation of the unemployment rate with respect to its reference value into the effect of log deviation of the separation hazard rate (C_s) and the log deviation of the finding rate (C_f). We then calculate the contributions of the hazard rates toward unemployment volatility by calculating the following:

$$\beta_i = \frac{cov(\hat{u}_t^*, C_{i,t})}{var(\hat{u}_t^*)}. \quad (10)$$

Our results are shown in table 2 where panel A refers to the entire sample 1962-2015 and panel B to the sub-sample 1996-2015. Our results indicate that changes in the finding rate have contributed more than the separation rate to changes in unemployment.²³ Our findings are similar to the results found by researchers for other labor markets as well as for Chile, in the sense that the separation rate is critical to explain large peaks in the unemployment rate, yet the evolution of unemployment is closely related to outflow behavior, that is, the finding rate. When considering the entire sample, our results indicate that changes to the finding rate contribute to about 60% of the unemployment variance, while the remaining 40% is explained by changes in the separation rate.

From an international perspective, Petrongolo and Pissarides (2008) find that contributions from the separation rate to unemployment volatility account for 33% for the UK, 20% for France, and 43.3% for Spain. Elsbey et al. (2013) determine that for Anglo-Saxon economies the separation rate accounts for roughly 20% of the unemployment variation. The separation rate in Continental European labor markets tends to explain close to 50% of unemployment volatility. The contribution of each of these flows to fluctuations in the unemployment rate for the United States labor market has been the subject of intense debate. On one side Shimer (2012) states that the separation rate accounts for 28% of variability in unemployment using H-P filtered data. Fujita and Ramey (2009) demonstrate that fluctuations in the separation rate explain between 40% and 50% of the fluctuations in the unemployment rate.

TABLE 2

Variance Decomposition

(percent)

| | Separation Rate | Finding Rate | Unemployment Rate |
|--------------------------|-----------------|--------------|-------------------|
| Panel A: 1962 - 2015 | | | |
| Correlation with | 80.0 | -78.3 | 93.7 |
| Contribution to variance | 42.2 | 59.0 | - |
| Obs. | 53 | 53 | 53 |
| Panel B: 1996 - 2015 | | | |
| Correlation with | 46.1 | -89.0 | 96.3 |
| Contribution to variance | 21.5 | 80.5 | - |
| Obs. | 20 | 20 | 20 |

Note: Methodology explained in section V.1. Panel A summarizes variance decomposition results for high frequency statistics for the entire sample. Panel B summarizes variance decomposition results for high frequency statistics for a shorter time span.

²³ For robustness, table A1 in the appendix shows the results for a similar exercise, where we have taken previous values as reference points: that is and defined accordingly. As before, the first panel refers to the period 1962–2015 and the second one to the period 1996–2015. Overall, the results reaffirm our conclusion that changes in the finding rate have contributed more than the separation rate to changes in unemployment.



2. Trends

In this section we refer to the trend unemployment rate as calculated in equation (11) below, rather than the H-P version previously mentioned. We adjust Shimer's steady state derivation of the unemployment rate from equation (10), and calculate the trend as the steady state unemployment rate when the separation and finding rates are at their respective steady state values, that is:

$$\bar{u}_t = \frac{\bar{s}_t}{\bar{s}_t + \bar{f}_t}, \quad (11)$$

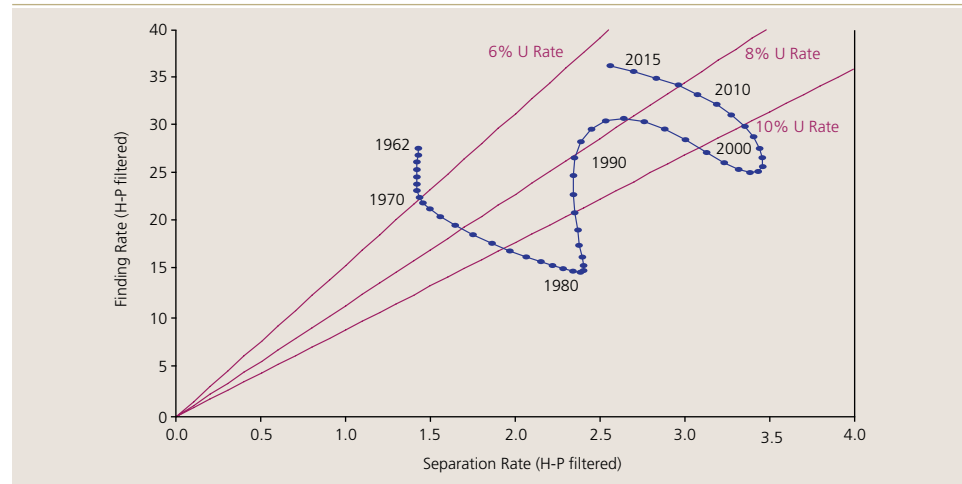
where \bar{s}_t and \bar{f}_t are the H-P filtered series of the separation and finding rate respectively (with smoothing parameter of 100). It is important to note that the trend unemployment rate as calculated in equation (11) is highly contemporaneously correlated (97.4%) with the H-P filtered unemployment rate series, thus we do not obtain significantly different results using either series. That being said, considering that the trend as calculated in equation (11) appears more consistent within the Shimer framework than an H-P filtered unemployment series, we decide to use equation (11) to describe the trend unemployment rate henceforth.

Before proceeding it is important to note two limitations in our analysis. First, at least theoretically, separation and finding rates are not necessarily orthogonal, and thus analyzing both independently could hide relevant interactions between both margins. However, as it is shown below, the different behavior of both series sheds light on the possible forces behind the steady rise in unemployment and lays plausible explanations to this phenomenon. Second, our decomposition of the unemployment rate does not consider movements in the participation rate (i.e. we assume a constant labor force) and as a result changes in labor force participation do not have an impact on the variance of the unemployment rate. This is of course a limitation, but as will be discussed later, our overall results still hold if we focus on labor market dynamics for prime-aged males, the group that has maintained a high participation rate throughout and moreover accounts for a large share of the labor force. Changes in the participation rate and composition of the labor force are further discussed in the next section.

To understand the relationship between trend unemployment and the long-run behavior of the hazard rates, figure 5 plots the trend hazard rates with the diagonal lines representing the different combinations of trend finding and trend separation rates that are consistent with different levels of trend unemployment rates calculated according to equation (11). The figure illustrates that the trend separation rate increased by two percentage points between 1962 and 2000, although the trend finding rate was essentially at the same level as it was fifty years ago, thus rendering a higher trend unemployment rate. The trend separation rate retraced partially thereafter, and the trend finding rate has increased, thus consistent with a lower trend unemployment rate with respect to 2000.

Figure 5

Evolution of Trend Hazard Rates (percent)



Note: The figure above displays the evolution of trend hazard rates over time. The calculation of hazard rates is described in the Methodology section. Hazard rates have been de-trended using a Hodrick-Prescott filter with a smoothing parameter of 100.

VI. DISCUSSION

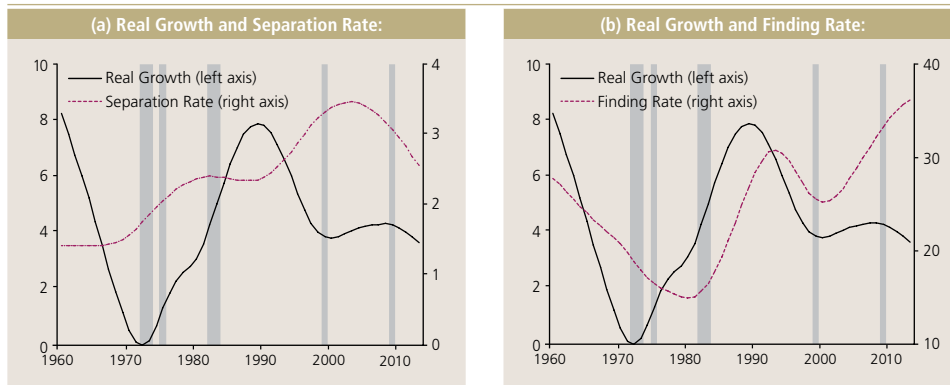
All together, the data shows that the unemployment rate is not that different today from what it was fifty years ago, yet the underlying dynamics in terms of hazard rates are considerably different, as the current trend unemployment rate is supported by significantly higher trend finding and separation rates. In the following sub-section we discuss possible factors that may have driven changes in trend hazard rates over time.

1. Economic growth and structural transformation

Chile's growth performance has varied considerably throughout the past fifty years, with periods of growth interrupted by deep recessions in the mid-1970s and early 1980s, and less severe downturns associated with the impact of the Asian financial crisis and the Global financial crisis. Rather than analyzing the cyclical relationship between hazard rates and growth, we look at the relationship over time focusing on trend series obtained by H-P filtering the series with a smoothing parameter of 100. Focusing on real economic growth in Greater Santiago (figure 6), growth on average has increased since the 1970s, peaking during the early 1990s and then decelerating, levelling out at around 4% since 2000.

Figure 6

Trend Economic Growth and Trend Hazard Rates
(percent)



Note: The figures above show trend real growth rates for Greater Santiago and trend hazard rates calculated from EOD data. Trend series were obtained with a Hodrick-Prescott filter with a smoothing parameter of 100. GDP data for the Metropolitan Region was obtained from the National Statistics Institute and Odeplan (1978, 1986). Gray bars on both charts represent years in which real output growth rate was negative: 1972-73, 1975, 1982-83, 1999, and 2009.

In this context, despite the fact that trend growth in Greater Santiago has varied considerably, the separation rate on average has increased throughout, falling only slightly during the past few years. The trend growth’s relationship with the trend finding rate looks clearer, with periods of faster economic growth associated with higher finding rates, although the relationship during the past few years diverges.

Also of importance, Chile’s economic growth over the past fifty years has been characterized by the ongoing reallocation of production across sectors over time, with the tertiary sector (services and others) gradually increasing its share relative to the primary sector (agriculture and livestock, fishing, mining and quarrying) and the secondary sector (manufacturing). Structural transformation across sectors is relevant for labor market outcomes since labor demand may vary across sectors and these may respond differently to shocks. Not surprisingly, employment shares by sector in Greater Santiago are consistent with the sectoral transformation nationwide, with the employment share of the tertiary sector steadily taking over the secondary sector, especially since the 1990s.²⁴ While the unemployment rate in the manufacturing sector is not that different from the services sector on average, the unemployment rate in the former tends to be considerably more volatile especially during—and in the immediate aftermath of—recessions (figure 7B).

²⁴ The employment share of the primary sector at the national level is significantly higher than that of Greater Santiago since mining and agricultural employment tends to be concentrated in other regions. According to INE data, the employment share of the primary sector nationwide has remained stable at roughly 10% since 2008, while the secondary sector accounts for roughly 11% of employment since 2008, and the remaining lion share accounted for by the tertiary sector.

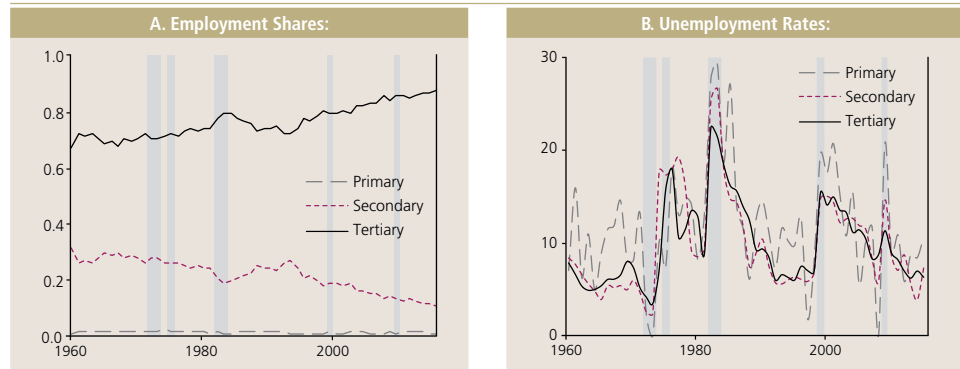
We estimate hazard rates across sectors since 1980 using the same methodology.²⁵ In addition, we assume unemployment in any given sector “x” is measured as the stock of unemployed whose most recent employment was in sector “x”.

Considering the small share of primary employment in Greater Santiago, we only report hazard rates for the secondary and tertiary sectors in figure 8. Although hazard rates on average for the tertiary sector are slightly greater in magnitude than the manufacturing sector, they are not statistically different from each other at the conventional significance levels.

Figure 7

Labor Market by Sector

(percent)

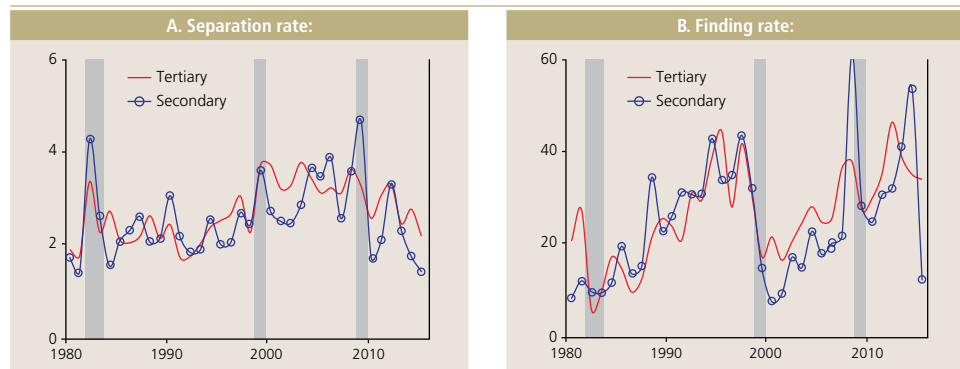


Note: The figures above display employment shares and unemployment rates by sector in Greater Santiago based on calculations from the EOD survey. Gray bars on both charts represent years in which real output growth rate was negative: 1972-73, 1975, 1982-83, 1999, and 2009.

Figure 8

Hazard Rates by Sector

(percent)



Note: The figures above display hazard rates for the secondary and tertiary sector in Greater Santiago based on calculations from the EOD survey. Gray bars on both charts represent years in which real output growth rate was negative: 1972-73, 1975, 1982-83, 1999, and 2009.

25 Microdata with short-term unemployment by sector is available for March and June since 1980.



2. Labor market institutions and changes to the regulatory environment

A second dimension to consider is the link between changes in labor market legislation and unemployment dynamics. Even though the impact of labor legislation in Chile's labor market has been studied profusely, strictly analyzing labor market flows within the paradigm of changes in labor legislation is interesting.²⁶ The increasing separation rate trend that began in the 1970s occurred despite changes in labor regulation that at times increased and other times decreased labor market flexibility. One possible explanation for increase in the trend separation rate may be changes in the interpretation of labor law by the judicial system that increased flexibility, amongst other important changes in labor regulation. Although between 1966 and 1973 "economic reasons" were included as a just cause for dismissal in labor law, the courts tended to rule these dismissals unjustified. Nevertheless, within a new political regime in 1973, courts began ruling in favor of firms in dismissal claims as the Ministry of Labor began to accept "economic reasons" as a justification for dismissal.²⁷ Throughout the 1980s, the trend separation rate oscillated between 2.3% and 2.4%, close to 0.6% above the average trend level of the previous decade despite the fact that labor regulation initially became even more flexible, and then, after 1984, returned to a more rigid structure as "economic needs" were no longer considered a just cause for dismissal. The implementation of labor laws by the new democratic government in 1990, which added rigidity to the labor market were still accompanied by an increasing trend in the separation rate. Moreover, the separation rate appears to have remained high in the aftermath of the implementation of a wide-ranging Labor Reform in 2001 that further added rigidity to the labor market by raising dismissal costs when considered unjustified, strengthening trade unions, creating and regulating part-time contracts, among other important aspects.²⁸

Chile tends to be flagged as an economy with a "dual-labor market," referring to the sizable share of fixed-term and temporary workers relative to workers on open-ended contracts. According to the OECD, Chile ranks highest among member economies in temporary contracts as a proportion of permanent contracts, and provides evidence suggesting that temporary workers have significantly higher job turnover rates relative to workers with permanent contracts (OECD, 2015). Along these lines, Silva and Vazquez-Grenno (2013) find evidence for Spain, another OECD economy with a high share of temporary contracts, that suggests that a large share (85%) of employment-to-unemployment flows are accounted for by temporary contracts. Moreover, they find that unemployment variability is driven overwhelmingly by movements to and from temporary jobs. Separately, Sala et al. (2012) find a wide gap in unemployment volatility (+33%) between

²⁶ For an analysis of changes in labor legislation and their impact on labor market outcomes in Chile, see Edwards and Edwards (2000); Micco and Pagés (2004). For a regional analysis, see Heckman and Pagés (2000); Micco and Pagés (2004).

²⁷ See Edwards and Edwards (2000) for a discussion on labor market regulation and job security legislation.

²⁸ The Labor Law 19 759 was published in the Official Gazette on 5 October, 2001 and came into legal effect on 1 December, 2001. The reform also included greater penalties for the violation of labor laws, the introduction of payments by firms to workers on strike if replaced during the strike, a reduction in the number of workers needed to set up a union, and a reduction in the work week from 48 to 45 hours.

certain OECD economies with relatively high employment protection with respect to other non-Anglo-Saxon economies.

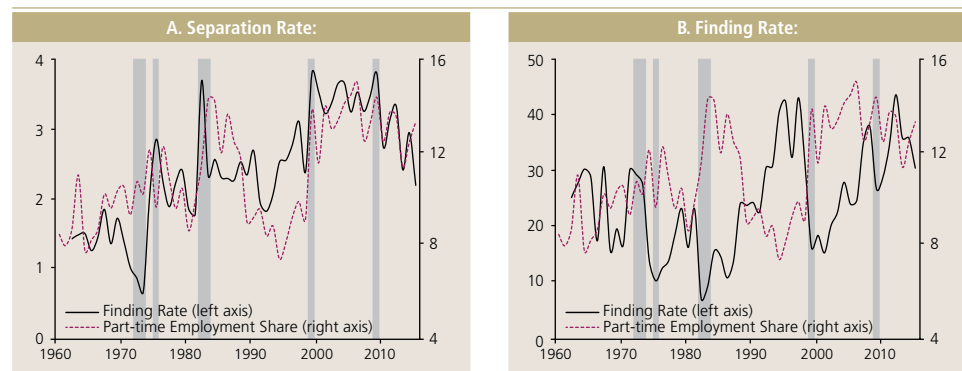
In order to assess whether the increase in our trend hazard rate results is due to greater turnover among temporary workers, we estimate hazard rates would ideally have data on contract duration. However, the EOD survey only recently began collecting this information, and the INE survey began collecting it only in 2010. As a second-best alternative we look at changes in the share of temporary employment over time and see if this share is associated with higher hazard rates over time.

As a proxy for temporary employment, we generate a series of part-time employment from the EOD survey considering all employed individuals working 30 hours or less.²⁹ Overall, our proxy for the share of part-time employment in Greater Santiago has increased from an average of 9.1% in the 1960s to an average of 12.9% between 2011 and 2015.³⁰ Throughout the past fifty years, the share of part-time employment spiked noticeably with the recession of 1982-83, then gradually declined during the Golden years of the Chilean economy (1985-1997), and then spiked again triggered by the recession of 1999. Since then, the share has remained relatively stable close to 13%, but appears to follow a declining trend especially in the aftermath of the 2009 recession. Importantly, the relatively stable share reached during the 2000s coincides with the Labor Reform of 2001.

Figure 9

Part-Time Share of Employment and Hazard Rates

(percent)



Note: The figures above display the share of part-time employment and hazard rates for Greater Santiago based on calculations from the EOD survey. Gray bars on both charts represent years in which real output growth rate was negative: 1972-73, 1975, 1982-83, 1999, and 2009.

²⁹ We decided to use this definition because it is consistent with the Chilean Labor Code and the OECDs definition. Note that the OECD defines part-time employment as people in employment (whether employees or self-employed) who usually work less than 30 hours per week in their main job. Our proxy may overstate the actual share of part-time employment because we account for total hours worked.

³⁰ The labor market survey of the Labor Directorate under the Labor Department conducted every few years since 1999 also shows a gradual increase in the share of non-permanent contracts, although at a significantly higher level, from 17.2% in 1999 to 25.2% in 2014.



The separation rate is reasonably contemporaneously correlated with the part-time employment share throughout the sample. Greater employment protection, especially in the aftermath of the Labor Reform of 2001 is associated with a higher separation rate and higher part-time employment. The finding rate tends to be negatively correlated with the share of part-time employment until 2001, when both series tend to increase. One possible explanation for this change is that outflows of unemployment may have been partly driven by gains in part-time employment.

3. Changes in the composition of the labor force

Throughout the past fifty years the Chilean labor market experienced significant changes in its composition, driven mainly by greater female labor force participation, lower (higher) participation among younger (older) age groups, and the impact of the gradual aging of the population.³¹ Since hazard rates tend to vary throughout the life cycle, the changes in the composition of the labor market should have affected our results. In order to assess the impact of the changes in composition of the labor force on our estimates, we perform a “shift-share” exercise in which we generate counterfactual hazard rates where we hold the labor force share of certain age groups constant at their 1980 levels, and compare these hazard rates to our current estimates. In doing so, we find that changes in the composition of the labor force did not have a material impact on the finding rate relative to our present results. In contrast, we find that changes in the composition of the labor force drove the separation rate down considerably.

TABLE 3

Variance Decomposition: Robustness Exercise

(percent)

| | Unemployment Rate | Separation Rate | Finding Rate |
|--------------|-------------------|-----------------|--------------|
| Total | 11.1 | 2.8 | 25.9 |
| Male | 11.2 | 2.9 | 26.2 |
| Female | 10.9 | 2.7 | 26.3 |
| By Age Group | | | |
| 15-24 | 21.5 | 7.2 | 28.9 |
| 25-54 Male | 9.3 | 2.3 | 25.2 |
| 25-54 Female | 8.7 | 1.9 | 25.1 |
| 55-64 | 7.7 | 1.5 | 23.8 |

Note: All are period averages expressed in percentage terms. Calculated from EOD data using March & June survey data from 1980-2015. Monthly hazard rates are calculated according to the procedure described in the Methodology section.

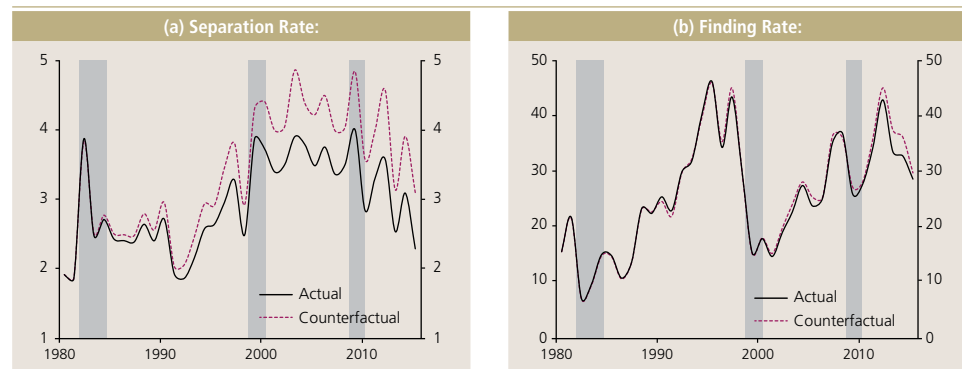
31 See figure A1 in the appendix for an illustration of the changes in the labor force across age groups.

Following the same methodology described before, we estimate hazard rates for four different age groups: 15-24 years, prime age (25-54 years) males and females, and individuals between 55-64 years. For the 1980-2015 period, average hazard rates between males and females are not significantly different from each other. However, important differences appear across age groups. The youngest age group has the highest average finding rate at 28.9% and also the highest average separation rate at 7.2%, both of which sustain a high average unemployment rate of 21.5%. Prime-age males and prime-age females have essentially the same average finding rate at 25%, although the former have a slightly higher average separation rate at 2.3%, while the separation rate of the latter reaches 1.9%. The eldest age group (55-64) has the lowest average unemployment rate at 7.7%, sustained by the lowest average finding and separation rates of all groups, 23.8% and 1.5%, respectively.

Our results appear somewhat in line with those estimated by Marcel and Naudon (2016). As mentioned earlier, these authors estimate hazard rates using another employment survey (NENE) for 1996-2016, and find that relative to prime-aged males, prime-aged women tend to have both lower finding and separation rates. As in our study, they also find that separation rates for the 15-24 age group are significantly above other age groups, while finding rates appear to be somewhat below other age groups. Results for the 55 years and older group are similar as well, with the separation rate at 1.1% (we obtain 1.5%) being the lowest among all groups, and the average finding rate at 25.5%, while we obtain 24.6%.

Figure 10

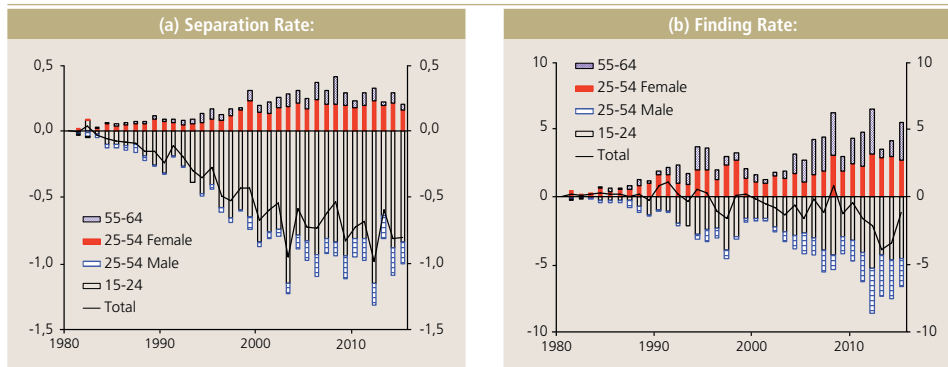
Hazard Rates: Actual and Counterfactual (percent)



Note: The figures above display monthly hazard rates estimated with EOD data. The counterfactual series holds labor force shares of each age group constant as of 1980.

Figure 11

Differences in Contribution to Hazard Rates: Actual and Counterfactual (percent)



Note: The figures above display the difference in contribution to hazard rates by age group and gender between their actual contribution and a counterfactual. The counterfactual series holds labor force shares of each age group constant as of 1980.

After briefly discussing our hazard rate results per group, we use these to construct counterfactual hazard rates holding the labor force shares of each age group constant at their 1980.³² As can be seen in the charts below, changes in the composition of the labor force since 1980 appear not to have materially affected the finding rate; however they do appear to have pulled down the separation rate.

In the figure above we observe which age groups drove the difference between the actual hazard rates and our counterfactual. In the case of the finding rate, falling shares of the 15-24 age group and prime age males were essentially offset by greater contributions by prime-age females and the eldest age group. In the case of inflows, the separation rate declined more than the counterfactual mainly because the share of the young age group was basically replaced by the eldest age group, which happens to have a considerably lower separation rate. As a result, the increasing trend in hazard rates appears to have occurred despite the impact of changes in labor force composition.

4. A Comment on Participation

A shortcoming of our methodology is that we assume individuals only transition between employment and unemployment, which is a strong assumption considering the increase in the participation rate in Chile (figure A1 in the appendix). The bias of our hazard rates depends on the magnitude of the flows across different states. To the extent that flows from inactivity to employment (unemployment) outweigh those from inactivity to unemployment, then we should expect our finding (separation) rate estimates to be upward (downward) biased. Since participation has been increasing, the net flows from inactivity to

³² Naturally these type of exercises are sensitive to the base year, but we obtain basically the same results when we construct another set of counterfactual series using the average labor force shares of 1980-1985 instead of the labor force shares of 1980.

employment or unemployment must be positive, which would suggest our hazard estimates are upward biased since they also capture direct flows from inactivity.

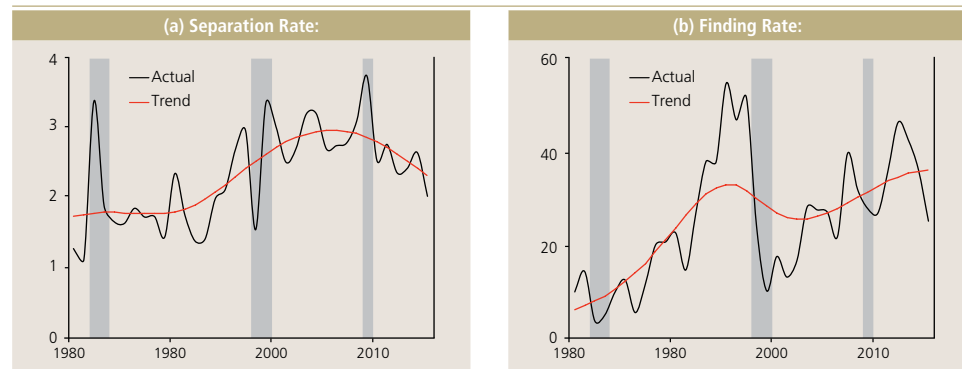
As a reference of the potential directional bias in our results, we compare our results with Marcel and Naudon (2016) which use a similar methodology but also account for movements in and out of the labor force. Differences in the magnitude of our hazard rate results relative to those of Marcel and Naudon (2016) may be partly due to the fact that unemployment in the NENE survey tends to be lower than the EOD survey; average unemployment rate for the NENE survey for the 2010-2016 period was 6.7%, while for the EOD survey the average unemployment rate during the same period was 7.7%. If we use the steady-state relationship $u_t^* = \frac{s_t}{s_t + f_t}$, a 1% difference in the unemployment rate may be generated by either a 4% difference in the finding rate or a 0.25% difference in the separation rate, *ceteris paribus*. The difference between our hazard rate estimates and those of Marcel and Naudon (2016) are considerably above those suggested solely by the differences in the level of the unemployment rate. Our average finding (separation) rate estimate is 34.8% (2.8%), while the corresponding flow estimate from Marcel and Naudon (2016) is 25.8% (1.9%), which suggests our hazard rates may be upward biased.

To isolate the potential bias of our results, we refer to the behavior of trend hazard rates for prime-aged males, a group that has not only shown a relatively constant participation rate since 1965—95% on average—but is also the group that accounts for the largest share of the labor force, currently roughly 40% (figure A1.D in the appendix). Again, as highlighted above in the shift-share exercise, data availability limits our results back to 1980. All in all, our results for prime-aged males (figure 12) also show the increasing trend in hazard rates, suggesting changes in the participation rate may not necessarily be that relevant for aggregate hazard rate dynamics.

Figure 12

Hazard Rates for Prime-Aged Males

(percent)



Note: The figures above display monthly hazard rates for prime-aged males estimated with EOD data. Trend series were obtained with a Hodrick-Prescott filter with smoothing parameter of 100.



VII. CONCLUSION

Using employment data from Greater Santiago as a proxy for Chile's labor market, we show that although the trend unemployment rate today is not materially different to what it was fifty years ago, the underlying dynamics sustaining the unemployment rate are considerably different. Job turnover, as measured by our hazard rate results, is considerably higher than it was half a century ago. While trend hazard rates have tended to increase over time, the average trend separation rate between 2010-2015 is practically twice its 1962-1970 level, and the average trend finding rate increased from 25% to 34% during the same period. Greater labor market dynamism occurred in the context of major structural changes in Chile's economy throughout the past half century. From a supply-side perspective, even though the share of the service sector has continued to increase, mainly at the expense of the share of the manufacturing sector, we do not find evidence that this structural shift has driven the trend increase in hazard rates. Chile also experienced significant regulatory changes that at times added rigidity and other times added flexibility to the labor market. In this context, trend job turnover rates increased throughout. Along these lines, we believe an interesting line of future work should be to analyze the importance of temporary and open-ended contracts on labor market transitions and unemployment variability.

Chile's labor market has also experienced important changes in its composition, including the increased participation of women and older age groups, as well as the decline in the participation of younger groups, along with the gradual aging of the population, which to a certain extent moderated growth in the separation rate, yet did not render a material impact on the finding rate.

Viewed from an international perspective, recent hazard rates actually indicate that in spite of relatively stringent labor legislation, the Chilean labor market appears to be as dynamic as that of the average Anglo-Saxon country, yet less dynamic than the labor market of the United States. Interestingly enough, to a certain extent these results defy conventional wisdom regarding the supposed rigidity of Chile's labor market.

Finally, from a historical perspective variations in the finding rate have contributed more than the separation rate to changes in the unemployment rate. If we strictly consider the last decade, changes in the unemployment rate have been overwhelmingly driven by changes in the finding rate relative to the separation rate. Our results regarding hazard rate contribution to unemployment variance are consistent with what has been observed in advanced economies' labor markets, where sharp swings in the unemployment rate in the short term seem to be explained by changes in the separation rate, yet the finding rate is increasingly important in explaining unemployment variability during the recovery and beyond.

REFERENCES

- Albagli, E., P. García, and J.E. Restrepo (2005). “Assessing the Flexibility of the Labor Market in Chile: An International Perspective.” In *Labor Markets and Institutions*, edited by J.E. Restrepo and K. Schmidt-Hebbel: Central Bank of Chile.
- Albagli, E. and A. Barrero (2015). “Tasa de Desempleo y Cambios Demográficos en Chile.” In *Monetary Policy Report*, Central Bank of Chile, March.
- Central Bank of Chile (2001). *Indicadores Económicos y Sociales de Chile, 1960 – 2000*. Bravo, D., C. Ferrada, and O. Landerretche (2005). “The Labor Market and Economic Cycles in Chile.” Mimeo, Universidad de Chile.
- Bravo, D., J. Ramos, and S. Urzúa (2003). “Las Diferencias en Desempleo INE-Universidad de Chile.” In: *Políticas de Empleo e Institucionalidad Laboral para el Siglo XXI*. Editorial Universitaria, October.
- Bregger, J. E. and C.E. Hoy (2006). “Report and Recommendations on Two Chilean Labor Force Surveys.” Economic Statistics Series No. 51, Central Bank of Chile.
- Castex, G., R. Gillmore, and I. Poblete (2014). “Análisis de Flujos en el Mercado Chileno” Working Paper N° 731, Central Bank of Chile.
- Edwards, S. and A.C. Edwards (2000). “Economic Reforms and Labor Markets: Policy Issues and Lessons from Chile.” *Economic Policy*, 15(30): 181–230.
- Elsby, M., B. Hobijn, and A. Sahin (2013). “Unemployment Dynamics in the OECD.” *Review of Economics and Statistics* 95(2): 530–48.
- Elsby, M., B. Hobijn, and A. Sahin (2015). “On the Importance of the Participation Margin for Labor Market Fluctuations.” *Journal of Monetary Economics* 72: 64–82.
- Fujita, S. and G. Ramey (2009). “The Cyclicalities of Separation and Job Finding Rates.” *International Economic Review* 50(2): 415–30.
- Gallego, F. and N. Loayza (2002). “The Golden Period for Growth in Chile: Explanations and Forecasts.” *Economía Chilena* 5(1): 37–67.
- Gallego, F. and J. Tessada (2012). “Sudden Stops, Financial Frictions, and Labor Market Flows: Evidence from Latin America.” *Journal of Development Economics* 97(2): 257–68.
- García, M. and A. Naudon (2012). “Dinámica Laboral en Chile.” Working Paper No. 659, Central Bank of Chile.
- Haindl, E. (1985). “Un Modelo para la Determinación de Flujos y Parámetros Dinámicos en el Mercado del Trabajo.” *Estudios de Economía* 12(1): 29–48.



Hall, R., (2006). “Job Loss, Job Finding, and Unemployment in the U.S. Economy over the Past Fifty Years.” NBER Chapters, in: NBER Macroeconomics Annual 2005, vol 20.

Heckman, R. and C. Pagés (2000). “The Cost of Job Security Regulation: Evidence from Latin American Labor Markets.” NBER Working Papers No. 7773.

Jones, I. and A. Naudon (2009). “Dinámica Laboral y Evolución del Desempleo en Chile.” *Economía Chilena* 12(3): 79–87.

Lima, V.O. and R.D. Paredes (2007). “The Dynamics of the Labor Markets in Chile.” *Estudios de Economía*, 34(2 year 20): 163–83.

Machin, S. and A. Manning (1999). “The Causes and Consequences of Long-Term Unemployment in Europe.” *Handbook of Labor Economics* 3: 3085–139.

Marcel, M. and A. Naudon (2016). “Transiciones Laborales y la Tasa de Desempleo en Chile.” Working Paper No. 787, Banco Central de Chile.

Micco, A. and C. Pagés (2004). “Employment Protection and Gross Job Flows: A Differences- in-Differences Approach.” *Research Department Publications* No. 4365, Inter-American Development Bank, Research Department.

Montenegro, C.E. and C. Pagés (2004). “Who Benefits from Labor Market Regulations? Chile, 1960–1998.” In *Law and Employment: Lessons from Latin America and the Caribbean*, NBER Chapters: 401–34. National Bureau of Economic Research.

OECD (2015). “OECD Economic Surveys: Chile.” OECD Publishing, Paris.

Petrongolo, B. and C.A. Pissarides (2008). “The Ins and Outs of European Unemployment.” *American Economic Review* 98(2): 256–62.

Pissarides, C.A. (2000). *Equilibrium Unemployment Theory*, 2nd edition, vol. 1 of *MIT Press Books*. MIT Press.

Rogerson, R. and R. Shimer (2010). “Search in Macroeconomic Models of the Labor Market.” NBER Working Papers No. 15901.

Schmidt-Hebbel, K. (2006). “Chile’s Economic Growth.” *Cuadernos de Economía – Latin American Journal of Economics* 43(127): 5–48.

Shimer, R. (2012). “Reassessing the Ins and Outs of Unemployment.” *Review of Economic Dynamics* 15(2).

Sala, H., J. Silva, and M. Toledo (2012). “Flexibility at the Margin and Labor Market Volatility.” *Scandinavian Journal of Economics* 114(3): 991–1017.

Silva, J. and J. Vázquez-Grenno (2013). “The Ins and Outs of Unemployment in a Two-Tier Labor Market.” *Labour Economics* 24: 161–9.

APPENDIX

Table A1

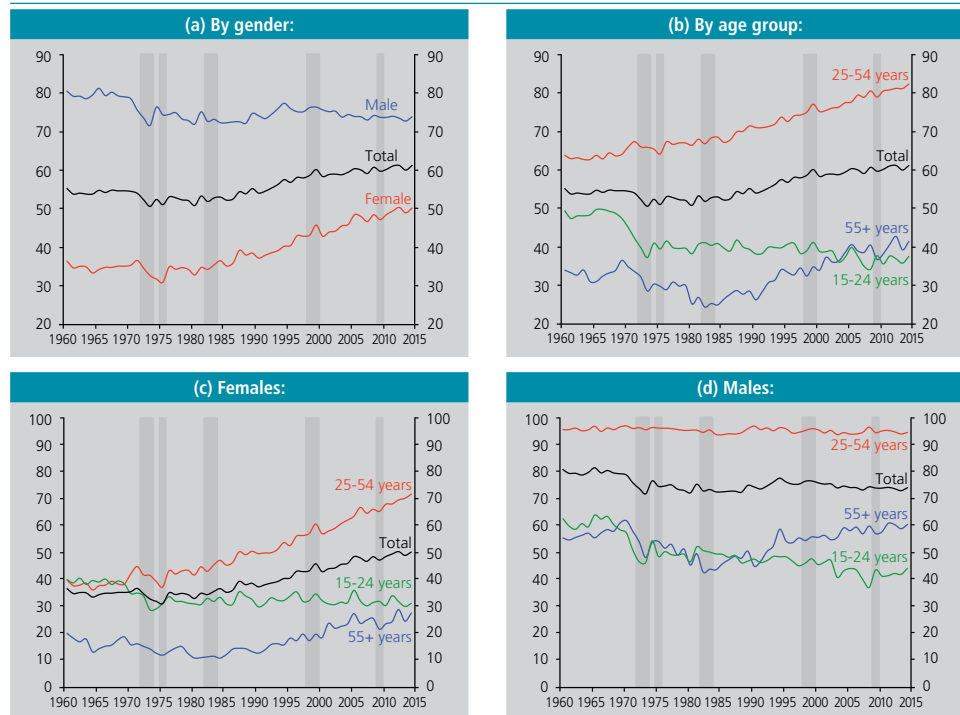
Variance Decomposition: Robustness Exercise (percent)

| | Separation Rate | Finding Rate | Unemployment Rate |
|-----------------------------|-----------------|--------------|-------------------|
| Panel A: 1962 - 2015 | | | |
| Correlation with $D\ln(ur)$ | 76.9 | -70.9 | 91.6 |
| Contribution to variance | 43.2 | 61.2 | - |
| Obs. | 53 | 53 | 53 |
| Panel B: 1996 - 2015 | | | |
| Correlation with $D\ln(ur)$ | 64.5 | -79.5 | 97.9 |
| Contribution to variance | 38.6 | 64.3 | - |
| Obs. | 20 | 20 | 20 |

Note: Methodology explained in section V.1. Panel A summarizes variance decomposition results for high frequency statistics for the entire sample. Panel B summarizes variance decomposition results for high frequency statistics for a shorter time-span.

Figure A1

Labor Force Participation Rate by Gender and Age Group (percent)



Note: The figures above display the participation rate (by gender and age group) calculated using EOD June data between 1960 and 2015 for individuals of age 15 and above. Gray bars on both charts represent years in which real output growth rate was negative: 1972-73, 1975, 1982-83, 1999, and 2009.