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Analyses of Topical Policy Issues

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

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ABSTRACT

This paper examines the impact of job losses on the subsequent earnings of formal workers in Chile using administrative data. It contributes to the literature by examining the impact of job losses across the earnings distribution using unconditional quantile regression analysis. The paper thus provides evidence on the costs of losing a formal job in an emerging economy that is now considered 'high-income' but still suffers from high earnings inequality and other issues that characterise labour markets in developing countries, such as high job rotation.

Our results show that, on average, wages decline by 42 % in the first month after an involuntary job loss and never fully recover their previous level within our observation period of 3 years after this loss. Workers in the bottom 10 per cent of the earnings distribution experience greater wage losses after unemployment and take longer than average to recover. Conversely, those in the top 5 per cent experience little or no wage loss and even increase their wages over time. By having a more pronounced effect at the bottom of the earnings distribution, our findings suggest that involuntary job losses reinforce earnings inequality in the Chilean labour market.

1. Introduction

Economic crises, technological change and regulatory reforms can trigger significant changes in employment at the firm level. These situations can contribute to productivity growth in the economy by allowing the most productive firms to grow while the least productive firms contract or even close (Syverson, 2011). However, such developments are also associated with negative consequences for displaced workers, which can be significant for them and their families (Brand, 2015). A large body of economic literature has analysed how involuntary job loss reduces future earnings (e.g. Jacobson et al., 1993; Couch and Placzek 2010), contributes to increased earnings instability (e.g. Stevens, 2001) and has serious negative effects on social outcomes such as crime, mortality, domestic violence, family dissolution and mental health (Brand, 2015; Britto et al., 2022; Sullivan and von Wachter, 2009; Bhalotra et al., 2021; Doiron & Mendolia, 2011; Zimmer, 2021).[1]

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[1] In addition, recent literature has examined the potential impact of job loss on divorce, fertility, and child outcomes (Del Bono et al. 2015; Eliason 2012; Rege et al., 2011).

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However, limited attention has focused on how involuntary job losses affect, first, the overall distribution of earnings and, second, how they affect the earnings of particular groups within this distribution, especially at the higher and lower ends.[2] We know that wage losses after dismissal result from a combination of factors: unemployment reduces earnings in the short term, while lower wages may persist in the medium- to long-term as new jobs often pay less.

Although it is important to quantify the average magnitude of these wage losses, these averages hide the size and nature of these effects across the earnings distribution. It is therefore even more important to know which workers are the *most* affected by job losses as these workers may require extra policy support.

Only a few studies in developed economies go beyond average estimates of wage losses of laid-off workers and focus on the distributional aspects of these losses. Korkeamäki & Kyyrä (2014) show that the displacement effect is more pronounced at the lower end of the earnings distribution among Finnish workers, while it is relatively small or negligible at the upper end. Azadikhah & Callaway (2022) and Faber (2017) find a heterogeneous effect of job losses on earnings in the US. Their research reveals that a considerable proportion of American workers earn higher incomes in their new jobs compared to their previous ones. However, a significant share of workers at the lower end of the income distribution also experience more pronounced negative effects compared to the average.

Other studies have demonstrated the impact of job losses in countries where formal employment and strong social protection systems are the norm (e.g. 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). While the results of these studies can be used to inform employment policies in the context of advanced economies, they cannot be directly extrapolated to other contexts, especially to emerging economies with weak social protection systems as well as high levels of informal employment, non-standard employment and high job rotation.

This article makes three contributions to this research. First, we provide evidence on the impact of displacement on the future earnings among workers in Chile, a country which is typical of such emerging economies where it is difficult to establish functioning social protection systems, in particular unemployment insurance, as a high proportion of jobs could be described as precarious or of poor quality (Sehnbruch et al., 2019, 2022). Chile has a particularly good administrative data infrastructure for analysing such issues, which allows for a granular analysis of its earnings distribution among formal workers in the private sector over time. Section 2.1 further discusses the relevance of the Chilean case to other emerging economies in more detail.

The second contribution of this paper makes is that it examines not only whether job losses can lead to wage losses on average, but also whether its effects vary across the earnings distribution. To the best of our knowledge, this is the first article to do so in Latin America. Specifically, we use administrative data from Chile to compare the wage gap between formal workers who lost their jobs and those who did not between January 2010 and December 2019. Our database follows a random sample of formal workers on a monthly basis from the moment they make their first contribution to the unemployment insurance system. We use Recentered Influence Functions (RIF) regressions to identify and estimate short- and long-term individual wage differentials, both on average and across the earnings distribution, thus providing a picture of the inequality underlying job displacement.

The third contribution of this paper is that it relates job loss and future earnings to the financial vulnerability of households.[3] Workers who experience earnings losses experience a substantial decrease in their savings. This becomes more relevant in societies with weak welfare states, where workers are not protected in the face of economic shocks such as illness, disability, job loss, or retirement. This significantly increases the negative impact of such shocks on the overall well-being of individuals and their families (e.g. Prieto, 2022).

To do this, we relate job losses to aggregate outcomes that estimate the accumulated wage gap between two different groups of formal workers: those who leave formal employment and those who do not. First, by reporting a job loss and subsequent recovery, we capture a period of low (or non-existent) income flows for households. Second, we relate job losses to the aggregate level of wage inequality. Depending on where in the distribution these job losses occur and how long they last, we can expect either decreasing or increasing levels of inequality. Our paper thus explores some of the macroeconomic consequences of a labour market with high turnover.

Our results show that, on average, workers experience a 42 per cent drop in wages in the first month after being made redundant, and that they never fully recover their pre-dismissal level, at least within the three-year window that we observe. This negative average effect suggests that displaced workers have little chance of finding a new formal job that is well-paid. This effect is particularly severe for workers in the lower tail of the distribution, with short-term losses of up to 53 per cent of formal wages, in part because they become unemployed or have to accept low-paid or informal jobs.

We find that those with the lowest wages suffer the most, with significant wage gaps that can take well over 18 months to reduce to negligible levels. As these effects are long-lasting, this group should be the focus of policy initiatives. On the other hand, those at the top of the earnings distribution suffer little or no impact and even move into higher paid jobs, increasing overall earnings inequality. Our research suggests that job losses are an important factor in perpetuating earnings inequality in the Chilean labour market.

The paper is structured as follows: Section 2 reviews the literature on job displacement and some of the distributional aspects of

[2] Job loss can be voluntary or involuntary. The latter refers to job losses due to redundancy, downsizing, restructuring, plant closures or company relocation. Job displacement is a specific form of involuntary job loss that refers to economic and business situations beyond the worker's control. Much of the literature uses these terms interchangeably though, as does this paper.

[3] Economic vulnerability has been linked to other phenomena such as social stratification, which indirectly linked to job loss does explicitly explore that association (Western et al., 2012).

earnings losses, while also discussing the relevance of the Chilean case. Section 3 then presents the administrative panel data we use and the restrictions we impose on it. Section 4 presents the model, and its estimation based on RIF regressions. This approach allows us to examine how job displacement affects both average wages and wage inequality, focusing on certain percentiles of the earnings distribution as well as on a summary measure such as the Gini coefficient. Section 5 presents our results and Section 6 concludes.

2. Related literature

Earnings inequality is a growing global concern that has generated an extensive literature discussing the relevance of different factors contributing to its increase. These include, among others, technological change, the role of international trade, the education premium and the relative supply of skills, heterogeneity across firms and economic sectors, and changes in labour market institutions, such as the level of unionisation and real minimum wages (e.g. Goldin & Katz, 2008; Pierce & Schott, 2016; Song et al., 2018; Author et al., 2016). Although earnings inequality has increased in both developed and developing countries (Alvaredo and Gasparini, 2015), there are regions such as Latin America where a reduction in labour income inequality has been achieved (Messina and Silva, 2021).

Such a reduction has been explained by factors that offset the influence of global factors (World Bank, 2016), particularly, the fact that real wages at the bottom of the wage distribution have grown faster than those at the top (Messina and Silva, 2021). Indeed, most of the decrease in wage inequality between 1995 and 2015 can be explained by two developments: first, a decline in the returns to secondary education over time and to tertiary education from the 2000s onwards (Acosta et al., 2019); and, second, a decline in the returns to labour market experience (Ferreira et al., 2022).[4] Although education and experience are important determinants of earnings, and changes in schooling and experience premiums are therefore associated with changes in inequality, there is another factor that affects labour income over time, which is the experience of job losses.

Research in developed countries has found that job displacement significantly reduces average wages when workers return to work and that this effect is persistent over time (e.g. Jacobson et al., 1993; Couch and Placzek, 2010). The available empirical evidence suggests that job losses lead to substantial reductions in annual earnings, ranging from 20 to 50 per cent of previous earnings in the short run (Farber, 2017; Illing et al., 2021; Bertheau et al., 2022). Although the magnitude of the losses diminishes over time, their effects persist in the long run.[5]

Another way to look at the negative effect of job displacement is the significant increase in the probability of falling into the bottom of the earnings distribution, not only in the year of displacement but for several years thereafter (e.g., Jolly 2013 for the United States using the PSID). In contrast to developed countries, research in Latin America is scarce and the results are mixed. Using administrative records from the Uruguayan unemployment insurance, Amarante et al. (2014) examine average wage losses associated with periods spent outside the formal labour market in Uruguay. They find that formal workers lose 38 per cent of their wages within the first three months of separation and that the losses persist after one year. Similarly, Kaplan et al. (2005) examine the Mexican case during an economic expansion also administrative records from the social protection system and find that displaced workers with longer tenure receive higher wages than non-displaced workers when they find a new job.[6]

By focusing on how job loss affects *average* changes in the future earnings of displaced workers, these studies are blind to the impact on different quantiles in the income distribution. Two recent studies, one in Finland and the other in the United States, go beyond average estimates of the earnings losses of displaced workers and focus on the distributional aspects of earnings losses. Using administrative data from different sources, Korkeamäki & Kyyrä (2014) analyse the earnings losses experienced by laid-off Finnish workers during recessions and recoveries, with a particular focus on the conditional quantile displacement effect. Their results show that the displacement effect is more pronounced at the lower end of the earnings distribution, while it is relatively small or negligible at the upper end. Furthermore, workers displaced during recessions experience significantly larger income losses than those displaced during recoveries.

Azadikhah & Callaway (2022) use survey data from the United States and compare the outcomes for displaced workers with the outcomes they would have experienced if they had not been displaced and had maintained the same rank in the earnings distribution. They find a heterogeneous effect of job displacement on earnings, with 42 % of workers earning more than they would have if they had not been displaced, and a large fraction experiencing more negative effects than average. This last result is consistent with Farber (2017), who shows that a significant number of American workers who lose their jobs and are replaced on a full-time basis are paid more in real terms in their new jobs than in their old jobs. This trend is particularly pronounced among the young and those with short tenures.

Another paper that studies the link between job loss and inequality in the US is Ananat et al. (2017). Their work focuses on geographical areas in high income countries that have suffered the most due to globalization and technological change and where the loss of manufacturing jobs has greatly affected whole cohorts of workers. The authors present an intergenerational framework and

[4] Other factors explaining the decline in earnings inequality are the reduction in the dispersion of salaries across firms (Messina & Silva, 2021) and the decrease in horizontal inequality, i.e. the decline in wage differentials associated with workers' race, gender and location (Ferreira et al., 2022).

[5] For example, in the US, the negative effect of job displacement on annual earnings is still visible after 20 years (Davis and von Wachter, 2011), and in the UK, losses are estimated to be around 10% of pre-displacement earnings after 10 years (Upward & Wright, 2019).

[6] It is worth mentioning that neither study can distinguish between displacements and voluntary separations, causing a selection problem that is well documented in this literature (e.g. Seim, 2019). While it is not possible to distinguish them in this case, the present article attempts to identify voluntary separations as those that happen without an unemployment period and where the new job has a higher wage. We discuss this criterion in section 3.2 and assess its sensitivity to alternative characterizations in section 5.5.

show that workers who lose their job are less able to help and support their children, resulting in worse mental health and lower academic performance, ultimately impacting college attendance and shaping income inequality in the next generation.

These studies highlight the importance of studying wage gains or losses across groups of workers. In countries where displaced workers at the top of the distribution improve their future earnings and those at the bottom are significantly worse off compared to their previous jobs an increase in wage inequality should result. The magnitude of this change is given by the size of the effect at both tails of the distribution (Palma, 2011).

Although the mechanisms explaining the impact of job losses on workers' future earnings have been well documented since the earliest theories of human capital, there is no clear explanation for the significant increase in earnings following displacement, particularly for those at the top of the income distribution.[7] However, matching theory provides an explanation, as the distribution of possible combinations between workers and jobs affects the distribution of positive wage changes (Carrington and Fallick, 2017). Workers often stop looking for a better job once they have found one that exceeds a minimum expected level of earnings, rather than continuing to search indefinitely. Therefore, the employment exercised prior to a job loss may not have been the best match for workers, so that some displaced workers may find a better job if they previously gave up looking.

In this context, Chile is a compelling case study because its labour market is characterised by features that are typical of both emerging and advanced economies. In 2013, the World Bank classified Chile as a high-income country, and in 2017 it was removed from the OECD's Development Assistance Committee (DAC) list. The country's institutional and legal framework for formal employment is similar to that of southern Europe, where strong employment protection legislation for permanent contracts contrasts with minimal regulation of temporary contracts, resulting in a high proportion of non-standard employment and high levels of job rotation.

In 2019, Chile had the second highest share of workers with contracts of one year or less among OECD countries (26.2 %), behind Colombia (37.3 %) and well above the OECD average of 19.5 %. Despite this, informal employment in Chile has not decreased, hovering around 30 % of the national labour force. While this proportion is low by Latin American standards, it is significantly higher than in more advanced economies, where informal employment averages 13.5 % of total employment (OECD, 2023).

A recent study of Chilean employment dynamics by the Ministry of Labour (2024) shows that workers in formal employment have an 80 per cent chance of continuing in a formal job in the next year. By contrast, informality is a highly dynamic condition. Those in informal jobs have a 50 per cent chance of moving into either formal employment, unemployment or inactivity between one year and the next.[8] Although there are no known studies that have examined the characteristics of workers who remain in formal jobs for long periods of time, Table E2 in Appendix E summarises what we can learn about them from Chile's Social Protection Survey, using panel data from 2010 to 2019.

Workers who have been in formal employment for more than 36 months tend to be older, with an average age of 35, and have higher incomes. However, they are less likely to have tertiary education (14.8 %) and are less likely to be women (40.9 %) than those with shorter job tenures. Employees with a formal job of less than 12 months are younger (27.1 years), are more likely to be women (53.8 %) and have a higher proportion of tertiary education (23.9 %), despite lower earnings.

While such a result may seem counterintuitive, they can be explained through a cohort effect. The increase in university enrolment in Chile over the last 15 years has led to a higher proportion of young people with advanced degrees entering the labour market. These workers often take short-term jobs while they look for jobs that better match their qualifications (Didier, 2024). As these cohorts grow older and transition towards open-ended contracts, we can expect longer tenures to become positively associated with higher levels of schooling.

3. Data

Our analysis uses administrative panel data from the Chilean unemployment insurance system.[9] This is an administrative register that includes all private formal workers in the country and reports their earnings as well as other job characteristics on a monthly basis. We use a publicly available 3 % sample from this database.[10] By definition, the unemployment insurance system does not include informal workers, domestic or public sector workers, employers or the self-employed. Together these groups account for around 40 % of the total labour force.

The dataset was created in 2002, and includes all formal contracts that have been established since then, as well as a small number of workers who opted-in voluntarily. This means that in the early years it over-represented younger workers, short-term jobs and fixed-term contracts as new entrants were included. As Sehnbruch et al. (2019) report, it was not until 2010 that the dataset matured and became representative of the formal workforce. We therefore use 2010 as the starting point for our analysis. Since 2010, the database accounts for just over half of the total labour force and 75 % of all formal private salaried workers.

[7] According to the specific human capital theory of Becker (1962) and Oi (1962) job displacement is associated with a decrease in earnings due to a lower demand for specific human capital, which cannot be controlled by the worker. Therefore, this theory explains that displaced workers can access salaries like those in their previous jobs if the demand for their specific human capital is maintained within their occupation and sector; however, it does not explain why workers' wages can increase substantially after displacement.

[8] Prieto et al. (2024) and Sehnbruch et al. (2025) analyse these transitions in more detail.

[9] Recent studies on intergenerational earnings mobility have also used this database (e.g. Cortés-Orihuela et al., 2024).

[10] This sample includes over 22 million observations, 3 million employment relationships and 320,000 workers.

3.1. Restrictions imposed on the data

To properly account for income trajectories, we need to study employment relationships that are sufficiently long. That is, that must have a minimum duration before the break in the relationship. Ideally – and in line with previous articles – we would need a longer period of continuous employment of at least 3 years. However, due to the nature of the Chilean labour market – with its high turnover and many short-term contracts – this would reduce our subsample to 40 % of all open-ended contracts and less than 10 % of fixed-term contracts (see Table 1). More importantly, these jobs are systematically different from the average worker, as they are 'better' jobs, i.e., they have higher incomes, more stability, and better overall conditions. We therefore focus on workers whose jobs lasted at least one year, whether fixed term or open ended. According to Table 1, workers with at least one year of tenure represent 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 most workers, particularly among those with open-ended contracts. We therefore use it to calculate our findings. However, we report results for the 36-month sample in Appendix A. As a result, our analysis will not be representative of all formal workers, but those with more stable employment relationships, which is particularly important when interpreting our distributional effects. Those at the bottom of our distribution of earnings will not be the worst-paying jobs in the formal sector.

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, which deliberately excludes the significantly negative effects of the social revolt that occurred in Santiago de Chile in mid-October on the economy (see, e.g., Garcés, 2019) as well as of the COVID-19 pandemic. To look only at workers who have actively participated in the formal labour market and following methodologies established in the existing literature, we include all workers who report income (and thus contributed to the unemployment insurance system) at least once a year between 2010 and 2019. This restriction allows us to focus on people who participate actively in the formal labour market rather than including workers who have mostly worked informally or outside of the private sector. To avoid potential life cycle biases, we also restrict the sample to workers in their 'prime' working age, that is, aged between 25 and 45 when first observed in the dataset.

Our subsample only includes employees with open-ended contracts. We have excluded workers with fixed-term contracts because we consider that the terms of their contracts do not constitute involuntary separations. Although these contracts have a fixed duration, they are still the result of a mutual agreement between the employer and the employee. In contrast to involuntary job losses, workers who enter fixed-term contracts usually do so with prior knowledge of their temporary nature. Moreover, in some cases these contracts provide a bridge to stable employment, and their duration is often sufficient to bring these workers closer to those with permanent contracts than to those experiencing involuntary job losses. For these reasons we opt to exclude fixed-term workers from our analysis, which account for 25 % to 30 % of our observations (see Table 2).

3.2. Defining involuntary job separations

As there is no information in the database on the reason for job separation, we propose a set of rules to identify potential involuntary separations.[11] First, if the separation leads to a gap between jobs and, second, if the earnings in the new job are not more than 25 % higher than in the separated job. This is operationalised by excluding workers who have moved to another job without a period of non-contribution and those whose earnings in their current job are at least 25 % higher than in their previous job.

It is important to recognise that these separations are not necessarily involuntary at all. Our definition of involuntary job separation might also include people who are fired for cause and people who voluntarily change jobs that do not result in higher wages. For example, workers might change jobs because of the prospect of a better career, because they expect to be made redundant or because of better non-monetary conditions, even if that results in lower short-term wages. Appendix D explores our main findings under alternative specifications for involuntary separations.

To better understand where in the distribution we find our excluded transitions, Fig. 1 shows the proportion of workers who change jobs without a period of non-contribution and a 25 % wage increase (grey diamonds). Most of the workers we remove from our sample are concentrated at the bottom of the wage distribution, with roughly 30 % of those in the bottom decile and less than 5 % at the top decile. This pattern is very similar if we were to cap wage increases at 50 % rather than 25 %, as shown by the (yellow) squares. On the other hand, if we considered all job changes (black circles) we would see a more uniform redistribution of workers, ranging from around 45 % of workers at the bottom 10 % and 35 % at the top 10 %, showing that a considerable share of workers switches between one job and the next without a non-contribution period. In addition, this shows that most of the workers whom we consider to be experiencing voluntary job changes are concentrated at the bottom of the distribution rather than at the top.[12]

[11] The database does include information on the cause of the job separation, whether it was a termination by the employer or a decision of the worker. However, that information is only available for those workers who requested unemployment insurance benefits, which is a small (and biased) sample of all job separations (see, e.g., Sehnbruch et al., 2022).

[12] As most workers with large wage increases are at the bottom of the distribution, we expect our findings to be lower bound estimates of the overall impact on wage inequality. Nonetheless, we believe this restriction to be important, as we would like to exclude voluntary transitions – at least in theory. To assess the impact of this restriction Appendix D replicates our main findings with alternative criteria.

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

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
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	21.9	21.4
1 to 2 years	14.3	14.2	13.6	14
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).

Table 2
Descriptive statistics under sample restrictions.

	Full sample	Formal job every year	Age restriction	Drop 'voluntary' transitions
Share open-ended	69.8 %	75.0 %	77.1 %	100 %
Share women	37.3 %	30.7 %	32.9 %	35.3 %
Age	38.2	39.8	39.2	39.6
Duration	33.4	43.0	44.3	52.9
Termination rate	85.0 %	81.5 %	80.6 %	73.4 %
Income (April 2020 CLP)				
Average	735,629	849,474	937,896	1068,417
P25	324,191	367,665	390,664	452,679
Median	495,886	593,920	659,050	757,651
P75	876,619	1037,744	1181,213	1388,366
Observations	14,979,602	7317,718	4610,361	3184,400

Note: Authors' calculations based on a random sample from UISA administrative data (3 % of the total). We report the last observation of each employment relationship across the January 2010 to November 2019 period. Each column imposes an additional restriction, as discussed in Section 4. The first columns report the full sample for the study period. The second includes workers who contribute to the UI (i.e., have a formal job) at least once month every year. The third columns restrict the age to 25–45, and the final column excludes workers who jump from one job to another with no unemployment period and with an increment of at least 25 % in their earnings, as a proxy of a voluntary transition into a better job. 1000 CLP = 1.3 USD (average 2020 rate).

3.3. Descriptive statistics

Table 2 summarises the changes in our sample due to the aforementioned restrictions. Columns 1 to 4 report descriptive statistics for the covariates as well as for the earnings distribution, going from the full sample all the way to the final sample that excludes immediate transitions into higher-paying jobs. We first see that the sample size is reduced considerably, going from just below 15 million observations to just over 3 million. This is mainly due to including only workers who actively participate in the formal labour force. We also see that these restrictions result in a sample of 'better' jobs, with a higher share of open-ended contracts, longer tenures, lower termination rates and higher wages across the distribution. They also reduce the share of women, from 37.3 % to 35.3 %, and the termination rate (i.e. the share of workers whose contracts ended within the observation period) from 85.0 % to 73.4 %.

Using the final sample from the last column of Table 2, we can evaluate job displacement rates across the earnings distribution. Fig. 2 breaks down the average termination rate shown in Table 2 (73.4 %) by earnings decile for open-ended contracts. We observe a downward slope, where higher-earning workers are less likely to experience job displacement. Therefore, earnings and tenure are negatively correlated among open-ended contracts.

As discussed before, estimating the effect of job displacement requires that we control for the pre-termination trend. With this objective in mind, we provide estimations for two samples, workers with a duration of at least 12 and of at least 36 months. While the latter resembles samples used in other papers on this topic, the former allows us to account for a much larger share of the formal workforce in the Chilean case, which is why we use jobs with at least a 12-month duration here. Specifically, for each worker we look at their first job in 2010 (or when they first appear in the sample, if they appear after 2010) and keep those workers whose jobs last at least 12 or 36 months, including all months before 2010 to capture fully their employment duration. That is, we keep all observations for workers whose first job in the database lasted at least 12 (or 36) months, including the complete duration of that job as well as any

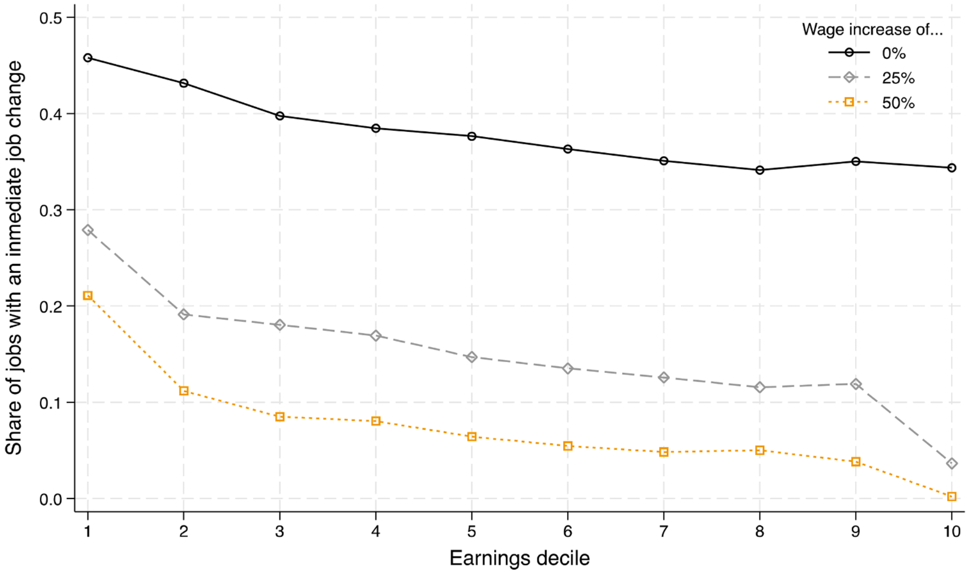

Fig. 1. Share of workers that switch jobs without a non-contribution period, by the change in their wage from one job to the next.
Source: Authors' calculations based on a random sample from UISA administrative data (3 % of the total). Includes all employment relations from January 2010 to November 2019. Includes all workers who had a job transition with no non-contribution period in between and whose wages increased by at least that amount. The yellow squares represent our benchmark estimation.

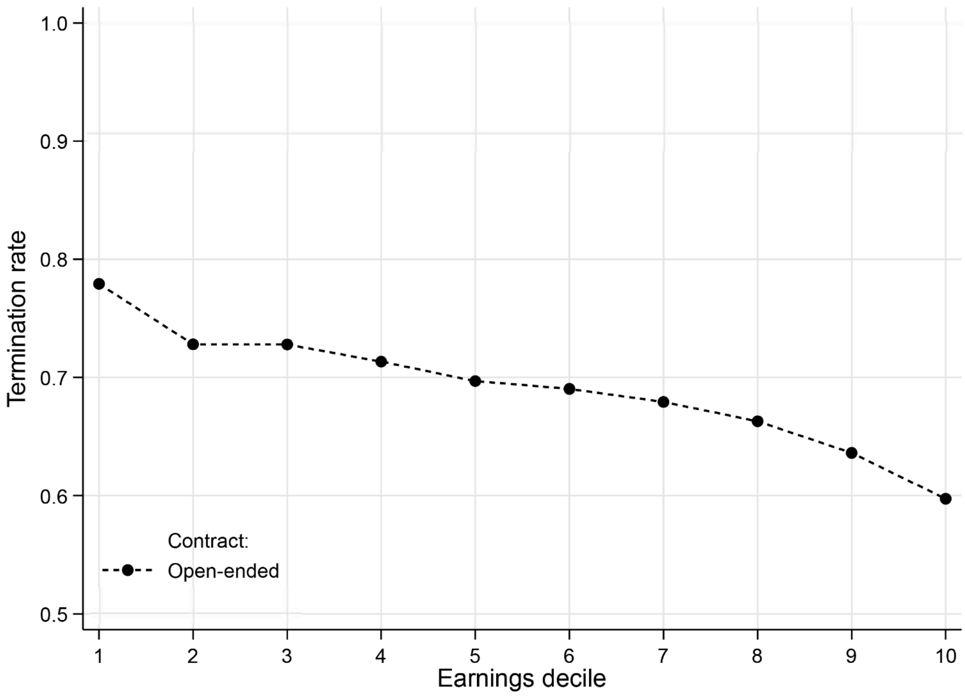

Fig. 2. Termination of open-ended contracts across the earnings distribution.
Source: Author's calculations. The termination rate is the share of workers who report a job separation at some point of the observed sample. Earnings deciles are constructed separately for each type of contract. Final sample before duration restrictions (i.e., last column of Table 2).

other jobs they held afterwards. For those workers we observe their entire earnings history between January 2010 and November 2019, including all subsequent formal jobs they hold.[13]

Table 3 summarises the main descriptive statistics for these two samples. It makes a distinction between separators and non-separators, i.e. those workers whose main job ended at some point and those whose jobs are still ongoing as of November 2019. Note that all subsequent jobs following the first separation are labelled under 'non-separators, as we do not examine these transitions. The result is that non-separators jobs account for most of the sample, from 70 % to 80 % depending on the sample. In addition, non-separators are somewhat older, have shorter durations. At the same time, they report higher wages throughout the earnings distribution. While the two groups show differences, we consider non-separators to be a reasonable 'control' group with which to compare those who suffer a job loss. For additional information on all variables used in our analysis, see Table E1 in Appendix E.

Table 3 also illustrates the sampling issues that arise when restricting job durations: The 36-month sample has a slightly higher share of open-ended contracts and a lower share of women. It also reports higher wages across the distribution and longer durations (at least for non-separators). This is a key aspect to consider when interpreting our distributional results. By restricting the sample to durations of 12 months or more we are focusing on the best jobs within the labour formal market, and the 36-month sample reinforces that trend. We cannot say anything about the earnings trajectories of those with shorter durations and therefore with worse jobs. 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 to unemployment insurance and pensions, as well as with higher incomes.

4. Econometric strategy

In this section we present a model to study the impact of job displacement on the earnings trajectories among formal workers. We begin with the standard approach to assess these loses, which we then expand to assess the role of job losses throughout the wage distribution. We then estimate this model using RIF regressions as presented by Firpo et al. (2009) to explore different features of the earnings distribution.

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. Such estimators are common in the program evaluation literature (see, e.g., Heckman and Robb, 1985). We expand their original specification to use the available data better and to account for lifecycle patterns that could also be having an impact on our results. The estimation formula uses longitudinal data for a fixed-effects model as follows:

$$\boldsymbol{Y_{ijkt}} = \boldsymbol{\omega} + \sum_{k\geq -m} \boldsymbol{D_{it}^{k}\delta_k} + \boldsymbol{\alpha_i} + \boldsymbol{\eta_j} + \boldsymbol{\pi_k} + \boldsymbol{\gamma_t} + \boldsymbol{X_{it}\beta} + \boldsymbol{\varepsilon_{it}} \tag{1}$$

where $\boldsymbol{Y_{ijkt}}$ is equal to the labour income of worker i in firm j, industry k and at time t.[14] D_{it} is a dichotomous variable that indicates whether a worker leaves her formal job in period $t-k$. The fixed effects include an individual term, α_i, a firm size term η_j, and industry term π_k as well as time term, γ_t, measured in months. This means that all individual time-invariant characteristics, including observed variables such as gender or education, but also unobserved characteristics such as cognitive skills or others.

The purpose of k is to index a set of dummy variables, D^k, starting m months before splitting up to n months after termination, which we set at $n = 36$ or three years. That is, $t-k$ will take positive values when the worker is k months away of losing their job or negative values when it has been k month since the termination. The parameters of interest are δ_k, which account for the earnings gap between separated and non-separated workers over time. In other words, δ_k measures the earnings losses of workers who leave their formal employment relative to the control group at each moment, where the control group includes all months before 12 months before the job separation and 36 months after separation.[15]

To provide a better reference of the size of the effects, and to compare them with previous studies we divide δ_k by the average wage at the beginning of the period of study, January 2010 (in 2020 real terms) – which was roughly equivalent to 1000 USD in 2020. This approximation is useful for international comparisons

Lastly, X_{it} is a vector of employment characteristics of the worker i in time t. It includes previous tenure and current tenure (both in months), as well as the square of both terms. Penultimate tenure is defined as the duration of employment in the job immediately preceding the last job; if the last job is the first job, penultimate tenure is set to zero. Similarly, the last tenure is the duration of the job that is about to end. All of these terms are interacted with a third-degree polynomial of age centred at 40 years. For age a_{it}, penultimate tenure PT_{it}, last tenure LT_{it} and type of contract C_{it}, then the vector X_{it} equals:

[13] Note that some of these workers might leave the formal job market and would therefore disappear from our database, thus making our estimates lower bounds of the 'real' wage loss. Figure E1 in Appendix E shows that among those workers we observe in 2010, 90% remain in the data after 3 years and just over 70% remain in the data over the entire period.

[14] Technically we group workers by firm size rather than their actual firms. This significantly reduces computation time thus allowing us to control for a proxy of time-invariant firm characteristics at the level of firm size. We include 8 categories by the number of workers: 1-5, 6-9, 10-25, 26-49, 50-99, 100-199, 200-999, and 1000 or more workers.

[15] An alternative perspective to the one outlined in the article draws on insights from the event study literature (e.g., Miller, 2023) and research on heterogeneous difference approaches (e.g., de Chaisemartin et al., 2024). This approach incorporates event-time dummies for each post-treatment and pre-treatment period, using the period immediately preceding the event (t = −1) as the reference category, effectively setting it to zero. In Appendix F we estimate the model including the full set of time dummies.

Table 3
Descriptive statistics across samples by minimum job duration.

	12-month sample			36-month sample		
	Non-separators	Separators	Total	Non-separators	Separators	Total
Share women	31.4 %	29.9 %	31.0 %	34.6 %	31.3 %	33.8 %
Age	41.3	37.8	40.3	40.6	37.3	39.8
Duration	67.2	85.9	72.9	55.1	75.9	59.8
Income (April 2020 CLP)						
Average	1206,014	1026,847	1151,864	1164,866	989,410	1124,875
P25	501,931	401,228	468,941	494,435	387,600	467,878
Median	864,707	705,695	813,782	837,921	675,118	799,165
P75	1667,071	1352,507	1576,752	1569,578	1283,696	1506,265
Observations	1011,420	438,086	1449,506	1774,160	523,748	2297,908
	69.8 %	30.2 %		77.2 %	22.8 %	

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. Separators include the first job that ended during the sample period among workers whose job lasted at least 12 or 36 months. Table only reports the final sample (last column of Table 2).

$$\boldsymbol{X_{it}} = \left[\sum_{h=1}^{3} (a_{it} - 40)^{h}\right] \times \left[\boldsymbol{C_{it}} + \boldsymbol{PT_{it}} + \boldsymbol{PT}_{it}^{2} + \boldsymbol{LT_{it}} + \boldsymbol{LT}_{it}^{2}\right] \tag{2}$$

Eq. (2) closely follows the specification in Lee and Solon (2009) who model the intergenerational elasticity of income to account for lifecycle bias. By relating employment characteristics to age, we can capture how the age profile shapes their impact. Specifically, it allows us to account for divergences across the lifecycle. By including a polynomial, we can model a non-linear age profile, thus capturing different functional shapes as age interacts with employment characteristics. Lastly, we centre age at 40 years so that the remaining coefficients can be interpreted at that specific age, rather than at the minimum age.

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 unconditional 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. For this purpose we use Recentred Influence Functions (RIFs), following the approach of Firpo, Fortin and Lemieux (2009) and the *rifhdreg* function in Stata developed by Rios-Avila (2020). The RIF regression approach has been used in several contexts to assess distributional implications, for example, to study the determinants behind the fall in inequality in Brazil around the commodity boom (Ferreira et al., 2022), the intergenerational transmission of wealth in Britain (Nolan et al., 2020) or the role of the immigrant labour force on wage inequality in Luxembourg (Choe and Van Kerm, 2018). Through RIF regressions, we can provide estimates for *unconditional* quantiles rather than quantiles conditional on observables. In addition, we can look into summary measures of inequality such as the Gini coefficient.

RIFs are based on Influence Functions (IF), which were developed as part of the literature on robust statistics (Hampel, 1974). IFs assess the sensitivity of a given feature of a distribution, such as the mean or the variance to changes in these features when we change one or more data points. These features include the mean, median or other quantiles, but also inequality measures such as the Gini coefficient or the Atkinson index. IFs are standardised to have a mean of zero, which is why we need to re-centre them around their mean value, therefore the name RIF. In this context, the methodology proposed by Firpo, Fortin and Lemieux (2009) expands this approach to include regression and decomposition analyses, estimating the effect of a marginal change in the distribution of covariates on a given distributional feature, while keeping the conditional distribution constant. This is referred to as the 'unconditional partial effect' or UPE.[16]

RIF regressions are estimated by replacing the dependent variable, e.g., the wage of a given worker, with the sample version of the relevant RIF. The different RIFs can be computed using a list of formulas or through the *rifhdreg* command in Stata, that already incorporates several of these formulas. Once you have the RIF value for each observation in the sample, we simply estimate a linear regression over the new outcome. Following the nomenclature of Eq. (1), the resulting equation can be written as:

$$\widehat{RIF}(y|\upsilon_y) = \boldsymbol{\omega}^{\upsilon_y} + \sum_{k\geq -m} \boldsymbol{D}_{it}^{k}\boldsymbol{\delta}_{k}^{\upsilon_y} + \boldsymbol{\alpha}_{i}^{\upsilon_y} + \boldsymbol{\eta}_{j}^{\upsilon_y} + \boldsymbol{\pi}_{k}^{\upsilon_y} + \boldsymbol{\gamma}_{t}^{\upsilon_y} + \boldsymbol{X}_{it}\boldsymbol{\beta}^{\upsilon_y} + \boldsymbol{\varepsilon}^{\upsilon_y} \tag{3}$$

Where $\widehat{RIF}(y|\upsilon_y)$ is the sample version of the RIF for feature υ_y – in our case the mean, percentiles 10 to 95, and the Gini coefficient. Note that when $\upsilon_y = \mu_y$ (i.e., the relevant feature is the mean of y), the regression is equivalent to a standard OLS regression. This

[16] RIF regressions rely on pre-determined formulas to compute the RIFs for a given functional statistic, as reported in Essama-Nssah and Lambert (2012) or Annex A in Rios-Avila (2020). This means that the dependent variable is transformed such that the average across all individual RIFs is equal to the desired statistic. For the mean, the formula would simply be $RIF = y$. For the unconditional pth quantile, it is $RIF = F_Y^{-1}(p) + \frac{p-1\{y\leq q_Y(p)\}}{f\{q_Y(p)\}}$, where $F(y)$ is the CDF and $f(y)$ the PDF. while for the Gini it is $RIF = 1 + \frac{2}{\mu_Y^2}R_Y - \frac{2}{\mu_Y}[y\{1 - F_Y(y)\}]$, where $R_Y = \int_0^1 GL_y(p)dp$ is the integral below the Generalized Lorenz curve defined as $GL_y(p) = \int_{-\infty}^{q_Y(p)} ydF_Y(y)$.

approach allows us to model not only the mean, as one normally would, but also other relevant features of the distribution.

The estimates from Eq. (3) are to be interpreted as the change of the relevant feature due to a *marginal* change in each covariate. This can be an issue when variables are binary as is the case for our interdependent variables of interest. A change from 0 to 1 would be too extreme, as it is closer to what Firpo and Pinto (2016) call an 'inequality treatment effect'. As such, these changes should be interpreted in marginal terms, for example, where the unemployment rate changes by one percentage point, rather than an average treatment effect where the independent variable goes from 0 to 1. This distinction is particularly relevant for summary measures such as the Gini, and we will discuss it when interpreting the results of that particular RIF regression.

Our parameters of interest are represented by $\delta_k^{\nu_y}$ in Eq. (3). They capture the change in a specific feature k months from having lost a job, where k is negative before losing the job and positive after losing it. These parameters are measured in CPI-adjusted Chilean pesos, but for the purposes of our work we standardise them by dividing them by the average wage at the beginning of our period of study. As such, we will report the wage loss as a percentage of the average wage.[17]

Moreover, we can use this vector of estimates to identify the cumulative wage loss over time, which we define as:

$$\sum_{k\geq 0}\left(\widehat{\delta}_k^{\nu_y}\right) \tag{4}$$

In other words, we define the cumulative wage loss as the sum of all monthly wage changes (whether positive or negative) starting from the moment of separation ($k \geq 0$) until the end of our observation period of 36 months. Just like the estimate itself, we present the cumulative loss as a percentage over average wages to simplify its interpretation.

5. Results and findings

Here we present our main findings based on the 12-month sample. The full set of regressions are reported in Tables A1 and A2 in Appendix A, while we present our findings as Figures here to depict better the dynamic aspect of our analysis. Across all Figures we will focus on the δ_k parameters in Eq. (3). That is, the difference in earnings between those $t-k$ periods away from losing their jobs at the mean as well as percentiles 10 to 95. We look at workers 12 months before losing their jobs and we follow their earnings trajectories for the next 36 months (Appendix A includes the equivalent figures for the 36-month sample). Before the job separation, these figures represent 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.

5.1. The average impact of a job loss

Fig. 3 shows the average earnings trajectories. Earnings are reported as the share of January 2010 wages, where our sample begins – roughly equivalent to 800,000 CLP or 1000 USD at the time. Overall, we see that earnings for those about to lose their job (i.e., before zero in the x-axis) are slightly higher but somewhat similar to those who do not lose their jobs. We see a sharp decline at $t = 0$, the last month of employment, this is because workers often terminate their jobs before the end of month when the database reports earnings. Workers are therefore only receiving a wage proportional to the days worked during their last month of employment. The wage loss 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 where employers cannot change the conditions of employment as easily as in the US.[18]

The fact that wages are slightly higher for separators is also found by Amarante et al. (2014) for Uruguay, but not by Jacobson et al. (1993) for the United States. One hypothesis that could explain this finding is that this could be a feature of less developed labour markets, where employers may seek to replace higher earning workers with cheaper ones. At termination, we see a fall of average wages of just over 40 %. While the wage gap does diminish it does not fully return to pre-termination levels within the observation period, not even to zero, resulting in separators having lower average earnings even three years after separation. This trend already gives us an idea of the long-term consequences of job displacement on inequality, at least when contrasting separators with non-separators.

In the context of the Chilean labour market, the relatively smaller economic impact of earnings losses following displacement may be partly explained by the combination of limited social protection policies and high levels of sectoral and occupational mobility. Given the less generous unemployment insurance system in Chile (Sehnbruch et al., 2019), displaced workers may be incentivized to re-enter the labour force to avoid prolonged periods of unemployment, often accepting jobs that may not match their previous earnings but still provide some income. This dynamic is further reinforced by the high degree of mobility across sectors, with workers frequently

[17] Consistent with the standard OLS estimation, RIF regressions using two-way fixed effects do not alleviate the potential bias in the presence of a time-varying treatment. Future research into the RIF framework should consider recent developments in the Differences-in-Differences literature (for a discussion of the OLS case, and therefore for the RIF regression under the mean, see, inter alia, de Chaisemartin & D'Haultfœuille, 2020; Goodman-Bacon, 2021; de Chaisemartin et al., 2024).

[18] In contrast to the US, formal employment relationships in Chile require formal written contracts, which specify the employment conditions associated with a job. Employers cannot easily change these conditions without amending these contracts. However, the decrease at $t = 0$ can be explained by jobs terminated before the end of the month, thus receiving a wage proportional to the days they worked that month.

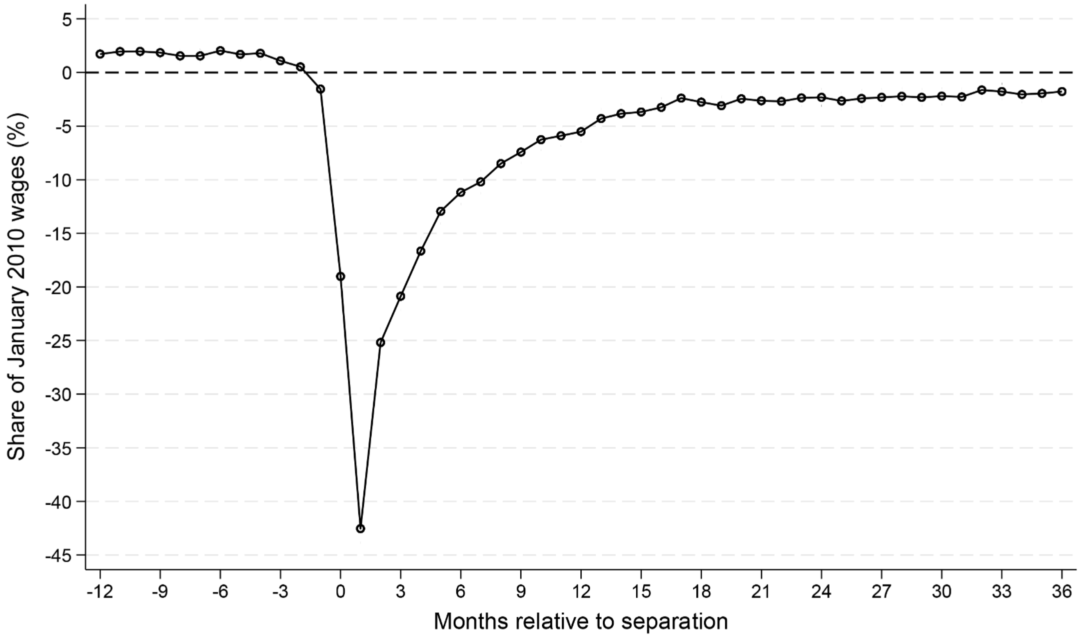

Fig. 3. Average earning losses for re-employed workers.
Source: Recentred Influence Function (RIF) regression at the mean of the wage distribution. Authors' calculations based on a random sample from UISA administrative data (3 % of the total). Job durations of 12 months or more. 95 % confidence interval reported.

moving from industries such as manufacturing to services (Aldunate et al., 2019). While these new positions may offer lower wages, the capacity for rapid re-employment helps to mitigate the long-term economic consequences observed in other labour markets with more rigid structures or stronger social safety nets.

5.2. *The impact of job losses across the wage distribution*

Fig. 4 shows an equivalent pattern to that of Fig. 3, but instead of showing the average effect it shows the evolution of earnings at three points in the earnings distribution: the median and the extremes of the distribution, represented by the 10th and 90th percentile. The difference between the three can give us an idea of whether job losses reinforce or diminish existing inequalities, and what the dynamics are behind the change in overall earnings inequality.

Looking at the median we see a very similar trend to that of the average, albeit slightly attenuated. The pre-termination trend shows no difference between separators and non-separators, and the drop in earnings after separations is just under 35 %, less than the average effect. The recovery trend is quite similar, on the other hand, never fully recovering but achieving small differences after the 18 month mark. The fact that the median impact is below the average suggests that there are larger losses somewhere in the upper half of the distribution, something we come back to below.

Meanwhile, the bottom 10 % of the distribution suffer significant losses at separation, equivalent to 53 % of the January 2010 wage. As with the median, the wage gap between separators and non-separators diminishes considerably at around 18 months but throughout the recovery that gap remains below the median, catching up at the two year mark. The top 10 % shows a job loss effect larger than the median but smaller than for the bottom of the distribution, at around 47 %. The recovery is also similar to that of the two other points, albeit much noisier. This potentially suggests a quicker recovery period as differences between separators and non-separators become non-statistically significant at the one year mark. These three points suggest somewhat similar transitions at these three points of the distribution, similar as well to the average transition. Differences lie in the immediate impact of job displacement, painting a picture of growing earnings inequality and more importantly, of large differences in wage accumulation over time.

To get a better idea of the complete distribution of earnings, we complement our discussion using Fig. 5, which changes the x-axis to account for percentiles in the distribution rather than months. Each of the lines represent a point in time rather than a point in the distribution. In other words, relative to Fig. 4, Fig. 5 switches the x-axis and the categories presented in the legend. It reports one specific coefficient, say the effect of wages after one month of unemployment (i.e., when $K = 1$), at different points of the wage distribution. We report the distribution of wage losses at four points in time: the first month, three months, a year, and two years after separation. Fig. 5 also reports the average effect at each point in time as a dashed horizontal line of the same colour.

Fig. 5 shows that most differences happen at the extremes. Right after separation the bottom 10 % suffers very large losses, equivalent to 53 % of January 2010 wages, decreasing to almost 27 % by month three, 5 % after a year and almost disappearing after three years. On the other hand, the top 5 % suffers only minimal losses at separation and over subsequent months, while improving after three years. Percentiles 20 to 70 show very similar impacts, with below-average effects that fall but do not fully disappear after three years. Those at the top 20 % but below the top 5 % suffer larger-than-average losses but then almost catch up with earnings levels.

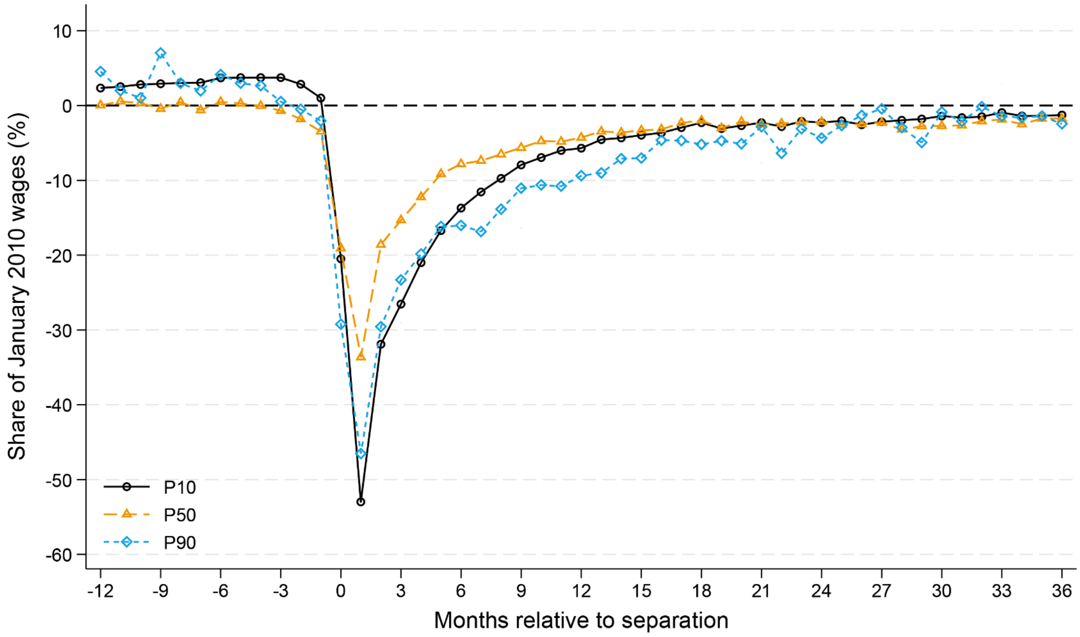

Fig. 4. Earning losses for re-employed workers (P10, P50, P90).
Source: Recentered Influence Function (RIF) regression at percentiles 10, 50 and 90 of the wage distribution. Authors' calculations based on a random sample from UISA administrative data (3 % of the total). Job durations of 12 months or more. 95 % confidence interval reported.

Within three years, however, most differences across the distribution disappear, except for those at the very top of the wage distribution who experience higher wages than before separation.

Overall, Fig. 5 illustrates significant earning inequalities at the extremes of the distribution. While workers at the bottom lose a substantial share of their wages, those at the very top see very little change in their wage trajectory. Similarly, low-income workers take longer to find a new job, whereas those at the very top are quick to transition and move to tend to move to better paying positions. The results are consistent with the theory of matching, which explains the positive and negative changes in wages after displacement (Carrington and Fallick, 2017). This is because some displaced workers have to accept a lower quality job, while others find better jobs

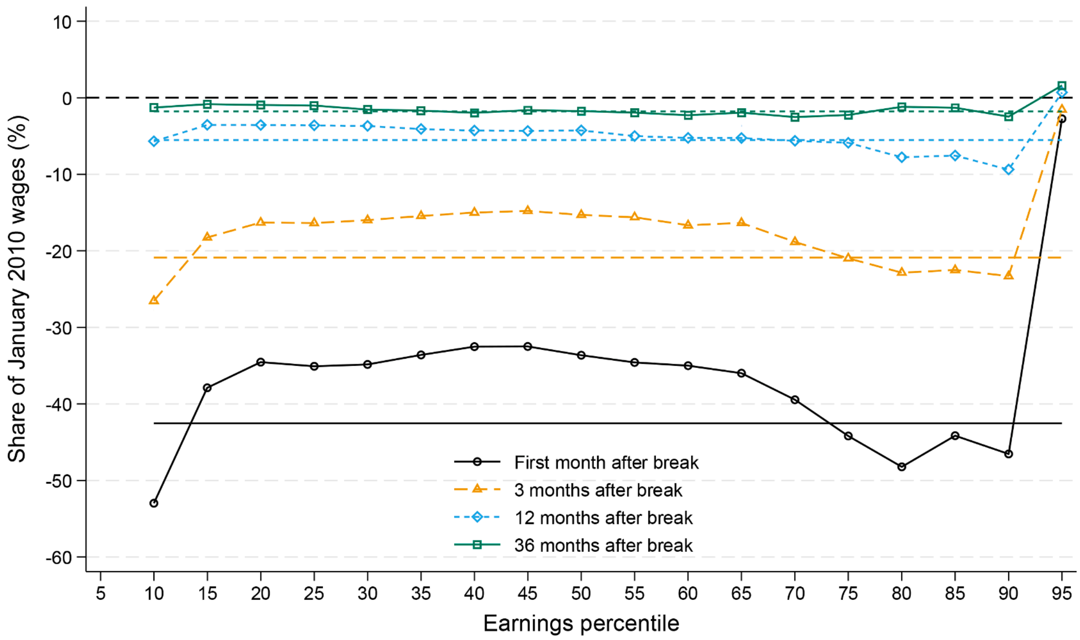

Fig. 5. Distribution of the effect of job loss on earnings at different months after separation.
Source: Recentred Influence Function (RIF) regression across the wage distribution at one, three and twelve months after termination. Authors' calculations based on a random sample from UISA administrative data (3 % of the total). Job durations of 12 months or more. 95 % confidence interval reported.

than they had before and receive a higher salary. Our results show that these two types of workers are at the extremes of the labour income distribution. Our findings tell the story of two very different labour markets – even within the limited sample of stable formal jobs – one of workers with low wages and long periods of unemployment who remain in similar jobs (in terms of their wages) and another of high earners with an incremental trajectory over time with few to no unemployment gaps.

5.3. The cumulative impact of a job losses on the wage distribution

As previously mentioned, a job loss and its subsequent recovery results in a period of lower wages and ultimately lowers the saving capacity of households. This wage loss is defined in Eq. (4) and represents the counterfactual sum of wages that workers have not received as a result of their job loss. Lower savings in turn impact a household's private wealth and their capacity to buffer economic shocks. A household that does not have an adequate buffer (wealth) against major economic shocks is aware of its economic vulnerability, which generates stress and anxiety among its members (Prieto, 2022). Following Eq. (4), we can construct the cumulative wage loss as the sum of all monthly changes in wages, starting from the job separation and up to 36 months, as shown in Fig. 6.

Summing up the wage loss over the whole period as shown in Eq. (4) we find that, on average, the cumulative wage loss is equivalent to 2.4 wages from January 2010, our reference wage throughout this paper. This is shown by the (red) dashed line in Fig. 6 and means that over the period between the job loss and finding another job the average worker stops earning the equivalent of more than two months of wages. This is a considerable amount considering, for example, that the social component of the Chilean unemployment insurance only covers up to 5 monthly payments with replacement rates that are quite low by international standards (Sehnbruch et al., 2019). The cumulative loss of wages is thus close to the average for most of the earnings distribution, which is consistent with the findings presented above. The clear exception happens at the tails. The cumulative wage loss at the bottom of the distribution is slightly more than the average while we find a cumulative gain at the top of the wage distribution equal to almost one wage.

Over a period of three years after a job separation, we find that most workers accumulate a loss of around 2 average wages. This is a substantial gap if we consider that the literature considers someone to be vulnerable if the household does not have enough savings to sustain itself for three months (Balestra and Tonkin, 2018). This is even more extreme at the bottom of the distribution, where saving gaps are even larger. Our findings therefore show how job losses not only impact wage inequality but can also impact savings and wealth inequalities. This result is consistent with the recent work of Barnette (2023), who finds that in the US, involuntary job displacement leads to a decline in relative wealth (18 %) that shows no signs of recovery even 12 years after the event.

5.4. The aggregate impact of job losses on the Gini coefficient

Lastly, we look at the impact of job loss using a summary measure of the entire wage distribution – the Gini coefficient. Fig. 7 presents the change in the Gini due to job displacement, showing that if all workers were to lose their employment at the same time, the Gini coefficient could increase by just over 20 points. This increase is quickly reduced to 5 points within 6 approximately months and

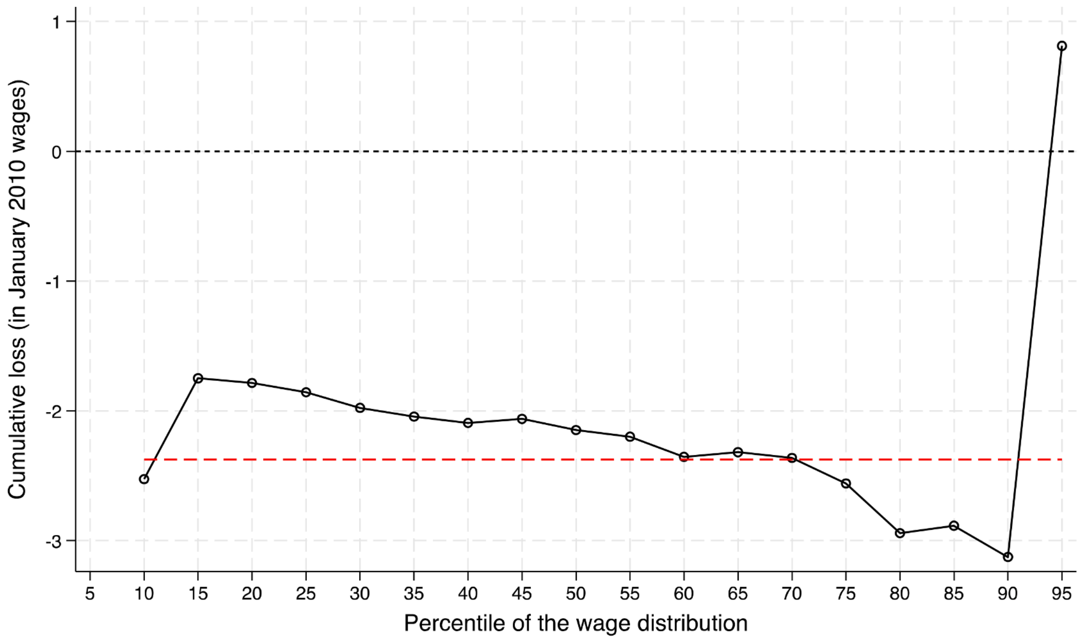

Fig. 6. Cumulative wage loss across the wage distribution.
Source: Estimation based on Eq. (4) using the results from Table A1 at each percentile of the wage distribution. All sums are divided by the average wage of January 2010 for reference. The black dashed line is set at zero loss while the red short-dashed line is the average cumulative loss (−2.37 wages). Negative values represent net wage losses while positive values represent net gains. Authors' calculations based on a random sample from UISA administrative data (3 % of the total). Job durations of 12 months or more.

subsequently to 2 points a year. Thus, the effect on the Gini coefficient remains positive well beyond our observation window of 36 months, which is also consistent with the findings presented above. The aggregate effect on the Gini index is such that job losses and subsequent re-employment in Chile result in an inequality-increasing pattern that persists over time.

To understand better the change in the Gini coefficient resulting from formal job losses – and to interpret correctly the coefficients from the RIF regression – we need to think of marginal changes in the share of employed workers. For example, between January 2011 – the highest unemployment rate following the Great Recession – and October 2013 – the lowest unemployment rate during the period we study –the 12-month average of the unemployment rate in Chile went from 8.1 % to 6.1 %. If we take this change of two percentage points and look at the immediate impact of job loss (i.e., the coefficient for $K = 1$) for our 12-month sample, this fall in unemployment would be equivalent to a reduction of the Gini coefficient of 0.41 points.

Similarly, looking at the impact of the COVID-19 recession, the unemployment rate went from 7 % in January 2018 to 11.2 % in March 2021. Given our estimates, this increase in the unemployment rate would translate to an increase of the Gini of 0.85 points. While on their own these values might seem small, it is important to note that the Gini coefficient tends to move quite slowly – after 2009 the Gini for Chile has not fallen by more than 1.4 points between any two consecutive survey years. These estimates show that the overall effect of job displacement on earnings inequality can be quite substantial, and while it quickly diminishes over time it never fully disappears, thus reinforcing existing inequalities.

5.5. *Heterogeneous findings and robustness checks*

We conclude this section by discussing potential heterogeneities in our findings as well as the relevant robustness. Although we have shown how important it is to study the impact of job losses on the aggregate earnings distribution, it is also relevant to explore differences across specific groups of workers, which can shed further light on how they can be impacted very differently by job losses. To avoid reducing our sample size, we focus on two groups that aggregate a large number of workers: gender and industrial sector. For the latter, we study the three sectors that employ proportionately the largest shares of workers: retail, manufacturing and construction, and we only focus on those workers whose job before termination was in that sector.

Figures C1 and C2 in Appendix C present these findings for average wages. We find that the average wage loss for women is slightly lower at around 33 %, versus slightly over 40 % for men. The wage recovery time is also faster women during the first 3 o 4 four months following job loss, but this converges with men during later periods. In terms of industry, we find that all three sectors experience very similar average wage losses at separation, at around 40 % of average wages. However, the recovery rate in construction is considerable quicker, returning to pre-termination wages within a year.

Appendices B and D explore the robustness of our main findings in terms of some of the methodological choices we made for this paper. These include the minimum duration of jobs, our definition of voluntary transitions, and the inclusion of fixed term contracts our sample. As the latter are expected to terminate, this could potentially alter our results and focus on involuntary pattens. However, the results derived from these alternative specifications are consistent with our main conclusions, both regarding the extent of the wage loss at termination and recovery times.

Appendix B replicates Figs. 5, 6, and 7 for a sample of jobs that lasted at least three years rather than the 12 months we defined in

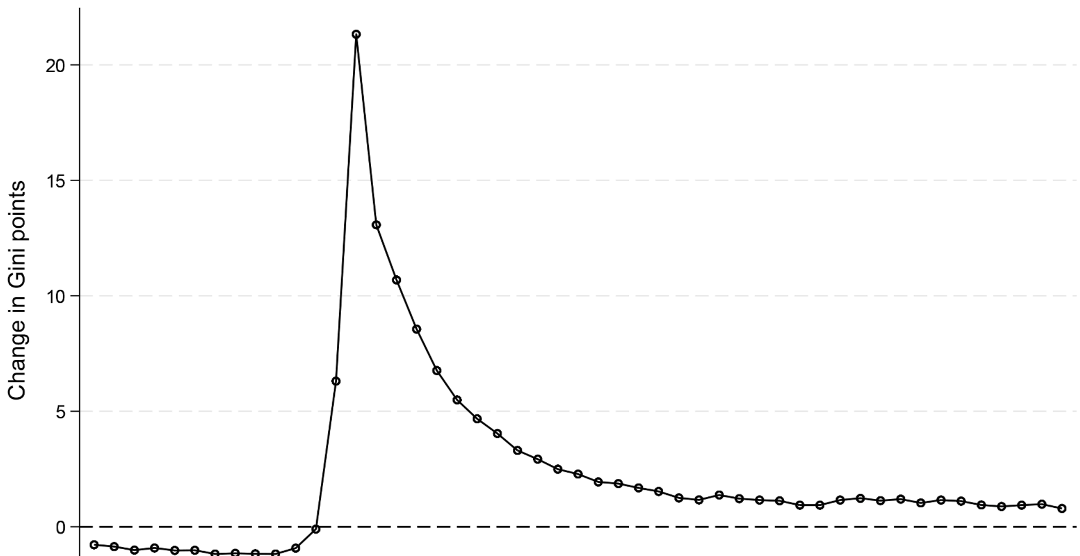

Fig. 7. Change in the Gini due to job loss and the and subsequent re-employment.
Source: Recentered Influence Function (RIF) regression over the Gini index of the wage distribution. Authors' calculations based on a random sample from UISA administrative data (3 % of the total). Job durations of 12 months or more. 95 % confidence interval reported.

the article. The reason for this robustness check is that one could argue that workers with longer tenures, who generally have open-ended contracts, constitute a better sample as they are less likely to expect a job loss, participate more frequently in the formal labour market, and may therefore be more affected by it. In the paper, we do not use this sub-sample as its size is reduced.

The figures in Appendix B, however, show that these results are similar to our benchmark estimates, albeit noisier at the top of the distribution, as shown by the confidence intervals. The average wage loss is slightly higher than 40 % and wages do not reach pre-termination levels within the three-year window of study. Distributional results are consistent, however, with a smaller wage loss at the bottom of the distribution and the impact on the Gini is equivalent to that shown in Fig. 7. Overall, these findings are largely consistent with our main estimates except at the bottom of the distribution, which changes as low wage jobs are also more like to have shorter tenures.

Appendix D in the article explores our sampling decisions, specifically the importance of excluding voluntary transitions by proposing alternative ways to identify them and the exclusion of fixed-term workers. Together with our benchmark estimates (excluding workers with no non-contribution period who also experienced a wage increase of 25 % or more), we now include estimates for four alternative samples: the first is the full sample, with no restrictions regarding non-contribution periods or wage changes. Second, we exclude all workers with no non-contribution period. That is, those who immediately transitioned from one job to the next. The last two alternative samples present estimates under samples with no non-contribution period where workers experienced (i) an increase or (ii) a decrease in their wage.

Our findings show that results are robust to the choice of sample. As Figures D1 and D2 show, our benchmark estimates, shown as alternative 2 in the Figures, are equivalent to those relying on the full sample (alternative 1) and quite close to those restricting the sample to positive changes in wages (alternative 5). Moreover, we show that our main findings are indeed lower bound estimates relative to the samples that include workers who experienced a reduction in their wage while excluding immediate job transitions (alternatives 3 and 4).

Lastly, Appendix F explores an alternative specification based on a full set of time fixed effects. Figure F2 focuses on the same time period as in our main estimates (i.e., 12 months before separation and 36 months after). Overall, results are ordinally equivalent. The average impact is higher than the median, and the loss at the bottom is larger than at the top. However, the size of the effects is slightly larger, with an average wage loss of 53 % of January 2010 wages and a median of 40 %. Results are also consistent in that pre-termination recovery is never fully achieved, although Figure F1 shows that the median effect reaches zero between years 5 and 6.

6. Conclusions

This paper shows that wage-earners in Chile suffer a significant loss of earnings in the immediate aftermath of dismissal of around 42 % on average. While this effect diminishes over time, it does not fully disappear even 3 years after a job loss. Moreover, our results show that workers at the top of the earnings distribution suffer little to no earnings losses and then increase their earnings over time. By contrast, workers at the bottom of the earnings distribution suffer larger losses as well as longer earnings recovery periods.

In addition, these effects can be heterogeneous across different groups within the labour force, such as men and women or workers in particular economic sectors. These groups exhibit differences in either the size of their wage loss or their recovery period. This potentially reinforces existing inequalities.

These effects are consistent with our finding that job losses increase inequality, which are shown by our analysis of the impact of displacement on the Gini coefficient. Overall, inequality increases right after job loss, with an impact that diminishes over time but never fully disappears, resulting in higher overall inequality even three years after the job loss.

Furthermore, job displacement has an important impact on the overall income of households and their capacity to save and accumulate wealth, as well as their ability to survive future economic shocks. Again, lower income workers are more impacted by this effect than higher income ones.

Our findings have important implications for labour market policies, which is especially relevant given the impact that new technologies could have in terms of generating higher levels of job displacement and potentially increasing levels of earning inequality (Autor, Mindell, and Reynolds 2023; Frey 2019; Susskind 2020; Pissarides 2022).

These results are also substantially different from the effect of job losses found in advanced economies such as Finland or the US, both in terms of the lost earnings and recovery times. Labour markets such as a the Chilean one, where a high proportion of workers have short-term contracts and where even the formal sector is characterised by high levels of job rotation, are particularly vulnerable to the impact of technological change.

Our findings are therefore likely to be very relevant to other emerging economies, especially in Latin America, which find themselves in a similar situation. Our paper thus serves to highlight the importance of producing context-specific studies of the impact of job losses on inequality, which acknowledge institutional differences across countries.

A more general point illustrated by our work is how indispensable it is to look beyond summary measures of inequality to understand their drivers better. As with research on the measurement of inequality, we must look into the entire distribution of earnings to explore whether the inequality-increasing impact of job displacement relates to dynamics at the bottom, middle or top of the distribution. Our findings can indeed be summarised by looking at the Gini, but to inform policy responses, we need to investigate these dynamics further.

In fact, this research can help inform the design and implementation of equality-reducing labour policies, as they show where job losses most exacerbate existing inequalities. In emerging economies, where active labour market policies are often under-resourced and institutionally under-developed, more attention must focus on helping workers find new jobs. Equally, better systems for providing publicly funded vocational (re)training must be established. While internet based "labour exchanges" may work for more educated, higher earners, more vulnerable workers will require more targeted support.

Support can be provided in part through existing institutions such as the unemployment insurance system. At present, the Chilean system is extremely regressive as it protects higher income workers with stable jobs much more than lower income workers with short-term contracts (Sehnbruch et al., 2019 and 2022). This therefore exacerbates rather than attenuates the unequal effect of job losses on inequality and vulnerability.

Finally, it is equally important to highlight the significant advantage that Chile has when it comes to thinking about public policies. The fact that the government makes administrative data readily available, not only in the form of the unemployment insurance data used in this article, but also though its integrated register of administrative databases from other areas of public policy, makes it much easier to design inequality reducing policies.[19] Equally, these databases permit further research into the connections between unemployment and other areas of social policy.

For example, the mechanisms through which job separations increase income inequality and decrease the educational outcomes of the children of workers should be examined as this would ultimately increase inequality in the next generation. Similarly, another relevant line of research is the role of social protection schemes other than unemployment insurance (such as family income support) and of informal work in the perpetuation of inequalities in the labour market. There is evidence that workers who are dismissed from formal employment may be at risk of moving into lower-income informal jobs or self-employment (Prieto et al., 2024; Sehnbruch et al., 2025). It is likely that these dynamics are not supported by existing social and labour policies, which also exacerbates inequalities. In short, more research should focus on the connections between employment, inequality, education and social protection mechanisms. Fortunately, all these subjects can be analysed with Chile's extensive administrate data infrastructure.

CRediT authorship contribution statement

Rafael Carranza: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Joaquín Prieto:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Kirsten Sehnbruch:** Writing – review & editing, Writing – original draft, Investigation, Funding acquisition, Conceptualization.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.eap.2025.02.021.

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