Job loss and earnings inequality: Distributional effects from re-employment in Chile

Rafael Carranza[a], Joaquín Prieto[b] and Kirsten Sehnbruch[b]

[a] *INET and DSPI, University of Oxford, UK*

[b] *International Inequalities Institute, London School of Economics and Political Science, UK*

[EARLY DRAFT – PLEASE DO NOT CITE]

Abstract

Existing research has shown that job displacement leads to significant and persistent earnings losses in Global North countries, but evidence for Global South countries is scarce. Using administrative data for Chile, we analyse the effects of formal job loss on workers' subsequent wages. The paper has two contributions. First, it provides evidence of the costs of losing formal employment in a country that has become a high-income country in recent years but with a weak labour protection system and high earnings inequality. Second, we examine the effect of job separation on earnings distribution using conditional quantile regressions. Our results show that workers, on average, lose 35 per cent of their previous earnings in the first month of separation and return to pre-termination levels after 12 months. Those in the bottom 10 per cent experience large wage losses after unemployment which might take over a year to recover. On the other hand, those in the top 5 per cent experience little to no losses and tend to switch to higher-paying jobs, thus increasing overall earnings inequality. By having a more prominent effect at the bottom of the earnings distribution, our findings suggest that job losses reinforce earnings inequality in the Chilean labour market.

JEL classification: C21; E24; D63

Keywords: Chile; distributive analysis; earnings inequality; formal employment; job displacement; wage losses.

1. Introduction

Economic crises, technological changes, and changes in the countries' regulatory policies can trigger significant modifications in the firm-level employment. It is argued that these situations have a positive side in terms of productivity growth in the economy (Syverson, 2011), but the other side of the coin is the adverse effects on laid-off workers, and these effects can be considerable. However, most existing evidence on the costs of labour displacement comes from countries of the Global North (e.g. Jacobson et al. 1993 or Couch and Placzek 2010 for the United States; Hijzen et al. 2010 for the United Kingdom; Schmieder et al. 2010 for Germany; Huttunen et al. 2011 for Norway). These studies have shown that job displacement of workers who had permanent jobs leads to a large reduction in their earnings, and this effect is persistent over time compared to workers who have not been displaced.

Existing research shows that earnings losses can result from unemployment, lower wages from replacement, or both. Unemployment reduces earnings after displacement in the short term while - relative to those who did not lose their jobs – the wage gap persists in the middle to long term due to wage losses in the new jobs. Although it is critical to know the average level of these wage losses among workers, knowing who is most affected is also essential. The mean impact does not indicate the displacement effect's size and nature at different points of the earnings distribution. How job losses affect income distribution has not been studied in depth despite decades of research on this topic. Understanding how job losses influence the earnings distribution can help us grasp whether or not they reinforce inequalities already present in the labour market and to better design and implements redistributive policies.

Most studies show evidence of the effects of job displacement in contexts where levels of labour informality are minimal, and their social protection systems are strong. Although these studies can inform policies and programs to support these workers in Global South countries, they cannot be directly extrapolated to other contexts. Indeed, there are considerable differences in labour market conditions, institutions and social safety nets between countries in the Global North and the Global South. To date, this type of research has not been carried out outside of the Global North due to the lack of longitudinal data on workers, with some exceptions (e.g. Amarante et al. (2014) for Uruguay). However, governments and their policymakers need rigorous and contextual evidence of the effects of formal job losses to understand how labour markets function when a considerable proportion of their workers have informal jobs.

In this context, we analyse wage gaps between formal workers who are displaced and those who are not using administrative data from Chile. The database follows individuals from the moment they make their first contribution to the unemployment insurance system and includes their monthly earnings between January 2010 and December 2019. In addition to average effects, we use quantile regressions to identify and estimate short- and long-term individual wage gaps across the wage distribution. Thus, we shed light on whether job losses can increase wage inequality if workers at the bottom of the distribution show larger declines and slower recoveries than those at the top of the earnings distribution.

The rest of the paper is structured as follows. In Section 2, we review the related literature, and in Section 3, we present the econometric approach based on conditional quantile with fixed effects. Section 4 describe our panel data and their limitations. In section 5 we present descriptive evidence and discuss the quantile regression results. Section 5 concludes.

2. Related literature

Studying the effect of job loss on future labour earnings is crucial to understanding the functioning of labour markets. Research in industrialized countries has consistently shown that job displacement substantially reduces workers' wages when they return to work and is persistent over time (e.g. Jacobson et al., 1993; Couch and Placzek, 2010; Illing et al., 2021). The empirical evidence for regions of the Global South is scarce but with similar results. Amarante et al. (2014) use unemployment insurance data from Uruguay to document short-term and long-term wage losses. They found that formal workers lose 38 per cent of their wages before the third month of separation, and after a year, the losses still exceed 14 per cent. Along the same lines, Kaplan et al. (2005) studied the Mexican case and encountered that workers with more extended tenure experience different salary losses depending on the economic period. Furthermore, they showed that displaced workers could earn higher wages than displaced workers re-employing during periods of economic expansion.

Despite the interest in the effect of displacement on the conditional mean of earnings, the effect on earnings in different subgroups of workers has not been analysed in depth. Recent studies have looked at the effect of job displacement across individuals (Korkeamäki & Kyyrä, 2014; Farber, 2017; Azadikhah Jahromi & Callaway, 2022). These studies identify those who experience relatively small effects of job displacement and individuals who experience significant adverse effects of job displacement. Some workers may find a similar job fast after being displaced. Still, others may have their future earnings affected by the inability to find a full-time job, loss of a job in a well-paying company, or loss of specific human capital, among others (see Carrington & Fallick, 2017 for more details). Distinguishing between these two subgroups allows us to account for the heterogeneity of the effect of job displacement, but at the same time requires studying the effect on the entire income distribution.

The nature and size of the job displacement effect across the earnings distribution is of primary interest when designing labour policies aimed at improving the income distribution. A negative average effect means that displaced workers have a lower chance of being replaced in a well-paid job. However, such an effect may be critical for workers at the lower tail of the distribution as it reinforces the risk of unemployment or accepting low-paying employment. If the effect becomes permanent, supportive actions from labour programs should focus on this worker group.

3. Econometric strategy

We use conditional quantile function models to study the effects of displacement at different points of the income distribution (Firpo et al. 2009). Our study adopts this approach to complement the conventional models of this type of study focused on changes in the conditional mean.

To estimate the earnings losses of workers who leave their formal employment compared to a control group of workers who remain in their formal jobs, we use the methodology proposed by Jacobson et al. (1993) in their seminal study on the wage effect of displaced workers.[1] The estimation formula uses longitudinal data for a fixed-effects model as follows:

$$Y_{it} = \alpha_i + \gamma_t + X_{it}\beta + \sum_{k \geq -m} D_{it}^k \, \delta_k + \varepsilon_{it} \tag{1}$$

where Y_{it} is equal to the labour income of worker i at time t and D_{it} is a dichotomous variable that indicates whether a worker leaves her formal job in period $t-k$. The parameters, α_i, represent the individual fixed effects; γ_t represents the fixed effects of time t measured in months; X is a matrix of observable characteristics of the worker and her firm, which includes gender, previous tenure and the square of the previous tenure, all interacted with age, as well as the current job's duration and its square, as well as education, industry and firm size dummies.

The purpose of k is to index a set of dummy variables, D^k, starting m months before splitting. That is, $t-k$ can take positive values (if the worker leaves his job in the future) or negative values (if he left his employment earlier). The main parameters of interest are δ_k, which estimate the earnings gap between separated and non-separated workers before, during and after the event. In other words, δ_k measure the earnings losses of workers who leave their formal employment relative to the control group at each moment (where δ_0 is the first month after the separation). Finally, ε_{it} is a stochastic error term.

The methodology of Jacobson et al. (1993) allows us to provide new evidence on the size of income losses among workers who leave their formal jobs in an emerging country of the Global South. We complement this analysis with a fixed-effects conditional quantile regression design that allows us to estimate these earnings losses (or wage gaps) across the wage distribution and the implications for changes in inequality levels.

To do so, we consider a model that specifies the "τ-th quantile" of the conditional distribution of Y_{it} given the observable variables X_{it} and the fixed effects of each individual α_i as a linear function of the covariates.

$$Q_{y_{it}}(\tau | x_{it}, \alpha_i) = \alpha(\tau) + x'_{it}\beta(\tau) \tag{2}$$

The inferences of the coefficients $\beta(\tau)$ together with their standard errors were calculated using the methodology developed by Machado & Santos Silva (2019). Specifically, we use this methodology to estimate the model described in equation 2 for percentiles 5 to 95, at 5 percentile increments (i.e., percentiles 10, 15… 90, 95).

---

[1] The estimators used with this technique are well known in the program evaluation literature (e.g. Heckman & Robb, 1985).

While here we describe the estimation of conditional quantiles all our distributional estimates are for unconditional quantiles, estimated using recentered influence functions (RIFs) following the approach of Firpo, Fortin and Lemieux (2009) and the `rifhdreg` function in Stata as developed by Rios-Avila (2020). We therefore interpret our findings in terms of *unconditional* quantiles rather than conditional on observables.

4. Data

Our analysis uses the Chilean unemployment insurance database. This is an administrative register that includes all formal workers in the country, reporting their earnings as well as other characteristics on a monthly basis, of which we use a publicly-available 3% sample.[2] By construction, the unemployment insurance does not include informal workers, nor does it include public sector workers, employers or the self-employed. The dataset was created in 2002 and included all new formal workers who were automatically registered. This meant that for its first few years it overrepresented short-term jobs and fixed term contracts as new entrants were being included. As Sehnbruch et al. (2018) report, it was not until 2010 that the dataset became representative of the formal workforce – which we use as the starting year for our analysis. Since 2010, the database accounts for just over half of the labour force and 75% of all salaried workers.

Table 1: Distribution of the duration of employment contracts by period

	Periods			
Duration in formal employment	2010-2012	2013-2016	2017-2020	2010-2020
Open-ended contracts				
Less than 7 months	11.3	12.5	12.8	12.3
Between 7 and 12 months	10.8	11.6	13.2	12.0
1 to 2 years	18.1	18.5	22.6	19.9
2 to 3 years	13.8	13.3	16.6	14.6
More than 3 years	46.1	44.2	34.8	41.1
Fixed contracts				
Less than 7 months	50.5	51.2	53.7	51.8
Between 7 and 12 months	21.3	21.0	21.9	21.4
1 to 2 years	14.3	14.2	13.6	14.0
2 to 3 years	5.8	5.4	4.8	5.3
More than 3 years	8.3	8.3	6.1	7.6

Source: Authors' calculations based on a random sample from UISA administrative data (3% of the total). Full sample (i.e., before constraining it by duration and other criteria).

To properly account for income trajectories, we need to study employment relationships that are sufficiently long. That is, that they have a minimum duration before the break of the relationship. Ideally – and in line with previous articles – we would need a very long period of at least 3 years. However, due to the nature of our sample that results in a relatively small subsample. Table 1 shows that focusing on those jobs with at least 3 years of duration leaves us with roughly 40% of all open-ended contracts and less than 10% of fixed-term contracts. More importantly, these jobs are systematically different from the average worker, as they are 'better' jobs – with higher incomes, more stability and better overall conditions. For that reason, we repeat our analysis with a second subsample of workers whose jobs lasted at least for a year.

[2] Including over 22 million observations, 3 million employment relationships and 320 thousand workers.

According to Table 1 that represents 75% of all open-ended contracts and over 25% of fixed-term contracts. While still not fully representative of the whole formal sector, our 12-month sample includes a large number of workers, particularly among those with open-ended contracts. Nonetheless, it is important to highlight that our analysis will be representative not of all formal workers, but those with slightly better off employment relationships, as this will be particularly important when interpreting the distributional effects.

In addition to the duration restriction, our final subsample also imposes additional restrictions. While our 3% sample goes all the way to April 2020, to avoid issues of right censoring in employment duration we restrict our final analysis to November 2019, also to exclude the effect of the social revolt that occurred in Santiago, the capital of Chile, in mid-October (see, e.g., Garcés, 2019) and the effect of the lockdowns due to COVID-19. We include all workers that report positive income (i.e., that contributed to the unemployment insurance) at least once a year between 2010 and 2019 and that were aged between 15 and 65 in 2010. To constraint employment duration, we focus on the first employment relationship for each worker. Due to the nature of our sample, that is the first job they held in 2010. We then measure the duration of that job and only keep those workers with a duration of at least 12 or 36 months. For each worker, our analysis focuses only on that employment relationship and its termination, measuring the evolution of their income until 2019.

Table 2: Descriptive statistics of our final sample

	Sample: 12 months or more			Sample: 36 months or more		
	Non-separators	Separators	Total	Non-separators	Separators	Total
Obs.	250,322	39,760	290,082	104,165	21,201	125,366
	86.3%	13.7%	100%	83.1%	16.9%	100%
Age	41.1	38.2	40.7	43.2	40.7	42.8
Share women	32.2%	31.2%	32.1%	31.4%	29.8%	31.1%
Share open-ended	62.6%	78.6%	64.8%	69.1%	87.4%	72.2%
Duration	14.6	46.2	18.9	19.0	68.5	27.4
Share duration 0-6 months	51.0%	3.5%	44.5%	45.2%	1.7%	37.8%
Duration of previous job	15.7	9.1	14.8	22.3	9.1	20.1
Income (April 2020 CLP)						
Average	$ 755,398	$ 662,824	$ 742,709	$ 835,134	$ 763,644	$ 823,044
P25	$ 306,503	$ 248,448	$ 299,716	$ 343,161	$ 281,793	$ 327,431
Median	$ 528,565	$ 423,754	$ 514,047	$ 577,185	$ 492,019	$ 564,062
P75	$ 944,369	$ 814,358	$ 927,764	$ 1,040,306	$ 954,825	$ 1,026,705

Note: Authors' calculations based on a random sample from UISA administrative data (3% of the total). We report the last observation per employment relationship across the January 2010 to November 2019 period.

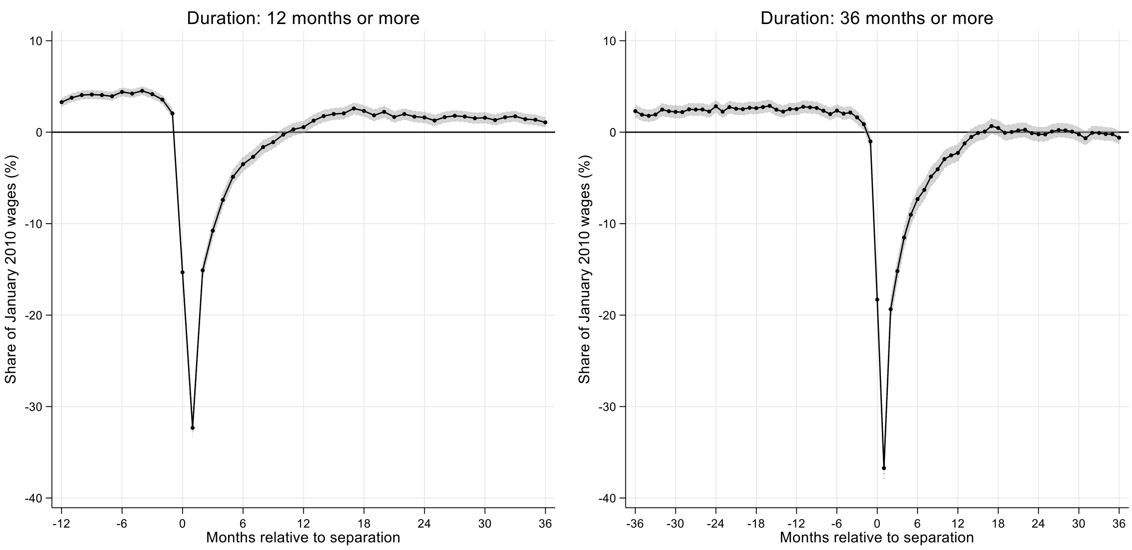
Table 2 summarises the main descriptive statistics of our 12-month and 36-month samples. It splits workers into separators, those whose main job ended at some point and non-separators, those whose jobs have not ended yet (until November 2019). Note that non-separators also include all subsequent jobs after the main one. Because our focus is on the first job in 2010, all following jobs fall within the 'non-separator' category. As such, we see that non-separators are most of the sample (over 80%), are older, with shorter durations and include a lower share of open-ended contracts. On the other hand, they have higher wages throughout the earnings distribution.

We also see that the smaller sample, where workers have at least 36 months of employment, has overall better working conditions. A slightly larger share of open-ended contracts, longer durations (at least for non-separators) and higher income throughout the earnings distribution. This is a key aspect to consider when interpreting our distributional results. By restricting the sample to durations of 36 months or more we are focusing in the best jobs within the labour formal market. We cannot say anything about the earnings trajectories of those with shorter durations and therefore with worse jobs. To some extent, looking at the 12-month sample helps us in that endeavour, but that still excludes around 25% of open-ended contracts and over 70% of fixed-term contracts. As such, our findings are representative of the best jobs in the formal labour market in Chile – those with longer durations and therefore longer periods of contributions towards unemployment insurance and pensions, as well as with higher incomes.

5. Results

Here we present our main findings. We chose to present them as figures rather than tables to better depict the dynamic aspect of our analysis. Across all Figures we will focus on the δ_k parameters in equation 1. That is, the difference in earnings between those $t-k$ periods away from losing their jobs. We look at workers either 12 or 36 months before losing their job, depending on the sample, and in both cases, we follow their earnings trajectories for the next 36 months. Before the job separation, we can interpret these figures as the average difference in earnings between those about to lose their jobs against those that are not. Following the separation, we can interpret these figures as the average path to earnings recovery following reemployment.

Figure 1: Average earning losses for re-employed salaried workers

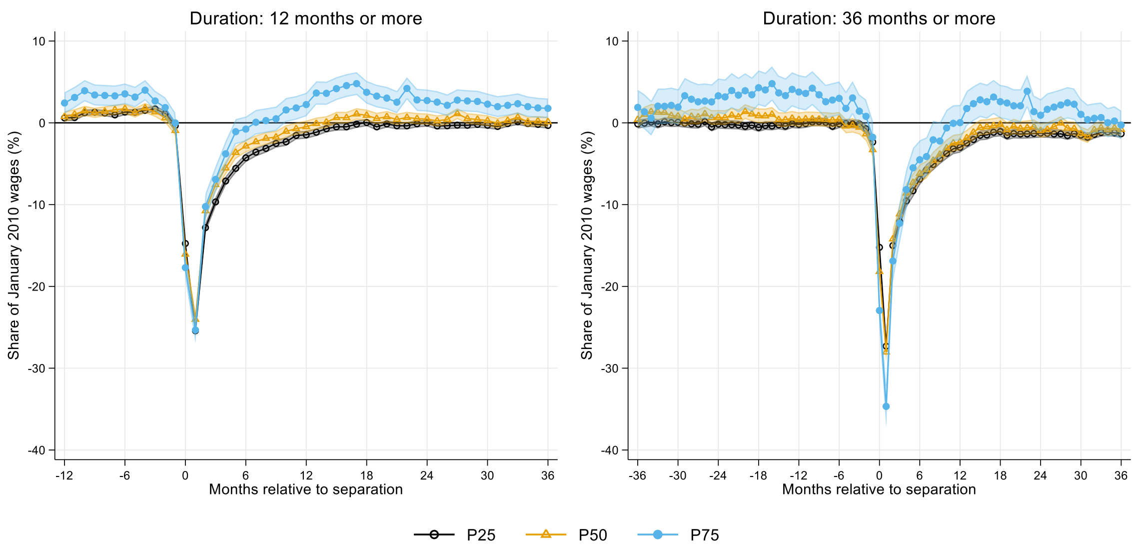


Source: Authors' calculations based on a random sample from UISA administrative data (3% of the total)

Figure 1 shows the average earnings trajectories for the 12 (left) and 36-month samples (right). Earnings are reported as the share of January 2010 wages, where our sample begins. Overall, we see similar trends, earnings for those about to lose their job (i.e, before 'zero' in the x-axis) are slightly higher than those that are not losing their jobs. We see a sharp decline at $t = 0$, the last month of employment, which further decreases the following month and recovers at a logarithmic rate as workers find new jobs. This drop in pre-termination wages as the separation point approaches is also noted in Jacobson et al. (1993) for the United States, which he attributes to the growing incidence of temporary layoffs, either in the form of lower wages or fewer hours, however, we find this pattern to be much weaker in the Chilean context.

While similar in structure, there are relevant differences between the two samples. Before termination, earnings of separators are slightly higher in the 12-month sample. The fact that wages are higher for separators is also found by Amarante et al. (2014) in Uruguay, but not by Jacobson et al. (1993) for the United States, and might be a characteristic of less-developed labour markets. The fact that this gap is smaller in the 36-month sample is consistent with this idea. At termination, we see a fall on average wages of around 35%, being slightly larger for the 36-month sample (33% versus 36%). Similarly, wages recover quicker at the 12-month sample, at around month 10, versus the 36-month sample where recovery happens at month 36. While the long-term wage (i.e., 36 months after separation) remains below the pre-separation level in both samples, we see that separators have higher wages on average in the 12-month sample. These findings show that the 12-month sample is less affected by termination, with lower average losses and quicker recover, and even recovering at higher levels, suggesting that less-established workers (i.e., those with between 12 and 35 months of duration) are quicker to bounce back than their longer tenured counterparts.

Figure 2: Earning losses for re-employed salaried workers for three points of the earnings distribution



Source: Authors' calculations based on a random sample from UISA administrative data (3% of the total)

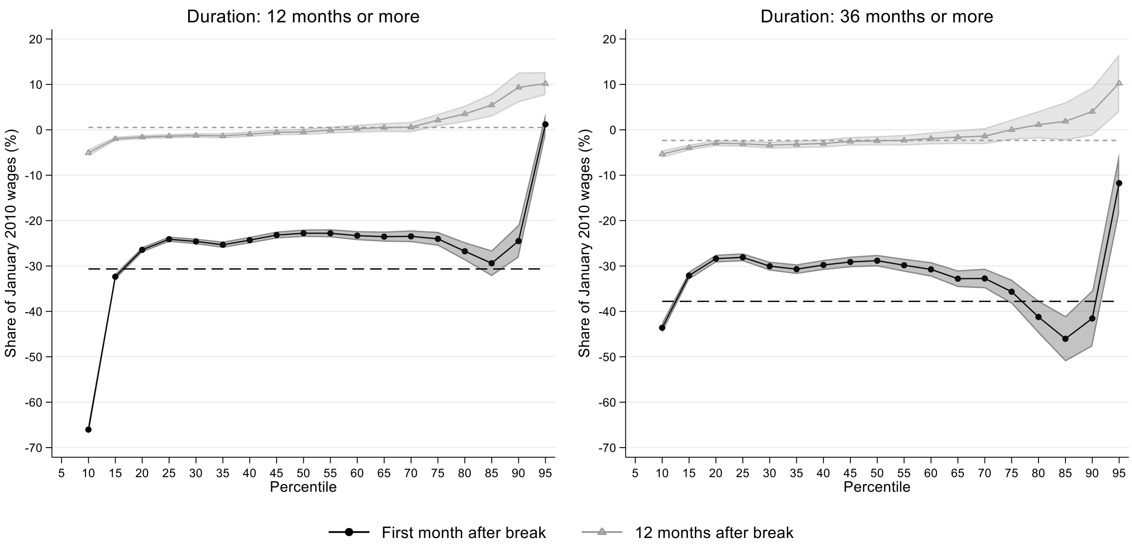
Average differences already tell us a lot about labour market dynamics. However, we need to look at the distribution of these trends in order to say anything about earnings inequality among formal workers. Figure two shows an equivalent pattern to that of Figure 1, but instead of showing the average dynamic, it shows the evolution of earnings at the 25th, 50th and 75th percentiles. The difference between the three can tell us much about earnings inequality, particularly whether job losses reinforce or diminish existing differences in the distribution. Together, these trends give us an idea of how job separation shapes the earnings distribution.

We begin with the similarities between the 12 and 36-month samples. In both cases we that wages among separators in the 75th percentile were higher than non-separators at the same position of the income distribution. We also see that workers at the top of the distribution also bounce back much quicker, at around 6 to 10 months, compared to those at the middle and bottom of the distribution, who see a recovery at around a year or 18 months. Moreover, we see that long-term post-termination wages for those at the top return to their pre-termination level after two or three years, which is not the case for the median and for the bottom of the distribution. Overall, these trend paint a picture of growing earnings inequality, and more importantly, of large differences in wage accumulation over time.

The 12-month sample shows that all three percentiles suffer the same wage loss at the point of separation, of about 25% of their earnings. This is not the case for the 36-month sample, where the 75th percentile suffers larger losses than the middle and bottom (35% against 28%). Similarly to the average case, we see that the 12-month sample is much quicker to bounce back than the other case. Considering the fact that the average loss is larger than the median loss for the 12-month sample, we can assume that there are a few high-earning workers to suffer the most in term of wage losses. The 36-month sample manages to capture some of that at their 75th percentile, which confirms this idea. The fact that they are also the quickest to recover suggest that this is a highly mobile group, capable of quickly finding a position that is at least as good as their previous one. This is not the case for the bottom and median of the 36-month, whose long-term wages after separation are below their previous trend. In other words, while the larger losses for high wage earnings might attenuate the increase in inequality due to separation, their quick recovery might result in higher overall levels of earnings inequality.

To get a better idea of the complete distribution of earnings, we complete our discussion through Figure 3. This Figure changes the x-axis to account for percentiles in the distribution rather than months, and the two trends representing different moments in time rather than different points of the distribution. In other words, relative to Figure 2, Figure 3 exchanges the x-axis and the categories presented in the legend. We report the distribution of wage losses at two points in time: at the first month and a year after termination.

Figure 3: Distribution of the effect of job separation on earnings at different months after the break



Source: Authors' calculations based on a random sample from UISA administrative data (3% of the total)

Unlike Figure 2, here the overall effect on inequality is much clearer. Looking at the first month after separation, we see large differences at the extremes – much larger than those between percentiles 25 and 75. Those at the very bottom, at the 10th percentile, see a large drop, below the average. This is particularly true for the 12-month sample where they see a loss of almost 70% of their wages. We see a much more uniform effect across the middle of the distribution, with a similar effect for half of workers, between percentiles 20 and 70. Those at the following percentiles, 75 to 90 also see a below average loss as reported in Figure 2 panel b. However, those at the very top in the 95th percentile see a much lower drop – a fourth of the average drop in the 36-month sample and no wage loss at all in the 12-month sample. The distribution of losses one year after termination is much more uniform, with a positive slope at the end of the distribution, such that those at the top 10% of their wage distribution have higher wages than before.

Overall, Figure 3 paints a picture of strong earning inequalities at the extremes of the distribution. While those at the bottom lose a substantial share of their wages, those at the very top see very little change in their wage trajectory, even ending up higher wages than before. While those at the bottom have a hard time finding a new job, those at the very top are quick to transition and move to tend to move to better positions. Our findings tell the story of two very different labour markets – even within the confines of formality – one of workers with long periods of unemployment who remain in similar jobs (at least in terms of their wages) and another of high earners with an incremental trajectory over time with little to no unemployment gaps. This of course indicates that job losses reinforce earnings inequality, and that a detailed description of the distributional impact of job losses might highlight these patterns better than a summary index such as the Gini might not be able to capture the extent of this trend.

6. Conclusions

- On average, workers experience losses of around 35% of their pre-termination wage after termination. These losses are slowly recovered and return to pre-termination levels by the first year.
- Comparing the 12 and 36-month sample, we find that the former is quicker to bounce back. This suggest that longer tenured jobs experience stronger inertia, taking longer to recover.
- These findings suggest an important wage gap between separators and non-separators, which takes about a year to close, resulting in substantially lower levels of wage accumulation over that time.
- Considering these wage gaps impacts savings and therefore assets, households with separators will be less prepared in case of economic shocks such as health issues or further employment in the household. This creates scope for compensatory policies, either in the form of unemployment insurance or other social protection nets.
- Those workers at the top of the distribution (P75) are quicker to recover from job loss and experience higher post-termination earnings than those at the middle and the bottom, suggesting that job termination dynamics reinforce existing earnings inequalities.
- There are strong differences at the very extremes of the distribution. Those in the bottom 10% experience large wage losses after unemployment which might take over a year to recover. Those at the top 5%, on the other hand, experience little to no losses and tend to switching to higher-paying jobs, thus increasing overall earnings inequality.
- While focusing on longer tenures helps us in excluding workers who might move into low-quality informality after their formal termination, we still might be omitting movements

from formal employment towards self-employment, either formal or informal. If substantial, this movement into self-employment might reinforce our findings, suggesting even larger increments in earnings (and income) inequality. To better understand earning dynamics, future work into this line of research should look into the destination of workers who do not go back into formal wage earning jobs.

References

Amarante, V., Arim, R., & Dean, A. (2014). The Effects of Being Out of the Labor Market on Subsequent Wages: Evidence for Uruguay. Journal of Labor Research, 35, 39–62.

Azadikhah Jahromi, A., & Callaway, B. (2022). Heterogeneous Effects of Job Displacement on Earnings. Empirical Economics, 62, 213–245.

Carrington, W. J., & Fallick, B. (2017). Why Do Earnings Fall with Job Displacement? Industrial Relations: A Journal of Economy and Society, 56, 688–722.

Couch, K. A., & Placzek, D. W. (2010). Earnings Losses of Displaced Workers Revisited. American Economic Review, 100, 572–589.

Farber, H. S. (2017). Employment, Hours, and Earnings Consequences of Job Loss: US Evidence from the Displaced Workers Survey. Journal of Labor Economics, 35, S235–S272.

Firpo, S., Fortin, N., & Lemieux, T. (2009). Unconditional Quantile Regressions. Econometrica, 77, 953–973.

Garcés, M. (2019) October 2019: Social Uprising in Neoliberal Chile, Journal of Latin American Cultural Studies, 28:3, 483-491.

Hijzen, A., Upward, R., & Wright, P. W. (2010). The income losses of displaced workers. Journal of Human Resources, 45, 243–269.

Huttunen, K., Møen, J., & Salvanes, K. G. (2011). How Destructive Is Creative Destruction? Effects of Job Loss on Job Mobility, Withdrawal and Income. Journal of the European Economic Association, 9, 840–870.

Illing, H., Schmieder, J. F., & Trenkle, S. (2021). The Gender Gap in Earnings Losses after Job Displacement (Working Paper No. 29251). National Bureau of Economic Research.

Jacobson, L. S., LaLonde, R. J., & Sullivan, D. G. (1993). Earnings Losses of Displaced Workers. The American Economic Review, 83, 685–709.

Kaplan, D. S., Martinez Gonzalez, G., & Robertson, R. (2005). What Happens to Wages after Displacement? Economía, 5, 197–242.

Korkeamäki, O., & Kyyrä, T. (2014). A Distributional Analysis of Earnings Losses of Displaced Workers in an Economic Depression and Recovery. Oxford Bulletin of Economics and Statistics, 76, 565–588.

Machado, J. A. F., & Santos Silva, J. M. C. (2019). Quantiles via moments. Journal of Econometrics, 213, 145–173.

Rios-Avila, F. (2020). Recentered influence functions (RIFs) in Stata: RIF regression and RIF decomposition. The Stata Journal, 20(1), 51–94.

Schmieder, J. F., Von Wachter, T., & Bender, S. (2010). The long-term impact of job displacement in Germany during the 1982 recession on earnings, income, and employment (No. 1/2010). Nürnberg: Institute for Employment Research.

Syverson, C. (2011). What Determines Productivity? Journal of Economic Literature, 49, 326–365.

Sehnbruch, K., Carranza, R. & Prieto, J. (2019). The Political Economy of Unemployment Insurance based on Individual Savings Accounts: Lessons from Chile. Development and Change 50(4), pp. 948-975.