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Alberto Naudon
Andrés Pérez

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UNEMPLOYMENT DYNAMICS IN CHILE: 1960-2015*

Alberto Naudon
Banco Central de Chile

Andrés Pérez
Banco Central de Chile

Abstract

As a proxy for Chile's labor market, we analyze labor market flows of the Metropolitan Region of Santiago throughout the last fifty years. Following Shimer (2012) and others, we calculate job finding and job separation rates (hazard rates) to and from employment and unemployment considering unemployment stocks. Interestingly enough, even though the current trend unemployment rate is not materially different to what it was fifty years ago, our results suggest the labor market is considerably more dynamic. The increase in trend hazard rates occurs in the context of significant changes in economic growth, ongoing reallocation of output towards services relative to manufacturing, important regulatory changes in the labor market, and a gradual shift in the composition of the labor force. In addition, our estimates suggest that changes in the finding rate are relatively more important than changes in the separation rate in explaining the variance of the unemployment rate. From an international perspective our estimates suggest that in spite of having relatively rigid labor legislation, the Chilean labor market appears to be as dynamic as an average Anglo-Saxon country, yet less dynamic than the labor market of the United States.

Resumen

En el presente estudio analizamos flujos en el mercado laboral del Gran Santiago durante los últimos cincuenta años. Siguiendo a Shimer (2012) y otros, estimamos tasas de ocurrencia entre estados laborales. Nuestros resultados indican que a pesar de que la tasa de desempleo de tendencia no es materialmente distinta a la de hace cincuenta años, el mercado laboral es considerablemente más dinámico. La tendencia al alza en las tasas de ocurrencia se produce en un contexto de cambios significativos en la tasa de crecimiento económico del país, mayor importancia del sector servicios relativo al manufacturero, importantes ajustes regulatorios al mercado laboral, y cambios en la composición de la fuerza laboral. Nuestras estimaciones también sugieren que cambios en los flujos de creación de empleo son relativamente más importantes que cambios en los flujos de destrucción de empleo para explicar cambios en la tasa de desempleo. Mirado desde un punto de vista internacional, el mercado laboral chileno parece tan dinámico como el de Australia, Canadá, Noruega y Nueva Zelanda, aunque menos dinámico que el de Estados Unidos.

* The views expressed in this paper are exclusively those of the authors and do not necessarily reflect the position of the Central Bank of Chile or it's Board members. Any errors or omissions are the responsibility of the authors. We thank the comments pf the anonymous referees. Emails: anaudon@bcentral.cl y aperezm@bcentral.cl.

1 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 the most relevant variable associated with 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, individual's 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 not able to reduce unemployment after structural reform are more likely to face increasing social pressure and demands.

Nowadays, there seems to be a consensus regarding the use of the Diamond-Mortensen-Pissarides search model in determining the evolution of unemployment and the labor market as a function of worker flows.[1] During the last few years a number of articles have focused on the behavior of labor market flows.[2] 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 Metropolitan Region between 1962 and 2015.

The study of the evolution of the Chilean labor market is interesting in itself since, in contrast with most advanced economies, the Chilean economy has undergone major changes during the past fifty years. In fact, Chile transits from being one of the most regulated and least productive economies in the world during the sixties, to becoming one of the most dynamic emerging economies during the nineties.[3] 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 which had a dramatic impact on the level of competition within the Chilean economy. Labor market regulation also suffered significant changes in both directions throughout the last fifty years that either increased or decreased the flexibility of the labor market.[4] 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.[5]

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 the Metropolitan Region, which accounts for a significant share of the country's labor market.[6] Throughout the paper, we refer to the labor market flows calculated from the Metropolitan Region as those from 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. Furthermore, we employ hazard rates to study the long and short-run behavior of the ins and outs of unemployment as well as to determine the contribution of their movements to unemployment variability. To place our numbers in an international perspective

[1] See Pissarides (2000) for a textbook presentation of these search models.

[2] See Shimer (2012), Elsby, Hobijn, and Sahin (2013) and Fujita and Ramey (2009) A summary of the literature with a special emphasis on search models is in Rogerson and Shimer (2010).

[3] According to Gallego & Loayza (2002), Chile's economic growth rate between 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 1985-2002 was actually the highest in the world.

[4] For a broader discussion on changes to labor market regulation in Chile see Edwards and Edwards (2000) and Montenegro and Pagés (2004) among others.

[5] 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.

[6] For further information on the survey see the Data section.

we also compare our results with those found for other labor markets in recent literature.

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%. From an international perspective these numbers indicate that in spite of a relatively rigid labor legislation, the Chilean labor market appears to be as dynamic as an average Anglo-Saxon country, yet considerably less dynamic than the labor market of the United States.[7] 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 more important in explaining fluctuations in unemployment. This behavior is consistent with what has been observed in advanced economies where despite sharp increases in the separation rate being responsible for increasing rates of unemployment in the short term, the slow gradual recovery of the outflow rate has been increasingly important in explaining unemployment variability (see Elsby, Hobijn, and Sahin (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 at the same level 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 these hazard rates have both increased significantly over time, rendering a trend unemployment rate that is not very different to the level of unemployment in the 1960s.[8] Albeit with significant variation, the separation rate more than doubles between 1962-71 and the past decade 1986-2015 from 1.5% to 3.1% and the finding rate increased from 24.3% to 33.4%. Of note, these increases occurred in the context of significant changes in the economy's trend growth, with the trend finding rate generally accompanying periods of higher trend growth, although the trend separation rate tended to increase regardless. Also it is important to mention that our results suggest that the ongoing sectoral reallocation towards services from manufacturing did not have an impact on the trend increase in hazard rates. The increase in trend hazard rates occurred as the economy experienced important changes to labor market legislation, that sometimes strengthened and other times weakened labor market institutions.

In addition to the significant changes in the regulatory environment, we believe it is important to note that our results may be at least partly driven by changes in the composition of the labor force, including the ongoing increase in the participation of women, the decline in youth participation, greater participation of individuals over 55 years of age, and the gradual aging of the population.

The paper is structured as follows. The next section briefly places this document in the context of related literature. In section 3, we describe the employment survey data. In section 4 we detail the methods and procedures we used to build our hazard rates. In section 5 we present our results from a high and low frequency perspective, compare our results to other economies, and also use our results to estimate how changes in hazard rates have affected changes in the unemployment rate. In section 6 we discuss our results in the context of greater macro trends that may drive our results, and propose further areas of related research. In the final section we highlight our main conclusions.

[7] 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, García, and Restrepo (2005). See section 5.1.2 of this paper for further discussion.

[8] 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.

2 Related Literature

From a thematic standpoint, this work is related to the 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, Hobijn, and Sahin (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 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 applying a different methodology.

In their analysis of 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 that 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. Bravo, Ferrada, and Landerretche (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 related 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 affecting 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 nineties improved 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.

As has been mentioned, this work builds on a considerable set of existing literature, not only in terms of the analysis of the Chilean labor market, but also in a wider thematic context. In the next section we describe the data that we use to analyze the dynamics of the Chilean labor market throughout the last fifty years.

3 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.[9]

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 $2.300-3.500$ households per survey, accounting for approximately $10.000-16.000$ observations of which $3.300-5.400$ 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 the Metropolitan area of 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.[10] Fortunately, quarterly aggregate labor market data from the survey since 1960 has been made available separately (Banco Central de 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 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.[11] One relevant caveat regarding our use of March and June data is that seasonal effects lead these months to have 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 Institute of Statistics (INE) since 1986. In practice, both questionnaires present important methodological differences that have an impact over the measurement of unemployment.[12] We take advantage of the long-lasting consistent structure and variables of the EOD to measure and analyze the dynamics of the Chile's labor market from a historical perspective.

[9] The first survey was originally carried out in October 1956, however the survey has been performed quarterly since 1960.

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

[11] Limitations to this approach are discussed in the end of the Methodology section.

[12] 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 Metropolitan area of the nation's capital) by monthly surveying roughly 36.000 randomly selected households. In practice, the EOD and the ENE questionnaires present important methodological differences that have an impact over the measurement of unemployment. For a detailed analysis of historic and methodological differences between the EOD and ENE see Bregger and Hoy (2006) and Bravo, Ramos, and Urzúa (2003).

4 Methodology

We conduct our analysis using EOD data restricting our sample to the working age population, explicitly individuals between 15-64 years of age. Our unemployment rate estimates are derived from EOD data, and as a result may differ significantly with ENE unemployment rates employed 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, Hobijn, and Sahin (2013).

Assuming a fixed and homogenous labor force[13], Shimer develops original measures to calculate the job finding and separation probabilities, and estimates these transition probabilities using monthly publicly available data from the United States labor market. 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 EOD data at 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 $t \in 0, 1, 2, ...$, 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:

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

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

In (1), the stock of unemployed increases when employment separations occur and decreases when 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:

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

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

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

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,

[13] As discussed in section 6, 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.

and the stock of incoming short-term unemployed that 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

$$F_t = 1 - \frac{u_{t+1} - u_{t+1}^s}{u_t}. \tag{5}$$

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

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

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):

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

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) reduces to:

$$u_t^* = \frac{s_t}{s_t + f_t} \tag{8}$$

As demonstrated by Shimer (2012), these estimates of the inflow and outflow rates 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 starting from the second quarter since 1962, it is possible to calculate the hazard rate corresponding to one quarter, a semester, three quarters and a year. However, in doing so, we would have to assume that the transition probabilities are the same for different durations. If there were no relationship between unemployment duration and the probability of finding a job this would not be a problem, and as suggested by, Elsby, Hobijn, and Sahin (2013), it would be more efficient to compute the hazard rates as a weighted average of finding rates at different durations.

Considering that job finding rates measured at different durations (one quarter, a semester, 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, Hobijn, and Sahin (2013) and reject the null of no duration dependence. Our results indicate evidence of negative duration dependence where the outflow hazard rate decreases with duration of the unemployment spell. This result is consistent with the findings of Elsby, Hobijn, and Sahin (2013) for Anglo-Saxon and Nordic countries as well as Japan. Even though the test for duration dependence is different, our findings are also consistent with the results of Machin and Manning (1999) for Australia, the U.K, and the U.S.

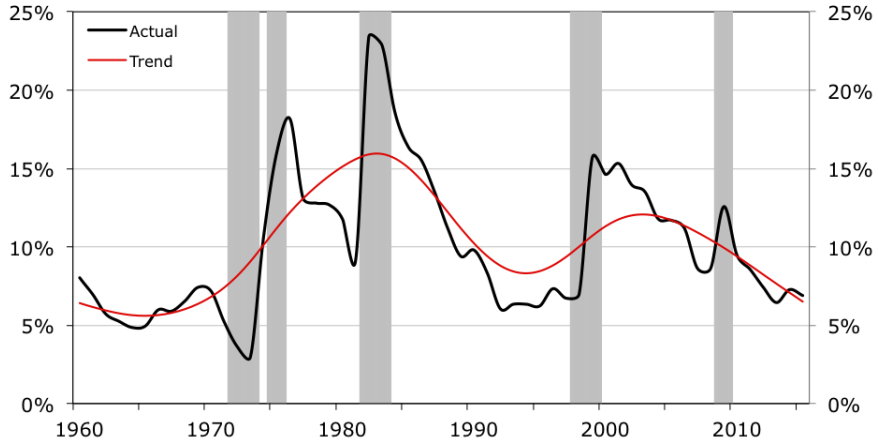
For the sake of transparency, it is important to note certain caveats with our methodological approach. First, since we estimate a single *monthly* hazard rate for every year which is approximated from data from one quarter of the year, we are significantly smoothing out seasonal and cyclical

properties of the time series. As mentioned in the Data section, seasonal effects lead March and June to 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.

On 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 might see a high correlation between separation rates and unemployment, while the relation between the latter and the finding rate will be underestimated since this hazard rate tends to lag unemployment. Finally, it is worth noting that in our methodology 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, on the outset we must reiterate that our results are obtained with a methodology that does not account for transitions in and out of the labor force. Considering the persistent increase in labor force participation in Chile over time, we believe our results may be biased upwards. That being said, the fact that trend hazard rates increase even among prime-age males, a group that has maintained a relatively stable labor force participation over time and has the greatest weight as a share of the labor force, suggests that our main result continues to hold despite potential upward bias. This issue is discussed in greater detail in the Discussion section.

Figure 1: Actual and Trend Unemployment Rate



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

5 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 subsections. 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 subsection, 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.

5.1 Evolution of Hazard Rates

The estimated hazard rates are summarized in Table 1, in which 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 period. On the other hand, 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.

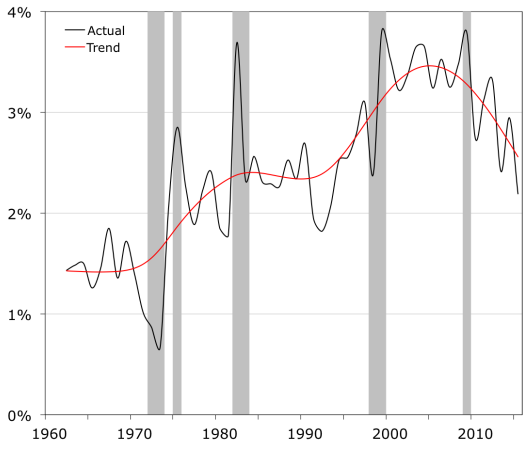
Table 1: Unemployment Rate & Monthly Hazard Rates

	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	34.8

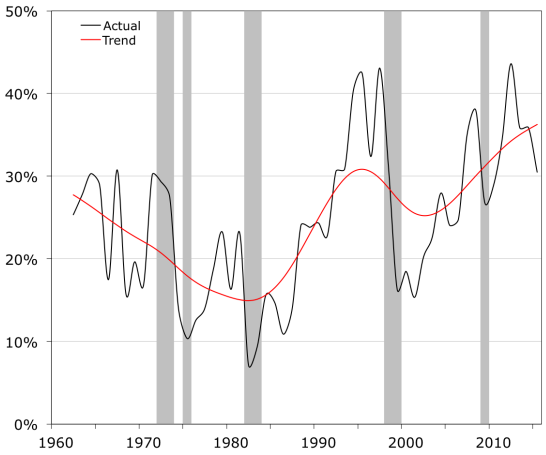
Note: All are period averages, expressed in percentage terms. Unemployment is calculated from EOD data. Monthly hazard rates are calculated according to the procedure described in the Methodology section.

Figure 2: Monthly Hazard Rates

(a) Separation Rate:



(b) Finding Rate:



Note: The figures above plot actual and trend hazard rates calculated from EOD data. Trend series were calculated using a Hodrick-Prescott filter with smoothing parameter of 100. Grey bars represent years in which Chile's real output growth rate was negative: 1972-73, 1975, 1982-83, 1999, and 2009. See section 3 for details about computation of both hazard rates.

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 periods of economic recession in 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 sixties to a level above 3% towards 2010. In fact, Figure 2 reveals a clear positive trend in the separation rate starting at the beginning of the seventies, 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, the separation rate 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 greater than 7% per year.[15] During these years the separation rate remained at similar levels as to those of the aftermath of the 1982 - 83 crisis, suggesting that "creative destruction" may have been an important source of growth and productivity increases.

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 points between the sixties (with an average of 24.5%) and the seventies (with an average of 19.7%). The reduction in the finding rate was further intensified by the international debt crisis of 1982, when the finding rate plummeted to single digits and reached its historical low of 7.2%; yet soon after began a steady increase. During the late

[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).

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; in fact, 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 rate 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, and has since fallen back to 30% in 2015.

Our results are similar to those obtained by previous 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: the 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. Similarly to our results, 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, Ferrada, and Landerretche (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%.

Several studies have continued to build on the work of Bravo, Ferrada, and Landerretche (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, since Jones and Naudon (2009) 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

[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.

[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

finding rate for the period 1993-2009 is the same (29%), however, our separation result is considerably greater at 3.2%. Finally, recently Marcel & Naudon (2016) further extend the ENE survey data with the new NENE data set through 2016, and find 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 due to the fact that the unemployment rate in the EOD survey tends to be above the ENE and NENE surveys.[19]

5.1.1 International Comparison

To place our results in a broader perspective we compare our findings with results found by other researchers for different economies worldwide. Before doing so, it is important to highlight the fact that the comparison of transition probabilities across economies must be done with certain reservations, since definitions and procedures used in the elaboration of labor markets statistics may differ across countries and as a result, labor market statistics are not entirely comparable.[20]

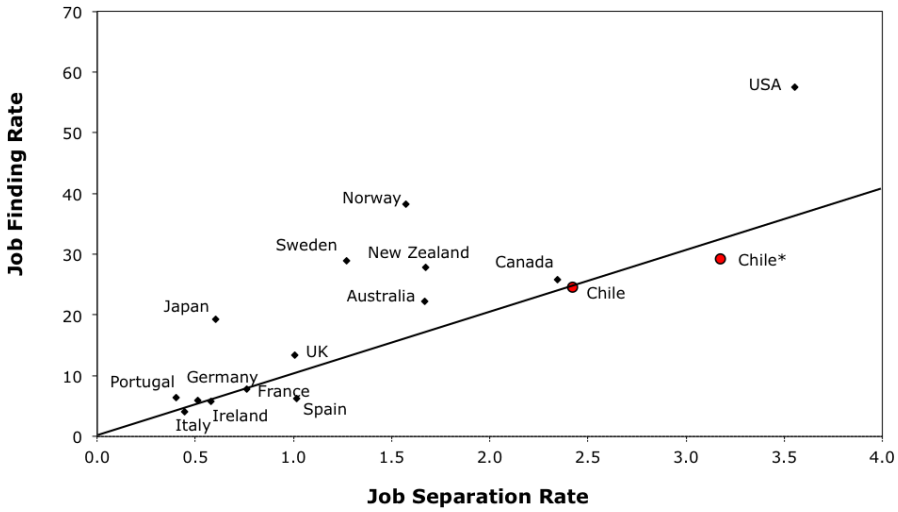
We compare our results to those obtained by Elsby, Hobijn, and Sahin (2013) since this study is not only the most comprehensive but also due to the fact that the methodology we apply is based on the one applied by these researchers (see also Rogerson & Shimer (2010)). Elsby, Hobijn, and Sahin (2013) study the evolution of ins and outs for fourteen OECD economies. 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 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 - 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%.

[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 was 8.5%.

[20] Furthermore, in this context, it is important to insist in the fact 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.

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

Figure 3: Average Monthly Hazard Rates Across Countries



Note: All expressed in percentage terms. Average hazard rates for Chile are in red and are calculated according to Section 4. "Chile" is for the entire sample, while "Chile*" is for the 1996-2015 period. Hazard rates for other countries are from Elsby et al. (2013).

The average finding and separation rates for the countries analyzed by Elsby, Hobijn, and Sahin (2013) as well as our results are presented in Figure 3. According to this figure, Chile ranks among the more dynamic labor markets in the sample, with average hazard rates that are somewhat similar to 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, Ferrada, and Landerretche (2005) find similar average finding and separation rates using ENE data. Using a very different methodology and data Albagli, García, and Restrepo (2005) reach the same conclusion; in particular, these authors anayze the dynamic response of unemployment in the presence of macroeconomic shocks identified with a structural VAR. Furthermore they proceed to rank a set of countries according to a measured half life of unemployment after a shock. Their results show that Chile ranks third among all countries in their sample that include (in order of labor market flexibility): Korea, Hong Kong, Chile, Mexico, United States, Germany, Sweden, Spain and Colombia.

An interesting insight of the analysis mentioned above is that even though the Chilean labor market is relatively dynamic, the unemployment rate in Chile has been on average higher than in the majority of the countries analyzed by Elsby, Hobijn, and Sahin (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 continuous black line represents combinations of separation (s_t) and finding rates (f_t) with the same steady state unemployment rate as Chile for the period 1962-2015 (i.e. all the combinations of s_t and f_t such that $\frac{s_t}{s_t+f_t} = 8.96\%$).[22] The slope

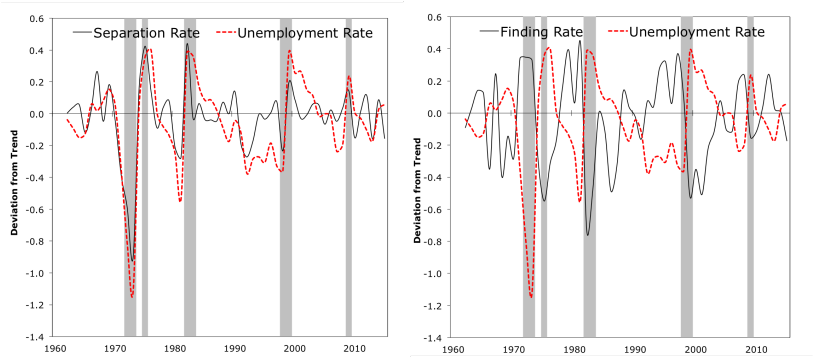
[22]The steady state unemployment rate is, in general, very similar to the actual unemployment rate, and it has

is evidently positive since conditional on a given unemployment rate, a larger chance of losing a job must be associated with a greater chance of finding a new job. Countries represented by points above the line represent economies with an average unemployment rate below 8.96%. This is even true 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. In particular, the separation rate seems to be particularly large, which goes against the mainstream view that the severance pay precludes the termination of contracts. We explore the connection between the evolution of the hazard rates and changes in labor market legislation in more detail in section 5.2.

5.1.2 Variance Decomposition

In this section we calculate the contribution of these hazard rates to the variation in the unemployment rate. For some time the literature has debated on the impact of labor market flows on unemployment variability. According to Shimer (2012), the main driving force behind the cyclical evolution of the unemployment rate has been the outflows, analogous to the finding rate in our terminology. At the time, Shimer's conclusions somewhat defied conventional wisdom that the separation rate was the most important force behind unemployment variations. Later studies somewhat moderated Shimer's statement leading to the consensus today in which the separation rate is important in explaining large swings in unemployment, mostly related with economic recessions, while prolonged declines in outflows from unemployment are much more relevant to explain the slow recovery in employment during the aftermath of an economic downturn.

Figure 4: Unemployment Rate & Hazard Rates: Deviations from Trend



Note: The panels plot the percentage deviation of hazard rates and unemployment with respect to their trend. The trends were calculated using a Hodrick-Prescott filter with smoothing parameter of 100.

Even though we mentioned this earlier, it is important to stress that the use of annual data may mask 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 might see a high correlation between separation rates and unemployment, while the relation between the latter and the finding rate will be underestimated since this hazard rate

the advantage of establishing a direct connection between the unemployment rate and the inflows and outflows of unemployment.

tends to lag unemployment.

With this reservation in mind, we start off with our analysis we observe 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 a Hodrick-Prescott filter with 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 Figure 1 and 2, the data suggests that while the unemployment rate gradually returned to its trend, the separation rate returned faster to its trend. In terms of levels, Figure 2 shows that only in the case of the recession in 1999, the separation rate did not return to previous pre-crisis levels; our interpretation is that when the crisis hit, the separation rate was already experiencing a positive trend, and as a result the relatively small decrease in the separation rate after the crisis must be interpreted as a return to the separation rate trend path.

The deviation of the job finding rate with respect to it's 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 aftermath of the crises of 1982, 1999, and 2009.

Having briefly discussed the behavior of the hazard rates with respect to their estimated trends and unemployment, we now proceed to 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). 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.

According to Shimer (2012), we can quantify the contributions of hazard rates to overall unemployment variability according to equation (8), that is by approximating $u_t \simeq \frac{s_t}{s_t+f_t} \equiv u_t^*$. Thus using this approximation, we proceed to calculate the variance decomposition, using a log-linear approximation of the changes in the unemployment rate as follows:

$$\widehat{u}_t^* \approx \underbrace{(1-u_t^*)\,\widehat{s}_t}_{C_s} - \underbrace{(1-u_t^*)\,\widehat{f}_t}_{C_f}, \tag{9}$$

where $\widehat{x} = \ln(x_t/\overline{x}_t)$ for some reference value x_t and trend value $\overline{x}_t$. We clarify that in this context, we calculate the trend value of the unemployment rate $\overline{u}_t \simeq \frac{\overline{s}_t}{\overline{s}_t+\overline{f}_t} \equiv \overline{u}_t^*$ where $\overline{s}_t$ and $\overline{f}_t$ 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:

$$\beta_i = \frac{cov\,(\widehat{u}_t^*, C_{it})}{var\,(\widehat{u}_t^*)}. \tag{10}$$

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. In fact, roughly 59% of the

variance of the deviation of unemployment rate with respect to its trend is related to the deviation of the finding rate with respect to its trend value, while the remaining share is related to cyclical deviation of the separation rate. This statement is also true for the sub-sample. In contrast to our results, Jones and Naudon (2009) find that 65% of the unemployment variance between 1997Q1 and 2009Q3 is due to variations in the job separation probability.

Table 2: Variance Decomposition

	Separation Rate	Finding Rate	Unemployment Rate
Panel A: 1962 - 2015			
Correlation with $\widehat{u}_t^*$	0.8	-0.78	0.94
Contribution to Variance	0.42	0.59	-
Obs.	53	53	53
Panel B: 1996 - 2015			
Correlation with $\widehat{u}_t^*$	0.46	-0.89	0.96
Contribution to Variance	0.22	0.8	-
Obs.	20	20	20

Note: Methodology explained in section 5.1.2. 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.

For robustness, Table 4 in the appendix shows the results for a similar exercise, where we have taken previous values as reference points: that is $\overline{s}_t = s_{t-1}$, $\overline{f}_t = f_{t-1}$ and $\overline{u}_t^*$ 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.

From an international perspective Petrongolo and Pissarides (2008) find that contributions from the separation rate to unemployment volatility account for 33% for the U.K, 20% for France, and 43.3% for Spain. Elsby, Hobijn, and Sahin (2013) determine that for Anglo-Saxon economies the separation rate accounts for approximately 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 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 $40 - 50\%$ of fluctuations in the unemployment rate.

5.2 Trends

In this section we study the long term evolution of unemployment and its relationship with the long run behavior of both separation and finding rates. We start off by analyzing the unemployment rate calculations from the EOD survey, as well as the H-P filtered unemployment rate, as shown in Figure 1. The first fact that emerges from our analysis is that ever since the economic downturns of the mid-seventies, the trend unemployment rate only recently returned to the low levels of the sixties.[23] In fact, between 1960 and 1974 the trend unemployment rate averaged a modest 6.7%, while the average for the 1975 to 2015 period was 11.3%. Notably, even if we do not consider crisis years (1975 - 1976, 1982-1983, 1999 - 2000, 2009) the average trend unemployment rate was close to

[23] Figure 6 shows that not only does the unemployment rate fluctuate at higher levels after the recession of 1975, but high frequency movements reveal significantly greater volatility.

10%. Consequently, it is possible to argue that trend unemployment moves in levels of 6% between the beginning of our sample until the end of the sixties, yet post-1975 remained at about 10% on average.[24] It must also be noted that this relatively high unemployment figure occurs in spite of the considerable decline in the trend unemployment rate during the "Golden Years" of the Chilean economy.

Rogerson and Shimer (2010) show that OECD economies also appear to have experienced increases in the trend unemployment rate throughout the last fifty years. In particular, these authors show in their analysis of of OECD economies, including France, Germany and the United Kingdom, that these economies experience a higher trend unemployment rate relative to the mid sixties. In this context though, what makes Chilean data particularly interesting is that the economic growth rate during the high unemployment period was considerably higher than it was prior to 1975.

5.2.1 Trend Unemployment Rate and its Relation with the Long Term Behavior of Hazard Rates

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:

$$\overline{u}_t = \frac{\overline{s}_t}{\overline{s}_t + \overline{f}_t}, \tag{11}$$

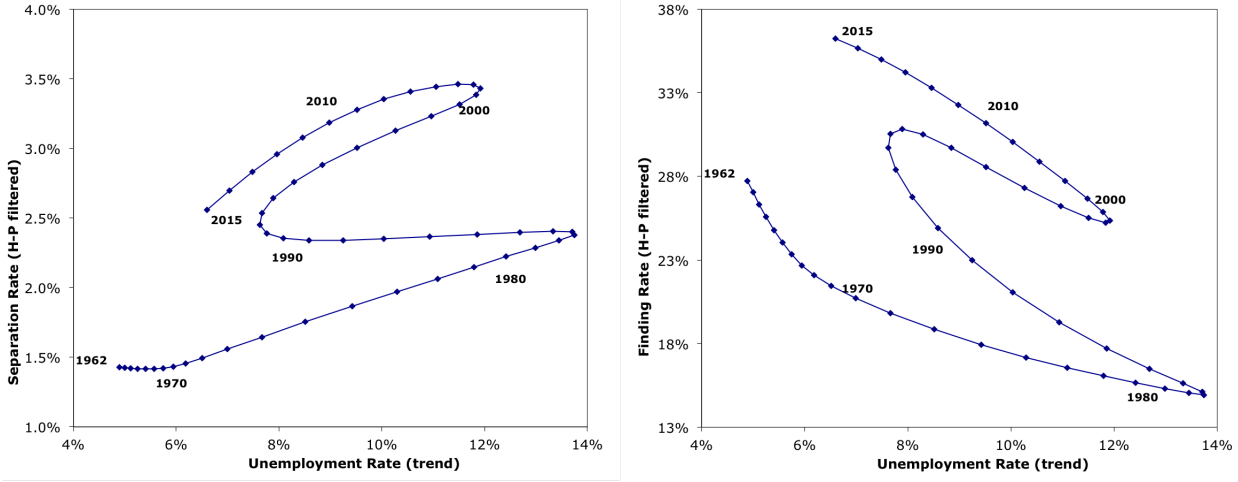
where $\overline{s}_t$ and $\overline{f_t}$ are the H-P filtered series of the separation and finding rate respectively (with smoothing parameter of 100). It is important to note that the trend unemployment rate as calculated in equation (11) is highly contemporaneously correlated (97.4%) with the H-P filtered unemployment rate series, thus we do not obtain significantly different results using either series.[25] That being said, considering that the trend as calculated in equation (11) appears more consistent within the Shimer framework than a 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, however as is 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.

[24] It is important to remember that our data is for the second quarter of each year (data collected in June) a period with high seasonal unemployment. As a result, our calculations may overstate the yearly average unemployment rate. These numbers were calculated using the H-P trend of unemployment to maximize the number of observations.

[25] For completeness we include a version of Figure (5) with the trend unemployment calculated as in equation 10 and 11 in the Appendix.

Figure 5: Evolution of Trend Hazard Rates and Trend Unemployment

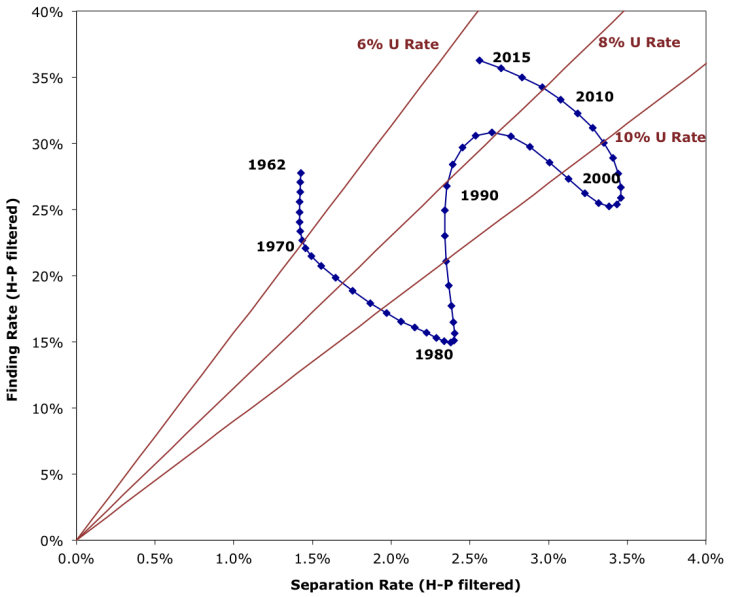


Note: The figures above display the evolution of H-P filtered hazard rates and the corresponding trend unemployment rate, as defined in equation 11. The calculation of hazard rates is described in the Methodology Section. Hazard rates have been de-trended using a Hodrick-Prescott filter with smoothing parameter of 100.

To understand the relationship between trend unemployment and the long run behavior of the hazard rates, we can first observe Figure 5. On the left we plot the H-P filtered separation rate with the corresponding results for the trend unemployment rate as calculated in equation (11). In this case, we can observe that the trend separation rate increases consistently during the seventies, associated with an ever larger trend unemployment rate, and then stabilizes during the mid eighties, a period in which trend unemployment declines. Even though the trend separation rate increases again in the nineties, and slightly declines at the turn of the millennium, what mostly grabs our attention is the fact that the trend separation rate has not returned to the levels of the sixties. In fact the trend unemployment rate has had upswings and downturns, but these in general are associated with a correspondingly higher trend separation rate over the last fifty years. On the right of Figure 5, we plot the H-P filtered finding rate with the trend unemployment rate. At a first glance, we cannot determine a clear relationship, but what we can claim is that the trend finding rate in 2015 is almost 10% above the trend finding rate in 1962.

To add further consistency to our analysis of the trend hazard rates and trend unemployment, Figure 6 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. Since however, the trend separation rate has retraced partially, and the trend finding rate has increased, thus consistent with a lower trend unemployment rate than in 2000.

Figure 6: Evolution of Trend Hazard Rates



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 smoothing parameter of 100.

6 Discussion

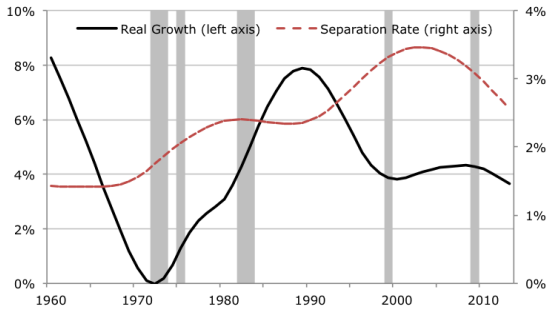
All together, the data shows that the unemployment rate is not that much different today than what it was fifty years ago, yet the underlying dynamics in terms of hazard rates are considerably different, as the current trend unemployment rate is supported by significantly higher trend finding and separation rates. In the following section we discuss potential drivers of the changes in trend hazard rates in the context of major macro trends that occurred in the Chilean economy during the past half century. The fact that several structural changes occurred during the studied period make it difficult to pinpoint the impact of one single phenomenon on labor market outcomes. That being said, it is important to view the increase in labor market dynamics in Chile in the context of structural change as a whole. First of all, while the trend finding rate is generally associated with higher levels of trend economic growth, the trend separation rate has tended to gradually increase, somewhat independent of trend growth. Furthermore, the increase in trend hazard rates has occurred in the context of the ongoing expansion of the service sector relative to manufacturing. Of note, according to our estimations, the reallocation of activity towards services has not driven the increase in hazard rates since both tend to have similar job turnover rates. In addition, greater labor market dynamics occurred despite the fact that labor market regulation at times increased and other times decreased labor market flexibility; that being said, hazard rates appear to have remained high especially after the Labor Reform of 2001 that notably increased labor market rigidity. Importantly, we find that changes in the composition of the labor force, including greater participation of women and elder age groups, falling participation of younger age groups, in the context of gradual population aging, to a certain extent limited a further increase in trend hazard rates.

6.1 Economic Growth & Structural Transformation

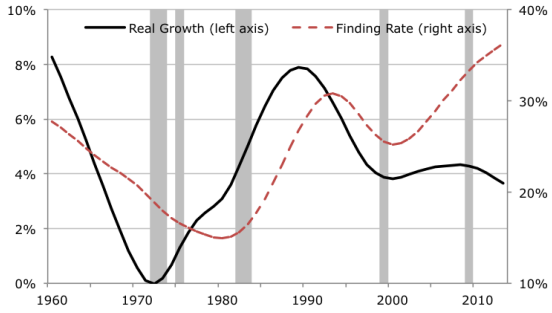
Considering that labor market outcomes tend to vary with economic growth performance, it is natural to first view the behavior of our hazard rate results with respect to economic activity. As mentioned previously, Chile's growth performance has varied considerably throughout the past fifty years, with periods of growth interrupted by deep recessions in the mid-1970s and early 1980s, and less severe recessions 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 filtering the series with a Hodrick-Prescott filter wtih smoothing parameter of 100. Focusing on real economic growth in the Metropolitan Region (Figure 7), growth on average has increased since the 1970s, peaking during the early nineties and then decelerating, levelling out at around 4% since 2000. As mentioned earlier, we recognize the limitations of using filters to obtain trends, but we simply wish to highlight the long-term relationship, if any, between growth and hazard rates.

Figure 7: Trend Economic Growth & Trend Hazard Rates

(a) Real Growth & Separation Rate:



(b) Real Growth & Hazard Rate:



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

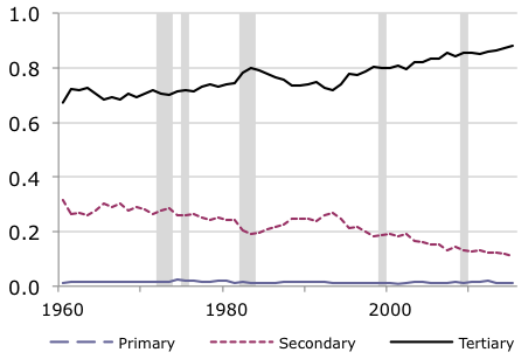
In this context, despite the fact that trend growth in the Metropolitan Region has varied considerably, the separation rate on average has increased throughout, falling only slightly during the past few years. The trend growth relationship with respect to the trend finding rate looks clearer, with periods 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 it's 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 the Metropolitan Region are consistent with the sectoral transformation nationwide, with the employment share of the tertiary sector steadily taking over the share of the secondary sector, especially

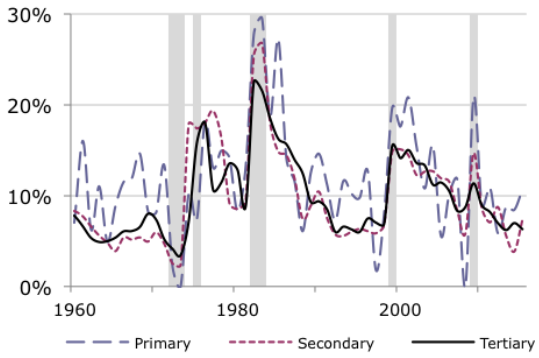
since the nineties.[26] While the unemployment rate in the manufacturing sector is not that different to the service sector on average, the unemployment rate in the former tends to be considerably more volatile especially during and the immediate aftermath of recessions (see right hand panel of Figure 9).

Figure 9: Labor Market by Sector

(a) Employment Shares:



(b) Unemployment Rates:



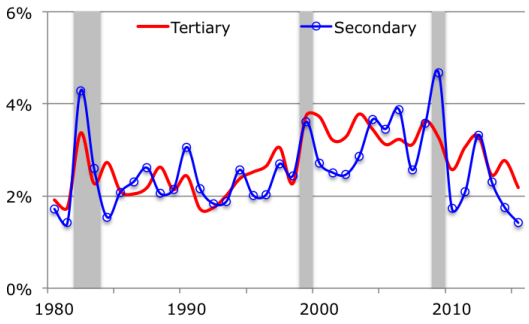
Note: The figures above display employment shares and unemployment rates by sector in the Metropolitan Region based on calculations from the EOD survey. Grey bars on both charts represent years in which real output growth rate was negative: 1972-73, 1975, 1982-83, 1999, and 2009.

To verify if the ongoing reallocation towards services has had an impact on hazard rates we estimate hazard rates by sector. As detailed earlier, data on aggregate labor market stocks are available on a quarterly basis all the way back to 1960, and unemployment duration data is only available for the June quarter back to 1962, which limits us to the calculation of aggregate hazard rates for the entire sample stretching back to 1962. However, since March data is available from 1980 onwards, we can obtain the micro data on the stock of unemployed per sector in the March quarter and combine this information with short term unemployment data from the June quarter to calculate hazard rates by sector for the past 35 years. Again, we consider "short-term" unemployment as being unemployed for less than 14 weeks. In addition, 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 the Metropolitan Region, we only report hazard rates for the secondary and tertiary sectors in Figure 11. 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. As a result, we believe the reallocation of activity from manufacturing towards services has not necessarily had an impact on the increasing trend in hazard rates since they both have similar job turnover rates.

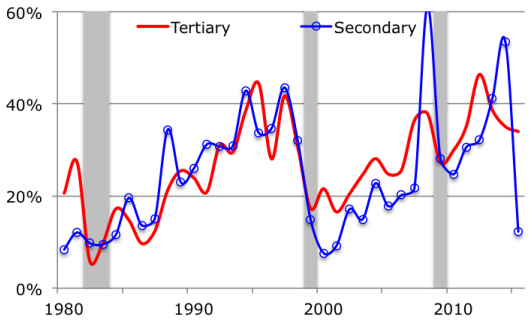
[26] The employment share of the primary sector at the national level is significantly higher than that of the Metropolitan Region since mining and agricultural employment tends to be concentrated in other regions. According to INE data, the employment share of the primary sector at the national level 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 by the tertiary sector.

Figure 11: Hazard Rates by Sector

(a) Separation Rate:



(b) Finding Rate:



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

6.2 Labor Market Institutions & 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.[27] In this context, the increasing trend of the separation rate during our sample occurs despite the changes in labor regulation that increased or decreased labor market flexibility. Upon analysis of the trend however, the trend separation rate begins to increase in the seventies, accentuated by the recession in 1975. The increase in the trend separation rate may be explained in part by a change in the interpretation of labor law by the judicial system which increased flexibility, amongst other important changes in labor regulation. Even though 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.[28] Throughout the 1980s, the trend separation rate oscillated between $2.3 - 2.4\%$, 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.[29] In sum, the separation rate

[27] For 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).

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

[29] The Labor Law 19.759 was published in the Diario Oficial on October 5, 2001 and came into legal effect on December 1, 2001. Other aspects that the reform included were greater penalties for the violation of labor laws, the introduction of payments by firms to workers on strike if they were replaced during the strike, a reduction in the

in our sample has maintained an increasing trend throughout with marked peaks during recessions, and appears to have stabilized at a high level in the aftermath of the Labor Reform of 2001.[30]
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 permanent contracts. According to the OECD, Chile ranks highest among OECD economies in temporary contracts as a share of permanent contracts, and further suggest that temporary workers have significantly higher job turnover rates relative to workers with permanent contracts (OECD, 2015). Along these lines, Silva & 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, Silva, & Toledo (2012) find a wide gap in unemployment volatility (+33%) between certain OECD economies with relatively high employment protection levels with respect to other non-Anglo Saxon economies.
In order to assess if the increase in our trend hazard rate results is due to greater turnover among temporary workers we would ideally have data on contract duration. However, the EOD survey only recently began collecting this information, and the INE survey only began collecting this information in 2010. As a second best alternative since we cannot estimate hazard rates by contract duration, we take a step back and see if changes in labor market regulation have had an impact on the share of temporary employment, and in turn, 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. We decided to use this definition because it is consistent with the Chilean Labor Code and the OECDs definition.[31] Overall, our proxy for the share of part-time employment in the Metropolitan Region has increased from an average of 9.1% in the 1960s to 12.9% in the last five years.[32] 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 show 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.
Along these lines, the separation rate is relatively highly 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 level 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, suggesting outflows of unemployment were partly driven by gains in part-time employment. Although we would like to

amount of workers needed to set up a union, and a reduction in the work week from 48 to 45 hours.

[30]Regarding research with EOD data, Montenegro and Pagés (2004) take advantage of the lengthy span of the 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 affecting their employment rates.

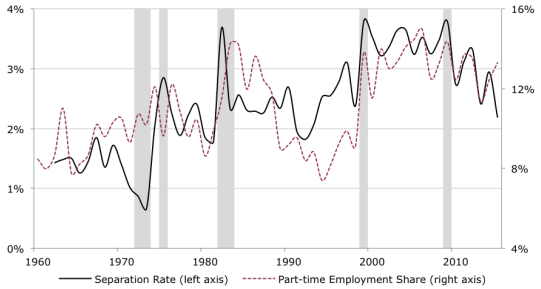
[31]Note that the OECD defines part-time employment as people in employment (whether employees or self-employed) who usually work less than 30 hours per week in their main job. Our proxy may overstate the actual share of part-time employment because we account for total hours worked.

[32]The labor market survey of the "Dirección del Trabajo" 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.

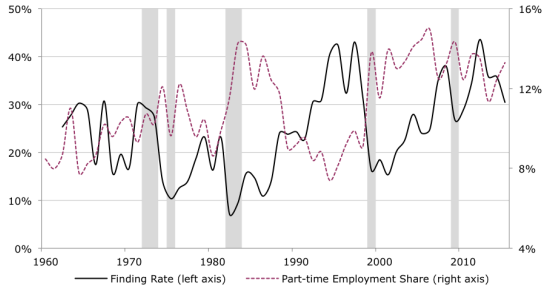
present more concrete evidence on hazard rates by contract duration, we can at least say that the high level of the separation rate in the 2000s and the increase in the finding rate during the same period coincide with the greater employment protection granted by the Labor Reform of 2001 and a larger share of part-time workers.

Figure 13: Part-Time Share of Employment & Hazard Rates

(a) Separation Rate:



(b) Finding Rate::



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

6.3 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 participation of women, lower (higher) participation among younger (older) age groups, and the impact of gradual aging of the population.[33] 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 actual 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 actual results. In contrast, we find that changes in the composition of the labor force drove the separation rate down considerably.

To perform this exercise we first need to estimate hazard rates by age group. We follow the same procedure described previously with the estimation of hazard rates by sector. For simplicity's sake and to compare our results with those of Marcel & Naudon (2016), we estimate results according to four different groups: individuals between 15-24 years, prime age females, prime age males, 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 (15-24) has the highest average finding rate at 28.9% and also the highest average separation rate at 7.2%, both which sustain a high average unemployment rate of 21.5%. Interestingly enough, prime age females and males do not have significantly different hazard rates. 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

[33] See Figure 22 in the Appendix for an illustration of the changes in the labor force across age groups

1.9%. The eldest age group (55-64) have 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.

Table 3: Unemployment Rate & Monthly Hazard Rates by Age Group: 1980-2015

	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.

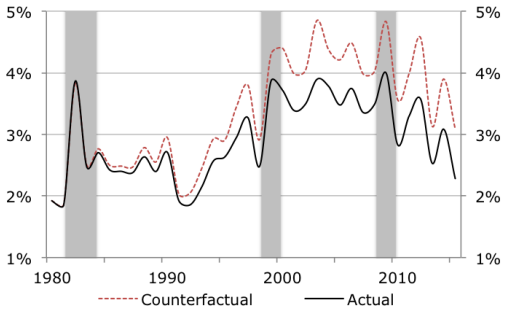
Our results appear somewhat in line with those estimated by Marcel & Naudon (2016). As mentioned earlier, these authors estimate hazard rates using another employment survey (NENE) for 1996-2016, and find that relative to prime-aged males (25-54 years), prime-aged women tend to have both lower finding 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%.

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.[34] As may be seen in the charts below, changes in the composition of the labor force since 1980 appear to not have materially affected the finding rate, however this is not the case of the separation rate in which changes in the composition of the labor force appear to have pulled down the separation rate.

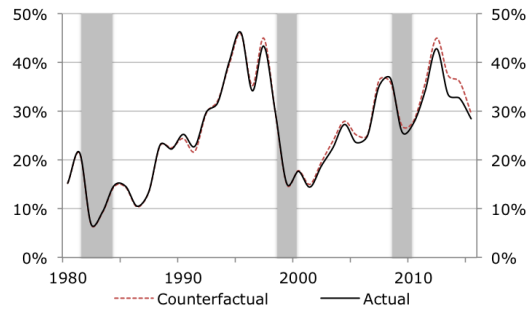
[34] Naturally these type of exercises are sensitive to the base year, but we obtain basically the same results when we construct another set of counterfactual series using the average labor force shares of 1980-1985 instead of the labor force shares of 1980.

Figure 15: Hazard Rates: Actual & Counterfactual

(a) Separation Rate:



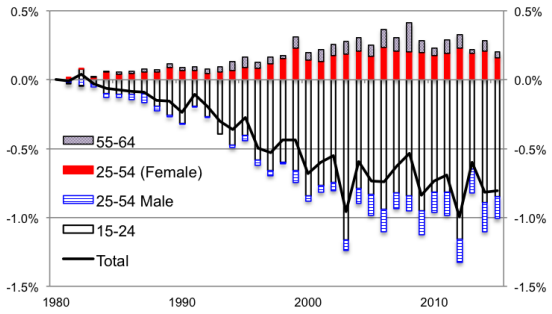
(b) Finding Rate:



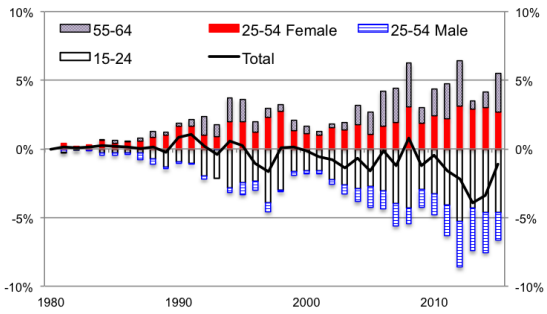
Note: The figures above display monthly hazard rates estimated with EOD data. The counterfactual series holds labor force shares of each age group constant as of 1980.

Figure 17: Differences in Contribution to Hazard Rates: Actual & Counterfactual

(a) Separation Rate:



(b) Finding Rate:



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

In the chart above we can 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 compensated 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 due to the fact that 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.

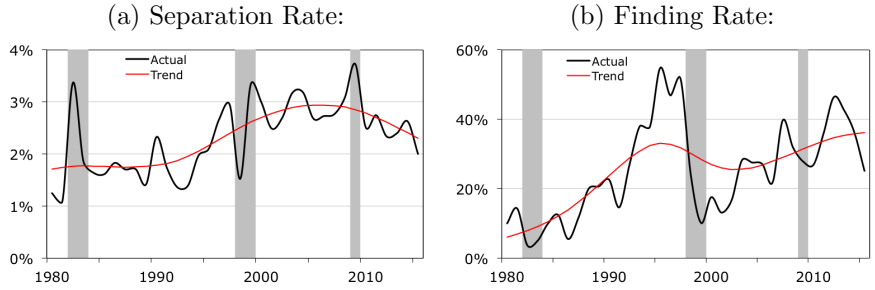
6.4 A Comment on Participation

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 (See Figure 22 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 outweigh those from employment to inactivity, then we should expect our finding rate estimates to be upwards biased. Along these lines, if flows from inactivity to unemployment outweigh those from unemployment to inactivity, then the separation rate will also be upwards biased. Since participation has been increasing, the net flows from inactivity to employment or unemployment must be positive, which would suggest our hazard estimates are upwards 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 & Naudon (2016) which use a similar methodology but also account for movements in and out of the labor force. First of all, we must note that the results obtained by Marcel & Naudon (2016) may differ since they include an additional year of data. Moreover, it is important to mention that the difference in the magnitude of our hazard rate results relative to those of Marcel & Naudon (2016) may be partly due to the fact that unemployment in the INE survey tends to be lower than the EOD survey; average unemployment rate for the INE 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 & 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 & Naudon (2016) is 25.8% (1.9%), which suggests our hazard rates are in fact upwards biased.

In order 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 had a relatively constant participation rate since 1965, averaging 95%, but is also the group that accounts for the largest share of the labor force, currently roughly 40% (See Figure 22 (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 19) 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 19: Hazard Rates for Prime-Aged Males



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.

7 Conclusion

Using employment data from the Metropolitan Region of Santiago as a proxy for Chile's labor market, we show that even though 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 what what it was fifty years ago. While trend hazard rates have tended to increase over time, the average trend separation rate between 2010-2015 is practically twice what it was between 1962-1970, and the average trend finding rate has increased from 25% to 34% during the same period. Greater labor market dynamism occurs 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 permanent contracts on labor market transitions and unemployment variability.

Finally, Chile's labor market has also experienced important changes in terms of its composition, including the increase in the participation rate of women and elder age groups, as well as the decline in participation of younger age groups, along with gradual aging of the population, which to a certain extent moderated the 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 rigid labor legislation, the Chilean labor market appears to be as dynamic as an 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 economy 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.

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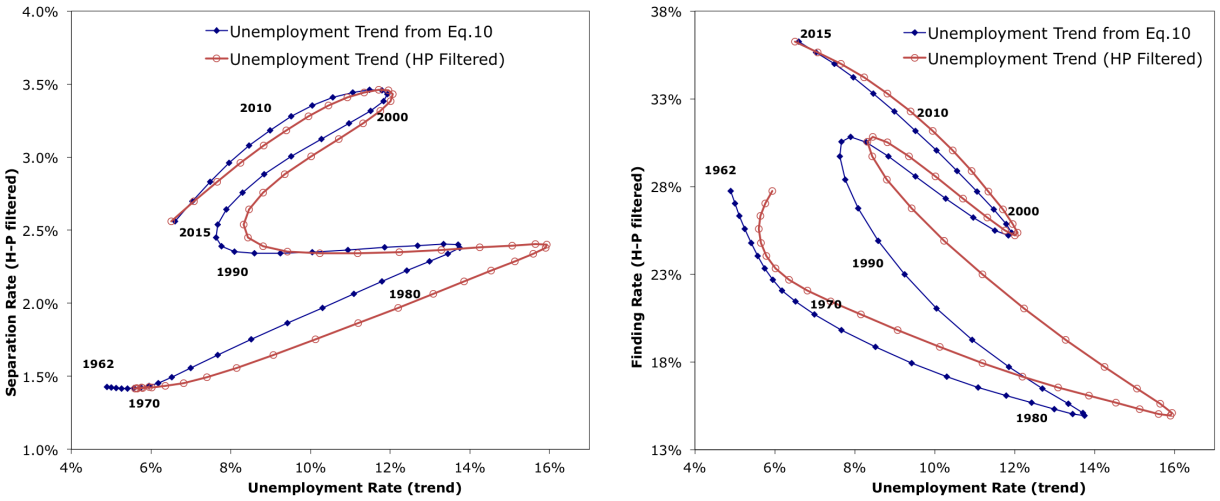
8 Appendix

Table 4: Variance Decomposition: Robustness Exercise

	Separation Rate	Finding Rate	Unemployment Rate
Panel A: 1962 - 2015			
Correlation with Dln(ur)	0.77	-0.71	0.92
Contribution to Variance	0.43	0.61	-
Obs.	53	53	53
Panel B: 1996 - 2015			
Correlation with Dln(ur)	0.65	-0.79	0.98
Contribution to Variance	0.39	0.64	-
Obs.	20	20	20

Note: Methodology explained in section 5.1.2. 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.

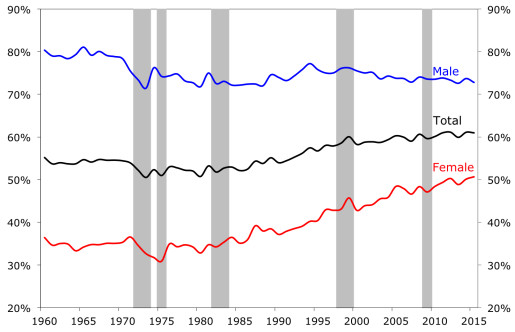
Figure 21: Evolution of Trend Hazard Rates and Trend Unemployment



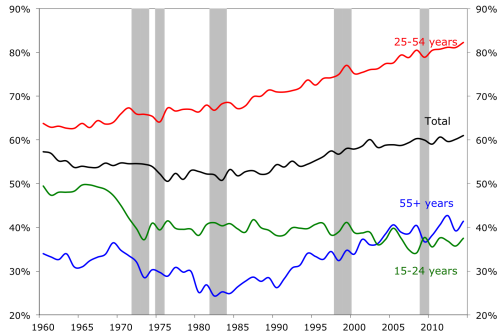
Note: The figures above display the evolution of H-P filtered hazard rates with different versions of the "trend" unemployment rate. The blue line corresponds to the trend unemployment rate as calculated from equation 11, while the red version corresponds to the H-P filtered version of the unemployment rate. The calculation of hazard rates is described in the Methodology Section. Hazard rates have been de-trended using a Hodrick-Prescott filter with smoothing parameter of 100.

Figure 22: Labor Force Participation Rate by Gender & Age Group

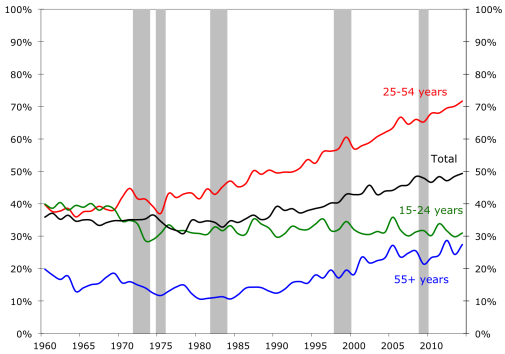
(a) By Gender:



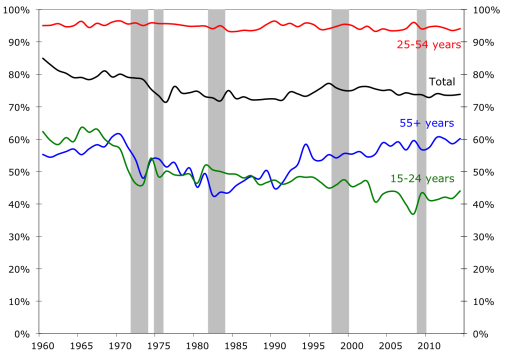
(b) By Age Group:



(c) Females:



(d) Males:



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

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