Voluntary Unemployment*

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Abstract

Using micro-data, we show that $15\% - 35\%$ of employment-to-unemployment transitions are done *voluntarily*. In many countries, the voluntarily unemployed are excluded from unemployment insurance. We analyze the implications of such policies. First, we estimate that the voluntarily unemployed do not experience a persistent drop in subsequent earnings, contrasting the earnings scars from involuntary unemployment. Second, we show that a structural model in which heterogeneous workers and firms search for efficient matches can account for these patterns. Excluding voluntarily unemployed from unemployment insurance reduces search incentives (for both workers and firms) and can substantially disrupt allocative efficiency at the aggregate level.

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1 Introduction

In the U.S., workers who leave employment *voluntarily* are ineligible for unemployment benefits. While similar policies are widespread also across other countries, relatively little is known about the distinction between the voluntarily and involuntarily unemployed.[1] In this paper, we study – both empirically and theoretically – individuals who enter unemployment voluntarily and their subsequent labor market outcomes. We do so in two steps.

First, using micro-data we show that voluntary unemployment is prevalent, especially among young workers. In particular, between 15% and 35% of moves from employment to unemployment are voluntary. However, earnings losses from such voluntary unemployment are shallower and less long-lived than those from involuntary job loss which have been shown to be substantial (see e.g. Davis et al. (2011)).

Second, we build a stylized structural labor market model and show that these patterns are consistent with workers and firms searching for productive employment matches. Our results suggest that voluntary unemployment is closer to job-to-job transitions then to involuntary unemployment spells. Therefore, decreasing the outside option of the voluntarily unemployed through lower unemployment insurance may hurt allocative efficiency at the aggregate level.

For our empirical analysis, we use data from Australia and the U.S. – two economies with datasets allowing us to identify voluntarily unemployed individuals. In particular, in Australia we make use of the Longitudinal Labour Force Survey (LLFS) and the Household and Income Dynamics in Australia (HILDA). For the US labor market, we make use of the Survey of Income and Program Participation (SIPP). Importantly, all these datasets report labor market transitions *by reason* which we use to identify voluntary and involuntary employment to unemployment (E2U) transitions.

More concretely, we define a voluntary E2U transition as one in which a worker leaves employment because of one of the following two reasons (i) unsatisfactory work arrangements, pay or hours,

[1] According to Immervoll and Knotz (2018), 17 OECD countries have the same or higher stringency (4-5 on their scale out of a total of 5) when dealing with voluntarily unemployed as the U.S. labor market. That said, even more lenient labor market policies often put restrictions on unemployment insurance when it comes to voluntary departures from employment. For instance, Australia which is ranked to have a stringency of 2 in Immervoll and Knotz (2018) requires a waiting period of up to 8 weeks before voluntarily unemployed individuals are eligible for unemployment insurance.

(ii) to obtain a better job, work conditions or for wanting a change.[2] Involuntary transitions are then the complement group, i.e. all other E2U moves[3].

We begin by documenting several stylized facts about individuals who voluntarily transition from employment to unemployment. These facts broadly hold in both Australia and the U.S. First, on average voluntary E2U moves account for between 15 and 33 percent of all transitions between employment and unemployment. Second, voluntarily unemployed individuals tend to be younger, less educated and with lower incomes in their jobs prior to separation, but they exit unemployment faster (either because of re-employment or a transition out of the labor force).

We move to estimating earnings profiles of the (in)voluntarily unemployed in their subsequent labor market experiences. Specifically, controlling for individual and time-fixed effects, as well as age, education and gender, we estimate the earnings profiles of the (in)voluntarily unemployed. In both cases, the transition to unemployment comes with a substantial drop in earnings. However, while this drop persists for several years in the case of the involuntarily unemployed, that for voluntary separations recovers faster. In fact, when focusing on workers who find employment within two years after separation, those who separated voluntarily display similar earnings to those who remained employed.

As a final step in our analysis, we interpret our findings through the lens of a structural model of the labor market. In particular, we consider a search and matching framework along the lines of Mortensen and Pissarides (1994), but extend it for heterogeneity in workers' and firms' productivity – and complementarity between the two. In our model, mismatched employment relationships are those which end up endogenously separating. We interpret such endogenous separations as "voluntary" when a productive worker is (mis)matched with a relatively unproductive firm. The opposite situation is then classified as an involuntary separation from the point of view of the worker.

Calibrating the model to the Australian economy, we find that the model closely replicates

[2] In most of our analysis we also consider separately a third reasons: (iii) the end of a temporary or seasonal job. While many workers in temporary and seasonal jobs may wish to continue in them (making them involuntarily unemployed), they also likely understand the fixed end date of such jobs (making them voluntarily unemployed).

[3] We exlcude workers who exit employment due to "lifecycle" reasons, for instance starting a family or retirement. Howvever, these workers make up a relatively small proportion of those who enter unemployment as they often do not search for a job and are therefore NILF.

the empirical earnings profiles when voluntary separations reflect productive workers leaving unproductive firms for better search prospects. Therefore, our structural model suggests that voluntary unemployment is closer in nature to job-to-job transitions than to involuntary unemployment. While our framework is too stylized for a careful quantitative analysis of existing policies, it is nevertheless useful for a qualitative conclusions. Towards this end, we use our model to highlight the qualitative impact of excluding the voluntarily unemployed from unemployment insurance – a reality in the U.S. labor market. Such a policy has two opposing effects.

On the one hand, it leads to a drop in separations and a considerably lower unemployment rate. This is intuitive as workers have more incentive to hold on to their existing jobs. On the other hand, and for the same reasons, it lowers match quality as workers tend to stay in (even bad) jobs rather than searching from unemployment. More importantly, the increased mismatch lowers incentives of high-productivity firms to create jobs. This is because skilled workers are less available to fill such jobs. Our framework, therefore, suggests that excluding voluntarily unemployed from unemployment insurance has the potential to reduce allocative efficiency at the aggregate level.

Our paper is related to the existing literature on the wage scar of job loss Jacobson, LaLonde, and Sullivan (1993), Ruhm (1991), Davis et al. (2011), Lachowska, Mas, and Woodbury (2020), Borland (2020), and Bertheau et al. (2023). Without potentially exogenous reasons for job separation, our work does not estimate the causal effect of job loss on earnings but instead describes the earnings trajectories of individuals who exit work for different reasons. Flaaen, Shapiro, and Sorkin (2019) also consider reasons for job exit in the U.S. using SIPP data, and match it with a mass layoff exercise using US administrative data. They find that there is significant heterogeneity in the reason why individuals exit during a mass layoff – and this leads to heterogeneity in the relative wage scars individuals face. For this reason, our event study analysis is used to describe the earnings trajectories of varying types of workers based on their reason for exit, with the aim of using a structural model to explain why these varying earnings outcomes occur.

Few papers consider voluntary separations into unemployment distinctly from overall quits (Nagypal 2008; Simmons 2023; Ellieroth and Michaud 2024). We establish that they are a large share of movements into unemployment (the most intensive searchers of all those in non-employment). There are other models with assortative matching such as (Nagypál 2007;

Faberman and Kudlyak 2019), we propose an additional channel of voluntary unemployment.[4]

The remainder of the paper is structured as follows, in the next section we describe the relative labo market institutions in Australia and the U.S. and how they discriminate based on the reason for job exit. In Section 3 we describe the data used, define the concepts of voluntary and involuntary job loss, and outline stylised facts about individuals transitioning to unemployment for different reasons. Section 4 provides the method and results used to estimate the earnings trajectories of individuals who transition to unemployment. Section 5 uses these stylised facts about voluntary and involuntary unemployment to calibrate and validate a search and matching model with worker and firm heterogeneity. This model is then used to qualitatively assess the economic consequences of excluding voluntarily unemployed individuals from the benefit system. Finally, Section 6 concludes.

2 Labor market institutions in Australia and the U.S.

Before we describe our main data sources and lay out key definitions, we begin with a brief comparison of labor market institutions in Australia and the U.S. economy. As will become clear, compared to the U.S. (and the rest of the OECD countries), Australia has a relatively unique set employment protections, redundancy payments, and unemployment benefits.

Redundancy payments. In Australia, redundancy payments are mandated for firms with over 15 employees, providing scaling benefits based on tenure, rising to 16 weeks of pay after 10 years of service. Many workers are covered by Enterprise Bargaining Agreements (EBAs), which often provide more generous redundancy terms. This is due to the Better Off Overall Test (BOOT), which requires that EBAs offer benefits exceeding the legislated minimum. In contrast, the United States lacks a federal mandate for redundancy payments, creating a stark difference in job security and post-separation income support between the two countries.

Employment protection. Australian law generally requires employers to justify terminations, whereas in the United States, employment can typically be terminated “at-will”, with fewer

[4] In contrast with some recent literature that seeks to identify latent types and heterogenity in wage dynamics within the stock of unemployed (Athey et al. 2023; Gregory, Menzio, and Wiczer 2024), we find that the reason given for a separation is indicative of ex-post wage outcomes. Which suggests that there are distinct observable types of workers in unemployment as well.

constraints apart from protections against discriminatory dismissal. This regulatory divergence has likely influenced the prevalence of casual contracts in Australia, with nearly a quarter of employees on flexible contracts that simplify termination processes.

Notice periods for job separations also highlight institutional differences. Australian employers must adhere to a tenure-based notice system for dismissals, while employees are expected to provide reasonable notice based on their tenure. By contrast, the United States imposes minimal restrictions on notice for both employers and employees, reflecting a more flexible but less secure labor market.

Unemployment benefits. The regulatory frameworks described above are complemented by differing unemployment benefit systems. Australia's income assistance policies provide only "unemployment assistance". This refers to a fixed payment that does not change with prior earnings or earnings histories.

For an average worker, the income replacement rate at unemployment is generally lower than in other OECD countries including the United States (for short-term unemployment). For low-income individuals, however, replacement rates can be higher, reflecting a more redistributive approach. Notably, Australia's eligibility requirements allow for income support within a few weeks for individuals who voluntarily separate from employment.[5]

In the United States, state-based programs reflect only an "unemployment insurance" payment, the level of which depends on prior earnings and earning histories - although the generosity can vary by state. Eligibility for unemployment benefits varies by state and typically requires that separations are "for good cause". Work testing and obligations are similarily determined at the state level, and vary significantly across the United States.

Together, these institutional differences create distinct labor market environments in Australia and the United States, affecting workers' separation choices and the incentives for voluntary and involuntary transitions into unemployment.

[5] To assist with improving work incentives Australia imposes mutual obligation requirements that vary with the individuals time in receipt of the benefit. Uniquely, significant elements of the employment support system privately managed, adding a competitive element to service provision.

3 (In)voluntary Unemployment in the Data

In this section, we describe our primary data sources, how we use them to measure (in)voluntary movements into unemployment and how important the latter are for determining overall unemployment. In doing so, we will draw upon data from two countries: Australia and the United States of America. The choice of these two countries is data-driven as they both offer detailed statistics on the *reasons* behind flows from employment into unemployment.

The available Australian data offers a slightly more comprehensive picture with panel information running for a longer period of time, compared to the US. Therefore, while we report empirical results for both countries, our model framework is geared towards the Australian economy.

3.1 Data

We now turn to describing our data sources and explaining definitions of key variables. More details on the data is presented in Appendix A.

For Australia, we use two datasets. First, we make use of the Longitudinal Labour Force Survey (LLFS),conducted by the Australian Bureau of Statistics (ABS), which we use as a primary source for information about labor market flows. Second, we supplement the LLFS with the Household and Income Dynamics in Australia (HILDA) survey which offers additional information on job search intensity and labor market participation, run by the Melbourne Institute.

For analyzing the US labor market, we make use of the Survey of Income and Program Participation (SIPP). The advantage of HILDA relative to the SIPP and LLFS is the longer panel dimension of the data, which allows us to consider the longer term consequences of transitions into types of unemployment.

Australia: Longitudinal Labour Force Survey. The LLFS is an 8 month rotating panel which collects information on a monthly basis about the labor market status of about 61 thousand individuals. For the purposes of our analysis we focus on the sample between 2011 and 2019.[6] The short rolling panel design of the LLFS is most similar in form to the US Current

[6]The LLFS dates back to 1983, but many of the survey questions central to our analysis have changed over time or in their frequency of collection. Starting in 2001 also aligns with information from HILDA which is

Population Survey (CPS), and is used for the monthly labor market statistics in Australia.

In addition to individuals' labor market status – which allows us to directly construct labor market transition rates – the LLFS also obtains information on the *reasons* for leaving the last job. This information – collected at a quarterly frequency – plays a key role in our analysis of involuntary and voluntary separations. Below, we describe this part of the LLFS in more detail and we explicitly state the definitions of (in)voluntary separations. The LLFS also contains a range of other individual and job characteristics such as worker age, education, income, years of tenure, hours worked, industry but also the *subjective* probabilities of losing and finding jobs.

Australia: Household and Income Dynamics. In contrast to the high frequency of the LLFS, the HILDA survey is conducted annually. That said, the survey includes a labor force status calendar which records spells in each labor market state at a monthly frequency. Therefore, despite being collected only annually, it is possible to construct monthly transition rates. We also observe the reason for separation at an annual frequency and can restrict the sample to those who only leave or lose their jobs once during the year.[7] In addition, a key advantage of HILDA is that it is a longitudinal survey allowing us to track individuals' labor market outcomes over their life-cycles.

HILDA is available from 2001 and includes a wide variety of individual information. Aside from basic demographic information, these include wage income, reasons for entry into unemployment as well as additional details about job search intensity and labor market participation.[8] Further details about HILDA can be found in Appendix A.

United States: Survey of Income and Program Participation. The SIPP is a long-running rotating panel survey. We make use of the 1996 to 2008 (our sample runs between March 1996 and December 2013) panels as prior to 1996 and post-2013 the survey was redesigned,

available from that year onwards.

[7]We look at the effects of time aggregation bias on gross flows in Appendix **??**. We find that this makes a fairly marginal difference to the overall rate of unemployment. We use the LLFS data instead of HILDA as the HILDA sample becomes less representative of the overall Australian workforce over time. As a result aggregate job finding and separation rates begin to diverge wildly. There is less of a concern of time aggregation bias in the HILDA sample simply because the calendar is recorded at a relatively high frequency through each month.

[8]Reasons for entry into unemployment are collected only annually. Therefore, the information relates only to the most recent unemployment spell within a given year.

making it difficult to create consistent estimates of labor market flows outside of this period.[9] We construct aggregate labor market flows using the methods outlined in Simmons (2023), Fujita, Nekarda, and Ramey (2007), and Nagypal (2008).[10]

The major advantage of using the SIPP Data in addition to HILDA and LLFS is that we are able to directly estimate the monthly wage dynamics for the same sample as our gross flows. The trade-off however, is that we have much shorter observation windows as the longest panel is approximately 4 years. Instead we use this data to show that the difference in wage trajectories by reason of unemployment is apparent in even the short-term and to comment on the high prevalence of voluntary separations in the US data.

3.2 Labor Market Flows and (In-)voluntary Separations

Central to our analysis are flows between employment and unemployment. Appendix F.2 provides further information on flows into and out of non-participation. In what follows, we denote the stock of individuals in unemployment and employment in period t by U_t and E_t, respectively.

Flows between employment and unemployment. Let EU_t denote the number of individuals who in period t report being unemployed, but who reported being employed in period $t-1$. Conversely, we will use UE_t to denote the number of individuals who in period t report to be employed, but who had reported being unemployed in the previous period.

Using the above notation, we define the period t "separation" (employment-to-unemployment or "EU") rate, s_t, and "job finding" (unemployment-to-employment or "UE") rate, f_t as

$$s_t = \frac{EU_t}{E_{t-1}}, \quad f_t = \frac{UE_t}{U_{t-1}}. \tag{1}$$

Employment separations by reason. As described above, both the LLFS and SIPP contain information on the (self-reported) reason behind employment separations. We use this

[9]The SIPP provides more detailed reasons for separation than does the Current Population Survey and does so without reference to the destination labor market state. We are also able to compare the relative size of these flows to Job-to-Job transitions because we are able to track transitions between employers accurately

[10]As in the studies mentioned above, we impute the gross flows for the missing months between waves. The method is outlined in Appendix **??**. In the results presented in this paper we do not currently impute values in the Australian data - as all the months are consecutive for the survey, and as a result we would only be imputing observations where the individual selected into non-response.

information to define measures of voluntary and involuntary separation rates (described below) as:

$$s_t^v = \frac{EU_t^v}{E_{t-1}}, \quad s_t^i = \frac{EU_t^i}{E_{t-1}}, \tag{2}$$

where the superscripts v and i indicate voluntary and involuntary transitions, respectively.

It will also prove useful to define the share of voluntary separations, υ^u, as:

$$\upsilon_t = \frac{EU_t^v}{EU_t}. \tag{3}$$

In our definitions above job-to-job transitions and transitions outside the labor force are explicitly excluded from voluntary separations. This make our flow the subset of labor market quits that transition into unemployment.

Measuring separations by reason. Table 1 lists the reasons individuals can provide for leaving employment voluntarily. While the reasons reported in the LLFS and SIPP differ slightly, we broadly classify voluntary separations as those where an individual has reported one of the following as a reason for leaving employment:

(i) Unsatisfactory work arrangements, pay or hours,

(ii) to obtain a better job, work conditions or wanting a change,

(iii) end of a temporary/seasonal job.[11]

We then work with a 'strict' definition of a voluntary separation– (i) and (ii) and a 'loose' definition– (i), (ii) and (iii). All other reasons are grouped together as involuntary separations.

Voluntary separations vs quits. A closely related concept to our voluntary separations are quits. For instance, the Job Openings and Labor Turnover Survey (JOLTS) of the Bureau of Labor Statistics (BLS) defines quits as the number of employees who left employment voluntarily.[12]

[11] this reflects that temporary and seasonal work typically has a defined end date, which allows workers to potentially engage in on-the-job search. It seems different in kind to a dismissal. Conversely the expiry of a contract may be used as an excuse to fire an unproductive worker. Because of this ambiguity we exclude these types of workers from our estimates of the wage scar.

[12] The definition of a voluntary separation is quite variable in the literature. This can refer to things as diverse as all movements out of the labor force to job-to-job transitions (both successful and failed). Part of our

The key distinction between quits and our measure of voluntary separations (into unemployment) is the *destination* of the worker flow. In particular, quits are defined only at the source of the transition and, therefore, include voluntary separations not only into unemployment, but also job-to-job transitions and moves out of the labor force. In fact, voluntary employment to employment flows dominate quit measures. In other words, voluntary separations in this paper are a subset of quits which correspond to voluntary moves between employment and unemployment.

Voluntary separations into unemployment are about 7.5% of voluntary "quits". Compared to employment to NILF (14.5%) and job to job transitions (78%). While voluntary "quits" into unemployment are small relative to the flow of job to job transitions, they are a quantitatively important component of flows into unemployment – we discuss these next.

3.3 Descriptive statistics

Before moving on to quantifying the importance of voluntary separations for unemployment, we first report a series of descriptive statistics. These pertain to the prevalence of voluntary separations into unemployment, the average characteristics of the voluntarily separated over the business cycle.

Prevalence. Table 1 reports the reasons for separations and the respective prevalence. As can be seen, in Australia, voluntary separations account for between 15 and 35 percent of all employment-to-unemployment transitions. The relatively wide range is driven by the importance of temporary and seasonal jobs in the Australian labor market. In contrast, these types of jobs are less common in the US and, therefore, voluntary moves into unemployment represent somewhere between 15 and 20 percent of all separations in the US economy. Note, however, that the fraction of "strictly" voluntary separations (those driven by unsatisfactory work conditions or a desire to obtain another job) is very similar in the two economies.

Next, in Australia, separations which can be classified as involuntary represent about another 30 percent of all employment-to-unemployment transitions. In the US, this fraction is about 23 percent. The remainder is accounted for either "other" reasons or by the fact that respondents

contribution therefore lies in exploring the value of defining voluntary unemployment as simply a movement into unemployment that is related to a desire to search for another job from non-employment

Table 1: Separations by reasons (% of all separations)

Reason	LLFS	SIPP
Voluntary separations		
"Strict" voluntary separations total (i+ii)	14.6	14.7
"Loose" voluntary separations total (i+ii+iii)	34.9	19.0
i) Unsatisfactory work arrangements, pay or hours	*12.7*	*4.3*
ii) To obtain a better job, work conditions or wanting change	*1.9*	*10.4*
iii) End of temporary/seasonal job	*20.3*	*4.3*
Involuntary separations		
Involuntary separations total (i+ii)	30.6	22.8
i) Laid off/discharged/fired/self-employed job loss	*2.5*	*17.3*
i) Retrenchment/redundancy/employer out of business	*28.1*	*5.5*
Other		
Other reasons	18.7	3.0
No reason given	15.8	55.1

Note: The table shows the share of total transitions between employment and unemployment by reason. The left panel reports Australian data ("LLFS"), while the right panel shows U.S. data ("SIPP"). All values are in percent.

do not report a reason for their move into unemployment.[13] The latter is especially prominent in the SIPP data, where more than half of all respondents do not provide a reason for their transition into unemployment. Therefore, the values presented in Table 1 should be viewed as lower bounds on the fractions of voluntary separations and, as such, are relatively conservative.

Characteristics of the voluntarily separated. Next, we study the individual characteristics of workers moving into unemployment for voluntary reasons, compared to those who report doing so involuntarily. Since raw, unconditional, averages may be driven by other underlying reasons, such as occupation or industry composition, we also report estimates from the following regression:

$$y_{i,t} = \alpha(1 - \mathbb{1}_{vol}\overline{y}_v) + \beta X_{i,t} + \epsilon_{i,t}, \tag{4}$$

[13]Other reasons for separation into unemployment include e.g. retirement, health or injury, school or training, holiday, family reasons, childcare.

Table 2: Characteristics of unemployed by reason of separation

	HILDA			SIPP		
Characteristic	Vol	Invol	$\bar{y}_v$	Vol	Invol	$\bar{y}_v$
Male (%)	44.3	61.2	13.3***	54.9	61.6	7.7**
Age (years)	34.2	36.0	-4.2**	33.0	38.0	13.8***
Part Time (%)	-	-	-	57.9	44.0	-1.6
Tenure (years)	3.3	4.1	4.4	2.1	2.2	-11.3
College (%)	34.0	37.6	-	10.0	9.7	–
High School (%)	27.4	23.2	2.2	61.1	63.4	2.3 ·
Less than High School (%)	38.6	39.2	-1.5	28.9	26.9	2.9*
Income (AUD/USD)	46.8	58.4	-9.4**	1,026	1,396	-3.3
Hours Worked	36.4	40.3	-8.2**	32.3	35.4	.1

Note: The table shows characteristics of voluntarily ("vol) and involuntarily ("invol") seperated individuals in the Australian data (HILDA) and in the US (SIPP). The values are presented as "raw" averages (columns "vol" and "invol"), but also conditionally on other observed variables as "$\overline{y}_v$" from regression (4).For non-binary variables we take the natural log in order to interpret the coefficients as a percent difference. The considered characteristics include the the fraction of "male" individuals, their "age", the proportion that are "part time" (SIPP only), their years of "tenure", the fractions of "college", "high school" and "less than high school" educated individuals, the "income" in thousands of AUD per year (HILDA) and USD per month (SIPP) and their usual weekly "hours worked". Stars indicate the usual levels of significance (three stars at 1%, two stars at 5% and one star at 10% of significance).

where $y_{i,t}$ are variables of interest, $\mathbb{1}_{vol}$ is an indicator function equal to 1 if an individual separates voluntarily and, therefore, $\overline{y}_v$ measures the difference in the given characteristic between involuntarily and voluntarily separated individuals. Note that this difference is estimated *conditionally* on additional explanatory variables in $X_{i,t}$ which include not only the individual's other personal characteristics, but also industry, occupation and time fixed effects. Table 2 shows the results of the estimation for both labor markets, together with the unconditional averages. The unconditional averages suggest that individuals who move into unemployment for voluntary reasons are younger, more often men, more likely in part-time jobs, with a high-school degree and earning less.

Many of these differences disappear when controlling for occupation, industry and time-fixed effects. However, in both samples, voluntary separators are more likely to be male, and younger.

Table 3: Unemployment rates: Steady state and counterfactual with involuntary separations only (in %)

	LLFS			SIPP		
	All	< 35	35+	All	< 35	35+
Steady state unemployment rate	3.5	4.4	1.9	5.0	6.5	4.2
Counterfactual unemployment rates (involuntary separations only)						
Temp jobs as involuntary separations						
Level	2.6	3.2	1.5	3.3	3.9	3.1
% of steady state	74.3	72.7	79.0	66.0	60.0	73.8
Temp jobs as voluntary separations						
Level	1.7	2.0	1.2	2.8	3.2	2.7
% of steady state	48.6	45.5	63.2	56.0	49.2	64.3

Note: The table reports the steady state unemployment rate (1st row), and using equation (6) counterfactual unemployment rates which ignore voluntary separations (with and without temporary/seasonal jobs, 2nd and 3rd rows). All unemployment rates are computed for the entire labor force ("all"), and for workers younger than 35 years ("<35") and the rest ("35+"). All values are in percent.

In addition, the Australian data suggests that voluntarily separated workers tend to have lower incomes and hours worked. In the US data, voluntarily separated workers seem to have somewhat lower levels of attained education on average.

Implications for Unemployment. In the following paragraphs, we investigate the role voluntary separations play for the unemployment rate on average. Towards this end, we make use of the "steady state" definition of the unemployment rate, given by:[14]

$$u_t^* = \frac{s_t}{s_t + f_t}. \tag{5}$$

[14]It has been shown that for fluid labor markets – like the U.S. economy – the steady state unemployment rate tracks the observed job-less rate quite well (Shimer 2005) after correcting for time aggregation. It tracks the Australian unemployment rate with more error as the labor market does not appear to adjust as quickly as in the U.S. However, it still serves as a reasonable proxy. See Appendix F for further discussion of steady state unemployment rates.

To understand how important voluntary separations are for unemployment on average, we compute a "counterfactual" unemployment rate in which we ignore voluntary separations:[15]

$$u_{c,t}^{*} = \frac{(1-\upsilon_t)s_t}{(1-\upsilon_t)s_t + f_t}. \tag{6}$$

Note that the above can be conducted for any definition of voluntary separations and for different age groups. We report various combinations of these counterfactuals in Table 3. Two patterns stand out.

First, voluntary separations are a quantitatively important determinant of unemployment. For example, in Australia they account for between 1/4 and 1/2 of all unemployment. In the US context, this range is between 1/3 and 1/2.

Second, voluntary separations are less important for older workers. Specifically, they account for between 1/5 and 1/3 of unemployment in Australia and between 1/4 and 1/3 in the US labor market. These findings conform well with our summary statistics above, which showed that voluntary separations are more prevalent among younger individuals.

4 (In)voluntary Separations and Subsequent Earnings

Having shown the importance of voluntary employment separations for unemployment on average, we now turn to their consequences for individual workers. In particular, in what follows we estimate the earnings outcomes of (in-)voluntary separations into unemployment relative to those who do not change their job.

4.1 Methodology and Data

We begin by describing our main methodology and how we measure the relevant information in our data sources.

Specification. Formally, we estimate the impact of (in-)voluntary separations on individual earnings using the following specification:

[15] For direct comparability, we scale up the counterfactual unemployment rates by the factor u/u^* representing the level difference between the actual and steady state unemployment rates.

$$y_{i,t} = \alpha_i + \gamma_t + \mathbf{X}_{it}^{'}\theta + \sum_{k=-4(\neq -1)}^{K=4} \mathbb{1}_{t=t^*+k} \left(\beta_k \mathbb{1}_i^{vol} + \delta_k \mathbb{1}_i^{invol}\right) + \epsilon_{i,t} \tag{7}$$

where $y_{i,t}$ is the disposable income of individual i in period t, t^* is the period of separation, α_i and γ_t are individual and time fixed effects and $X_{i,t}$ is a set of control variables. The later include age, age squared, education and gender. Our primary interest, however, lies in the coefficients β_k and δ_k which measure, the (conditional) impact of a voluntary and involuntary separations. Voluntary and involuntary separations are marked by an indicator functions $\mathbb{1}^{vol}$ and $\mathbb{1}^{invol}$, respectively. Aside from estimating the impact effects (β_0 and δ_0), we also estimate the effect in k periods before and after the separation, indicated by $\mathbb{1}_{t=t^*+k}$. Note that we are excluding $t^* - 1$ as our reference period. Alternative specifications are outlined in Appendix C.2.

This specification enables a direct comparison of the income penalties for voluntary and involuntary separations, and the estimated difference is then the difference between these penalties. The significance of the difference in penalties can be statistically tested using the covariance matrix of the estimated coefficients.

At this point, let us stress that our estimates do not attempt to correct for selection into job loss - which differs from the focus of the wage scarring literature (i.e. Bertheau et al. (2023), Schmieder, Wachter, and Heining (2023)). Therefore, our results should not be interpreted as causal estimates of the wage loss from job loss. Instead, they provide a description of the relative wage outcomes of those who separate into unemployment either for voluntary or involuntary reasons.

Reference groups. Since labor market transitions occur for different individuals at different times, we use a staggered treatment event study design. The reference group is defined as individuals that remain in the same job during the period. We use an event study approach, combined with an assumption of irreversible treatment, to prevent concerns about *forbidden comparisons* when estimating this treatment effect (Baker, Larcker, and Wang 2022). Such comparisons would occur if we used previously treated individuals as controls for currently treated individuals. In addition, we exclude job-to-job transitions and permanent flows into non-participation from the reference group. We also exclude individuals who left their job for sickness, pregnancy, or retirement.

Finally, we also present consider specifications that compare only workers who are reemployed within a 24 and 4 month period for HILDA and the SIPP, respectively. We do this to show that we are not merely picking up a difference in the likelihood of reemployment but to show there are also income differences between these groups upon reemployment and in future earnings conditional on employment.[16]

Data and restrictions. In what follows, we describe our preferred setting and we defer a suite of robustness checks to Appendix C. For Australia, we use the HILDA survey for our measure of disposable income, that is annual wage earnings as well as transfers and other asset income minus tax paid.

In our sample we drop individuals without employment income in the year prior to job loss. We focus on the pre-COVID period of 2001-2019 and estimate our specification using an unbalanced panel of individuals.[17]

For the US, we use information from the SIPP. We focus on gross disposable income, as the SIPP captures both labor and asset income as well as government transfers. Note, however, that the SIPP does not capture taxes.

Restrictions. In our estimation, we apply the following restrictions. First, we focus on prime-aged workers (aged 25-50 at treatment). Second, we focus on individuals who report employment in the prior year. Finally, we focus on "first time treated", i.e. individuals must not report zero earnings in years prior to separation. Note that these restrictions allow for individuals to move out of the labor force during their time out of work, but they do need to report unemployment at some stage.

Furthermore, the timing of unemployment is based on the financial year the job ended which generated the flow into this form of unemployment. A series of alternative specifications are provided in Appendix C.2, to show that the estimated difference between voluntary and

[16]The 4 month reemployment requirement in the SIPP data is notably restrictive. However, due to the very short observation window of the SIPP we believe it strikes the right balance between excluding the long-term unemployed but including enough workers to be able to comment on the wage differences

[17]Estimating an event study using an unbalanced panel implicitly imputes values for periods of non-response with the conditional mean of responding units. To check for bias due to this, we also estimate the same event studies using a balanced panel as described in Appendix C.2 - and find similar results to those described below.

involuntary is robust - but the level of the decline/gain for the unemployment types varies by specification.

4.2 Event Study Results

In what follows, we report results of our estimates of Equation 7. We do so by plotting the coefficients of interest, β_k and γ_k, which represent the path of earnings outcomes of voluntarily and involuntarily separated workers relative to the reference group of workers who remain in their jobs. In addition, we also depict directly the estimated difference in the earnings paths of voluntarily and involuntarily separated workers.

Baseline results. Figure 1 shows how earnings of voluntarily and involuntarily separated workers differ to those who have remained on the job (left panels) and the difference between the latter two (right panels). In addition, the top panels show the results for Australia, while the bottom panels depict US estimates.

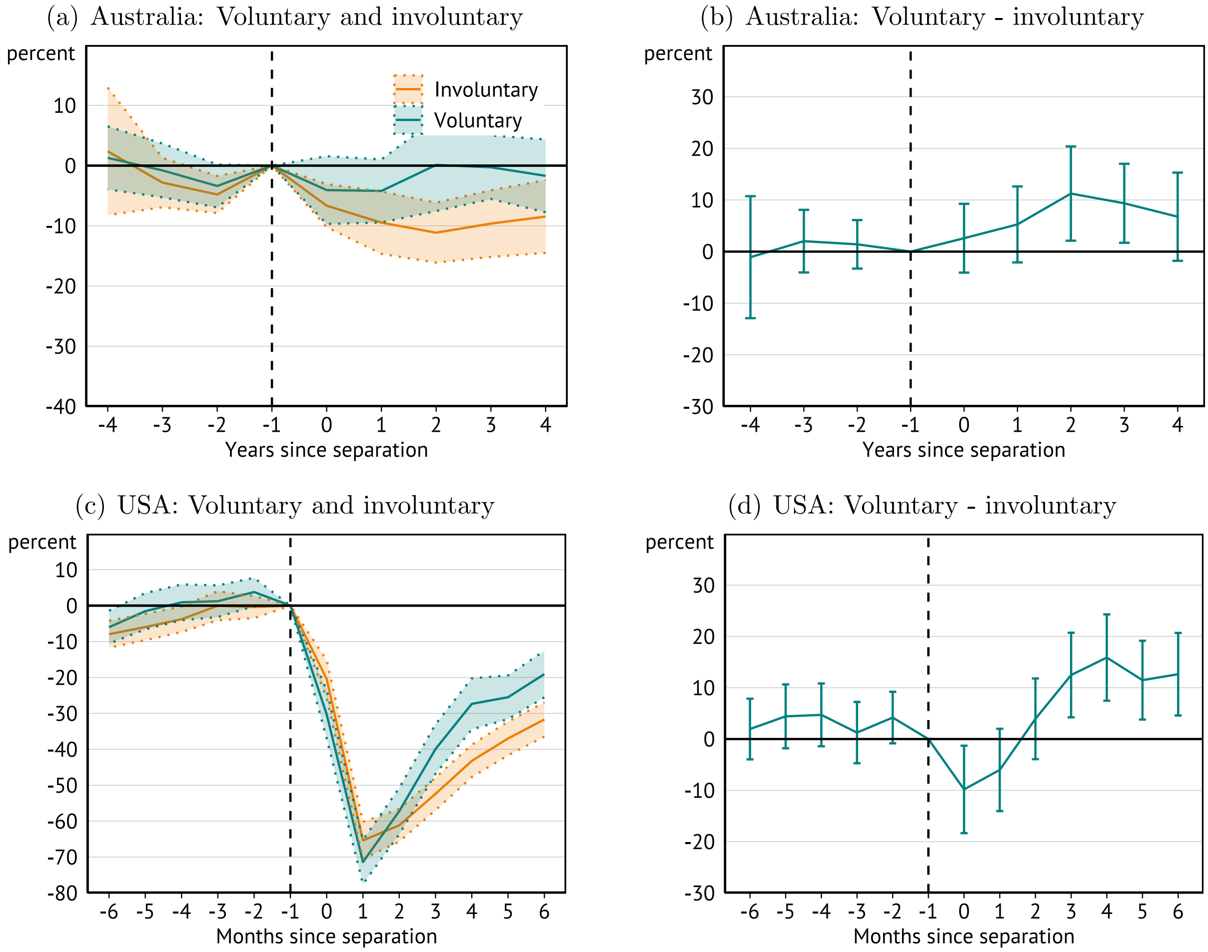
As can be seen, both groups of separated workers experience a strong and persistent earnings decline. For Australia, earnings fail to recover even four years after separation. Importantly, however, there is a noticeable difference in this regard between voluntarily and involuntarily separated workers.

In particular, earnings of voluntarily separated workers recover somewhat faster (right panels). While in Australia, 2 years after separation those who transitioned into unemployment voluntarily enjoy about 10% higher earnings compared to who ended up unemployed for involuntary reasons. In the US, a similar result is observed after 6 months since separation.

Re-employment. The estimates presented above are a mix of "extensive" margin effects – differences in the probability of re-employment – and and "intensive" margin effects – differences in earnings conditional on re-employment. To isolate the latter, we now consider estimates where we restrict the post-treatment labor market history of individuals.

In particular, for Australia we restrict our attention to individuals who transition into unemployment, but manage to return to employment within two years. Moreover, we require these individuals to remain in employment in the 3rd-5th year since separation. Analogously for the US, we restrict our sample to individuals who get re-employed within 4 months and stay in that

Figure 1: Model validation: Entry and disposable income



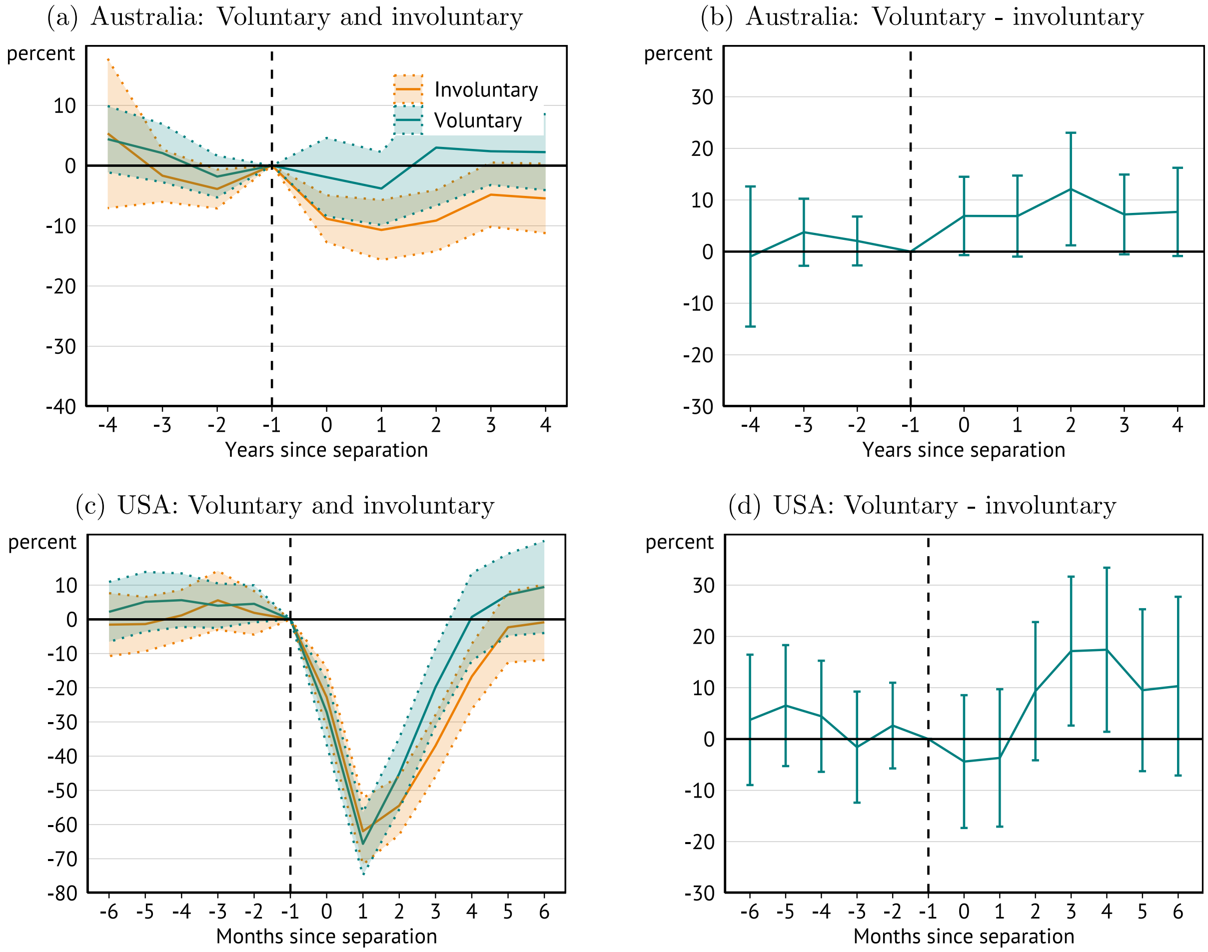
Note: Panels a) and c) are stacked event studies of the % difference in the disposable income of the involuntary and voluntary groups and workers who make no-transitions over the same period, relative to the period prior to the separation event. Panels b) and d) are the difference between the voluntary and involuntary coefficients of the regression shown in equation 7.

job thereafter.

The results of this set of estimates is presented in Figure 2. Qualitatively and quantitatively the difference in earnings of voluntarily and involuntarily separated workers (right panels) is the same as in our baseline results where we do not restrict post-separation labor market histories. However, the levels are considerably different (left panels). In particular, while voluntarily separated workers actually enjoy an earnings gain (relative to their pre-separation earnings), involuntarily separated workers are characterized by a persistent loss (less so for the US).

In combination, these estimates suggest that voluntarily separated workers enjoy (relatively)

Figure 2: Model validation: Entry and wages



Note:Panels a) and c) are stacked event studies of the % difference in the disposable income of the involuntary and voluntary groups and workers who make no-transitions over the same period, relative to the period prior to the separation event. Panels b) and d) are the difference between the voluntary and involuntary coefficients of the regression shown in Equation 7. Individuals must become reemployed within 2 years in the HILDA data and 4 months in the SIPP.

higher earnings post-separation compared to their involuntarily separated counterparts. While the absolute level of earnings is, intuitively, quite heavily affected by re-employment chances, the relative difference between voluntary and involuntary separations is not. This suggests that both groups of workers have quite similar job finding probabilities. This aspect will be important for our model analysis in the next section.

Pre-trends. Before moving on to our structural analysis, let us comment on earnings prior to separation. Specifically, in both sets of results there is a downward pre-trend several years prior to separation – perhaps more strongly so for those who voluntarily separate into unemployment.

For voluntarily separated workers, a downward pre-trend may be seen as evidence that the quality of the job match for the voluntarily unemployed individual was deteriorating in the lead up to the separation.

However, for the balanced sample discussed in Appendix C.2, the pre-trends are instead observed for the involuntarily displaced - who appear to earn a premium in the year prior to job loss - indicating that the driver of this gap is unclear. Note, in addition, that there is no such difference in the relative estimates between voluntary and involuntary separations (right panels of Figures 1 and 2).

5 Model of (In)voluntary Separations

In this section, we propose a model of labor market matching between heterogeneous firms and workers. The main purpose of this framework is to highlight that a relatively standard (and stylized) modeling of the labor market can account well for the patterns estimated in the previous section. At the end of this section, we use our model to sketch the implications of a policy change mimicking the U.S. status quo – an exclusion of voluntarily unemployed from unemployment insurance.[18]

5.1 Model

In this subsection, we describe our structural model aimed at understanding the distinction between voluntary and involuntary separations.

Firms, workers and matching. Consider K_f different types of firms and K_w different types of workers. In what follows, we will use subscripts $i = 1, ..., K_f$ and $j = 1, ..., K_w$ to denote, respectively, firm and worker types.

Each firm is characterized by a permanent level of firm-specific productivity, z_i. Similarly, each worker is characterized by a permanent worker-specific productivity, p_j. Without loss of generality, we assume that productivity is increasing in type, i.e. $z_1 < ... < z_K$ and $p_1 < ... < p_K$.

[18]A richer model – including on the job search and a more realistic modeling of firm and worker heterogeneity – is beyond the scope of the current paper and we leave such an analysis, as well as the study of *optimal* unemployment insurance to future research.

We assume that firms and workers know their own level of productivity, but they cannot perfectly observe productivity of their matching partner. Instead, they learn about it over time through production. For tractability, we assume that types are revealed after one period of production.

Production and costs of mismatch. Firms are assumed to produce with labor as the only input:

$$y_{i,j} = (z_i + p_j). \tag{8}$$

Crucially, we assume that mismatch between a firm's and worker's productivity levels creates (potentially match-specific) costs to the firm, $\phi_{i,j} > 0$. In the spirit of Cooper and Haltiwanger (2006), these may represent disruptions to production, costs of worker training or lack of effort.

Hiring. We assume that workers and firms match randomly on the labor market. Recall that types are revealed during the first period of production. Matches are allowed to endogenously separate *at the end* of a given period. In addition, there are also exogenous separations which happen at rate δ, common to all types of matches.

Let us define the job values of a firm of type i:

$$\mathbb{J}_{i,j} = y_{i,j} - w_{i,j} - \mathbb{1}_{z_i \neq p_j}\phi_{i,j} - \kappa_o + \beta(1-\delta)\max[\mathbb{J}_{i,j}, \mathbb{V}_i] + \beta\delta\mathbb{V}_i, \tag{9}$$

where $w_{i,j}$ are wages, defined below, $\mathbb{1}_{z_i \neq p_j}$ is an indicator function equal to 1 when a firm's and worker's productivity levels mismatch and zero otherwise, $\beta \in (0,1)$ is a discount factor and $\mathbb{V}_i$ is the value of an open vacancy:

$$\mathbb{V}_i = -\kappa + \beta q(1-\delta)\sum_j \pi_j^w \mathbb{J}_{i,j} + \beta(\delta + (1-\delta)(1-q))\mathbb{V}_i, \tag{10}$$

where κ is the costs of open vacancies (common across job types), $\pi_j^w = U_j/U$ represent the fractions of *workers* of type j in the unemployment pool (with $\sum_j \pi_j^w = 1$) and where $q = M/V$ is the probability of finding a worker with M and V representing total matches and vacancies, respectively. The job filling probability, q, is common to all firms due to random search.

Worker values. Let us define the (un)employment value of a worker of type j as:

$$\mathbb{W}_{i,j} = w_{i,j} + \beta(1-\delta)\max[\mathbb{W}_{i,j}, \mathbb{U}_j] + \beta\delta\mathbb{U}_j, \tag{11}$$

where U_j is the value of unemployment given by

$$\mathbb{U}_j = b + \beta f(1-\delta)\sum_i \pi_i^f \mathbb{W}_{i,j} + \beta(f\delta + 1 - f)\mathbb{U}_j, \tag{12}$$

where b is the unemployment benefit (or value of home-production), $f = M/U$ is the job finding probability (common across workers) with U representing total unemployment and where $\pi_i^f = V_i/V$ are the shares of *firms* of type i among all businesses posting vacancies.

Free entry and matching. Assuming free entry implies that values of an open vacancy are driven down to zero and, given the common cost of opening vacancies all jobs have the same value in expectation (i.e. given the distribution of worker types in the unemployment pool):

$$\frac{\kappa}{q} = \beta(1-\delta)\sum_j^w \pi_j \mathbb{J}_{i,j}. \tag{13}$$

We assume the following matching function:

$$M = mU^\alpha V^{1-\alpha}, \tag{14}$$

where $U = \sum_j u_j$ is total unemployment and $V = \sum_i v_i$ are aggregate vacancies. The law of motion for unemployment is given by

$$U = (1-f)U + \rho(1-U) + (1-\rho)\delta(1-U), \tag{15}$$

where ρ is the fraction of employment relationships which get dissolved endogenously and which we describe in detail below.

Wages. We assume that wages are determined according to Nash bargaining:

$$w_{i,j} = \text{argmax}_{w_{i,j}}(\mathbb{J}_{i,j} - \mathbb{V}_i)^{1-\eta}(\mathbb{W}_{i,j} - \mathbb{U}_j)^\eta, \tag{16}$$

where η is workers' bargaining power (assumed to be common across worker types). In this setting, wages are given by

$$w_{i,j} = \eta\left(y_{i,j} + \beta(1-\delta)f\sum_i \pi_i^f(\mathbb{W}_{i,j} - \mathbb{U}_j) - \mathbb{1}_{z_i \neq p_j}\phi_{i,j}\right) + (1-\eta)b, \tag{17}$$

where the term $\beta(1-\delta)f\sum_i \pi_i^f(\mathbb{W}_{i,j} - \mathbb{U}_j)$ represents the saving on hiring costs which, without firm or worker heterogeneity, collapses to $\kappa\theta$ (where $\theta = V/U$ is labor market tightness). With firm and worker heterogeneity, this term depends on the distribution of worker and firm types. Notice also that mismatch costs enter wages.

(In)voluntary separations. We now turn to defining endogenous separations and classifying them as (in)voluntary. Note that under Nash bargaining, endogenous separations always happen as an "agreement" between the firm and worker when the *joint* surplus, $\mathbb{S}_{i,j} = \mathbb{W}_{i,j} - \mathbb{U}_j + \mathbb{J}_{i,j}$, falls below zero. Under Nash bargaining, this is equivalent to $\mathbb{J}_{i,j} \leq 0$, i.e. firms are willing to retain a job as long as it has positive value.

Note that since both worker and firm types are permanent and since there is no aggregate uncertainty, all endogenous separations happen after the first period of production. In this case, job values are simply given by profits because the continuation value is zero. The fraction of employment relationships which get dissolved endogenously is then given by a cutoff value $\widetilde{\phi}_{i,j}$, the mismatch cost implicitly given by the following expression which is conditional on mismatch, i.e. $z_i \neq p_j$:

$$J^{sep}_{i,j} = y_{i,j} - w_{i,j} - \widetilde{\phi}_{i,j} = 0.$$

Letting $e_{i,j}$ denote the mass of employment relationships of worker types j and firm types i, the endogenous separation rate is given by

$$\rho = \frac{1}{E} \sum_i \sum_j \mathbb{1}_{\phi_{i,j} \leq \widetilde{\phi}_{i,j}} e_{i,j},$$

where $E = \sum_i \sum_j e_{i,j}$ is total employment (with the labor force normalized to 1 s.t. $1 = E + U$) and where $\mathbb{1}_{\phi_{i,j} \leq \widetilde{\phi}_{i,j}}$ is an indicator function equal to 1 when an employment relationship is not viable. Note that we can also define type-specific masses of separations as

$$\rho_j = \frac{1}{E_j} \sum_i \mathbb{1}_{\phi_{i,j} \leq \widetilde{\phi}_{i,j}} e_{i,j}.$$

Among all endogenous separations, we denote those as "voluntary" in which workers were of a higher type than firms, i.e. $i > j$. We denote the voluntary separation rate by ρ_v and the endogenous involuntary separation rate by ρ_x, such that $\rho = \rho_v + \rho_x$. Voluntary separations are given by $(1-U)\rho_v$. Involuntary separations are then given by $s_i = (1-U)(\delta + (1-\delta)\rho_x)$.

(Un-)employment by worker types. The laws of motion of a given worker type are given by

$$u_j = (1-f)u_j + \rho_j e_j + (1-\rho_j)\delta e_j \tag{18}$$

$$e_j = (1-\rho_j)(1-\delta)e_j + f u_j. \tag{19}$$

5.2 Parametrization

Given that Australian data is somewhat more suited for our analysis, we parameterize the model to the Australian context. In what follows, we first describe a set of parameters which we set externally following common practice in the literature or using estimates from existing studies. Thereafter, we move to parameters determined internally to match various moments of the data. Highlighting the key novel feature of our model, we devote separate attention to parameters governing worker and firm types and, in turn, (in)voluntary separations. All model parameters are summarized in Table 4 and the Appendix provides further details and robustness exercises.

Externally set parameters. We assume a monthly model period and set the discount factor to $\beta = 0.996$ to reflect a roughly 4% annual interest rate. The elasticity of the matching function, μ, is set to 0.5 which is a mid-point in the Australian literature (see e.g. **??**). In turn, we let workers' bargaining power be $\eta = \mu$, in the spirit of the Hosios condition.

Parameters set to match moments: Firm and worker types. Our framework allows for both worker and firm heterogeneity. For tractability, we restrict our attention to the case of two worker and firm types, i.e. $K_f = K_w = 2$. We denote each of the two types with subscripts "l" (low) and "h" (high).

Note that worker and firm productivity enter additively in our production function (8). Without loss of generality, we normalize $z_l = 1$ and assume that worker and firm productivity values are symmetric, $p_h = z_h$ and $p_l = z_l$.

Interpreting the two types of workers as representing below and above median groups of individuals, we target the overall share of each type to be 50%. We use this target to discipline the productivity of high-type workers, p_h.

In addition to the levels of worker and firm productivity, we must also determine the mismatch cost, $\phi_{i,j}$. Given the symmetry in production between workers and firms the mismatch cost is constant, $\phi_{i,j} = \phi > 0$ for $z_j \neq p_j$. We use this parameter to generate endogenous separations in our framework and, therefore, normalize it such that the most profitable mismatched job value is equal to 0. In this setting, all mismatched employment relationships endogenously separate.

Parameters set to match moments: Remaining parameters. There are four remaining parameters: value of unemployment (b), match efficiency (m), exogenous separations (δ) and the cost of posting vacancies (κ). We pin these down by targeting the following four moments.

To determine the value of unemployment, we make use of OECD data which suggests an average Australian replacement rate in years between 2001 and 2022 of 0.34. Accounting for non-benefit value of leisure of about 0.15 as in Fujita and Ramey (2012), we target $b/\overline{w}$ of 0.49 where $\overline{w}$ are average wages.

We use the LLFS and measure an average job finding probability of 17% at the monthly frequency. We use this value as a target to inform the level of matching efficiency, m.

The same dataset is then used to also measure a 1% monthly probability that employed workers transition into unemployment (for any reason). Together with the endogenous (voluntary and involuntary) separations, this value determines exogenous separations, δ, in our framework. Finally, to determine the level of vacancy posting costs, we target an average labor market tightness of 0.28 (data on vacancies comes from the Jobs Vacancies Survey of the ABS).

Model performance. Aside from our model matching the calibration targets well, see Table 4, we also note that our framework delivers reasonable parameter values comparable to those found in other studies. For instance, the implied vacancy posting costs amount to about 6 weeks of wages (OECD 2019). In addition, the implied high-type productivity is about 60% higher than that of low-types, roughly consistent with the skill wage premium (Broecke, Quintini, and Vandeweyer 2018).

5.3 Model Results

With our calibrated model at hand, we consider two exercises. First, we show that our model is capable of rationalizing the penalties from unemployment estimated in Section 4.2. Next, we analyze the effects of labor market policies in this environment.

5.4 Penalties from (in)voluntary unemployment

To rationalize the estimated earnings penalties from (in)voluntary unemployment, we replicate our empirical exercise on model-generated data. Towards this end, we simulate a panel of

Table 4: Parameter values and targeted moments

	Parameter	Value	Target/Source	Data	Model
β	Discount factor	0.996	Interest rate of approx. 4%		
μ	Matching elasticity	0.50	between Wesselbaum (2014) and Chindamo and Uren (2010)		
η	Bargaining power	0.50	Hosios condition		
$p_L = z_L$	Low productivity, firm and worker	1.00	normalization		
$p_H = z_H$	High productivity, firm and worker	1.57	share of high types in population	0.50	0.50
ϕ	Mismatch cost	0.38	Max mismatched job value	0	0
b	Unemployment benefit	0.59	Replacement rate (OECD) + leisure Fujita and Ramey (2012)	0.49	0.49
m	Match efficiency	0.32	Job finding rate, LLFS	0.17	0.17
δ	Exogenous separations	0.007	Overall separation rate, LLFS	0.01	0.01
κ_H	Vacancy posting cost	1.85	Labor market tightness, ABS	0.28	0.28

Note: The table presents values for all model parameters. The first three columns describe each parameter and its parameterized value, while the last two columns indicate the most relevant target or data source.

voluntarily and involuntarily separated workers, allowing them to re-enter employment according to the endogenous job finding probability. Importantly, these workers match with different types of firms according to the job creation condition (Equation 14) and, therefore, face the possibility of becoming mismatched again. It is precisely the equilibrium dynamics of job finding rates and (mis)match which determine post-separation earnings dynamics. We defer details of the simulation procedure to the Appendix.

Earnings dynamics following (in)voluntary separations. Figure 3 shows model-implied earnings dynamics of (in)voluntarily separated workers and compares them to the data. As can be seen, the model does well in replicating the patterns estimated in Section 4.2. In particular, involuntarily separated workers face a persistent penalty – about 5% after 4 years, as in the data. This is because their pre-separation earnings were higher than their "sustainable" earnings as they took advantage of being (temporarily) matched with a more productive business. However, as the firms recognize such a mismatch, these workers involuntarily separate into unemployment. Gradually, they find employment again and eventually settle into jobs where they are well matched, but which carry with them lower earnings.

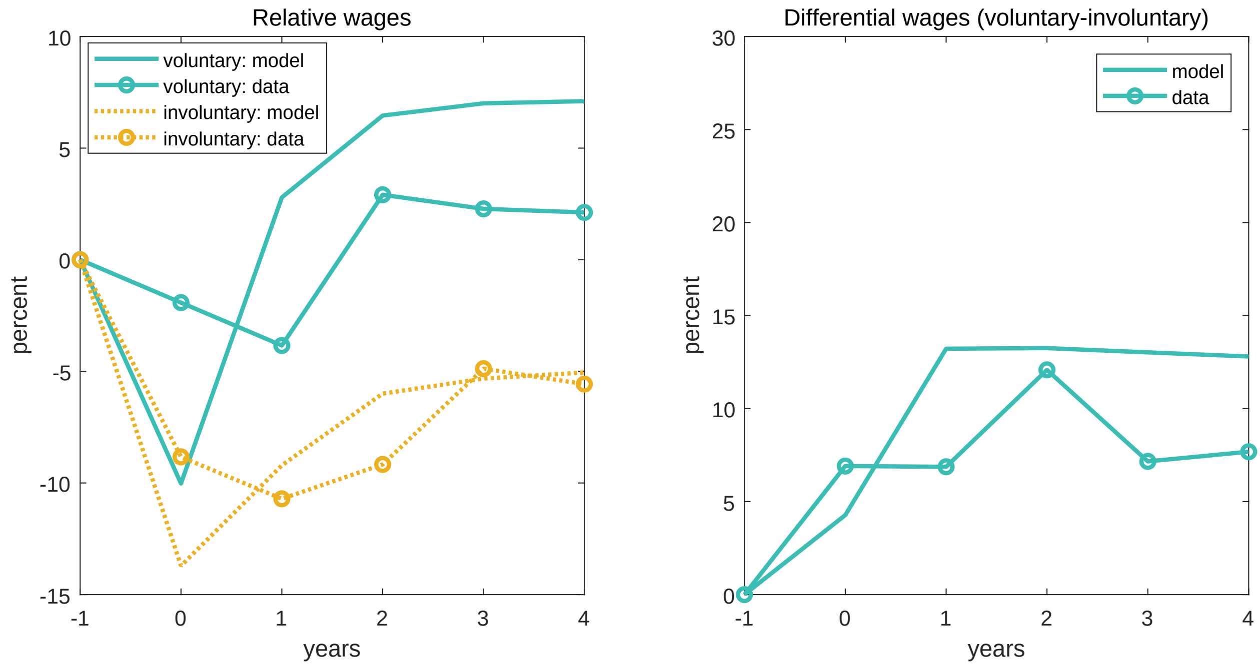
In contrast, voluntarily separated workers see their earnings improve in the long run. In the model, this value is about 7%, compared to about 2% in the data but still within the empirical confidence bands. The reason for this is that productive workers employed in unproductive firms rather voluntarily separate into unemployment and, eventually, find a better match with productive firms which comes with an earnings increase.[19]

5.5 Policy Analysis

As a final step in our analysis, we consider the implications of a particular labor market policy. Specifically, we use our model to evaluate the implications of completely abandoning unemployment benefits for individuals who enter unemployment voluntarily which mimicks the reality in the U.S. economy. In particular, eligibility for unemployment insurance is based on a requirement that individuals leave a job based on a *good cause* - such as involuntary job loss or a forced voluntary separation (i.e. an unsafe work environment). Although good cause rules

[19]The initial drop in earnings is somewhat exaggerated in the model (especially for voluntary separations). This suggests that individuals in the data are better equipped at insuring themselves against unemployment risk, which is not modeled in our framework.

Figure 3: Earnings dynamics by unemployment reason: Model and data



Note: The left panel shows earnings dynamics by unemployment reason relative to pre-separation values. The right panel highlights the difference between the two. Both panels show values implied by the model and those estimated in our data.

do vary across U.S. state, they do exclude true voluntary separations from the unemployment benefit system (Immervoll and Knotz (2018)).

Eliminating unemployment benefits for voluntarily unemployed: Worker values. In the context of our framework, the elimination of unemployment benefits for voluntarily unemployed individuals appears "only" in employment relationships between high type workers and low type firms. In particular, the value of that employment relationship for workers becomes

$$\mathbb{W}_{LH} = w_{LH} + \beta \max[(1-\delta)(\mathbb{W}_{LH} - \mathbb{U}_H) + \beta \mathbb{U}_H, \mathbb{U}_H^v], \tag{20}$$

where $\mathbb{U}_H^v$ indicates the value of unemployment of a voluntarily separated workers given by

$$\mathbb{U}_H^v = b^v + \beta(1-\delta) f \sum_i \pi_i^f \mathbb{W}_{i,H} + \beta(f\delta + (1-f))\mathbb{U}_H^v, \tag{21}$$

where b^v is the value of leisure. Note that we can write the following relationship between the unemployment values of (in)voluntarily separated high type workers:

$$\mathbb{U}_H^v = \mathbb{U}_H - \frac{b - b^v}{1 - \beta(f\delta + 1 - f)}. \tag{22}$$

The above simply states that the value of unemployment for those who leave employment voluntarily is the same as for those who fall into unemployment involuntarily, adjusted for the net present value difference of unemployment benefits.

Eliminating unemployment benefits for voluntarily unemployed: Allocative implications. As we have discussed, the purpose of our model is to show that a relatively standard and stylized modeling of the labor market can in fact account for our estimated patterns related to the earnings profiles of the (in)voluntarily unemployed. While a careful, quantitative, evaluation of policies is beyond the scope of this paper,in what follows we nevertheless investigate its qualitative implications.

In particular, we solve the model – extended for different unemployment insurance between (in)voluntarily unemployed – under the same parameter values as those in Table 4. The only exception is the value of leisure for the voluntarily unemployed, which we set to 0.15 following Fujita and Ramey (2012).

There are both direct and indirect effects related to this policy change. First, when unemployment benefits are not available for individuals who voluntarily separate into unemployment, such workers optimally choose to stay in employment (until they separate exogenously). This has direct effects on the separation rate which declines. With this drop in separations comes also a considerably lower unemployment rate. While the above effects may come with substantial savings on unemployment benefit payments, they occur at the expense of allocative efficiency.

In particular, high type workers now tend to remain in mismatched employment relationships. This directly reduces output. However, there is also an important indirect effect. In particular, because high-type workers remain mismatched in existing employment relationships, there are fewer such workers to match with high type employers seeking to fill new vacancies. This reduces the incentives of high type firms to create jobs and the job finding probability affecting *all* workers drops.

Most importantly, however, since it is high type employers who are affected by the lack of appropriate workers, the share of high-type job vacancies in the economy plummets. Ultimately, this leads to a shift in job quality towards low types, further reducing aggregate output.

In short, since workers separate voluntarily in search of better matches, making their outside option worse reduces their incentive to do so. While our framework is too stylized for a *quantitative* analysis of this phenomenon, it does highlight an important policy trade-off: balancing incentives for search and match quality.

Specifically, through the lens of our model, voluntary separations are closer to job-to-job transitions associated with finding better matches. Therefore, while eliminating them reduces unemployment, it comes at a cost of lower average productivity.

6 Conclusion

This paper contributes to the literature on labor market transitions by examining *voluntary* transitions into unemployment. We show that voluntary separations account for a substantial share of transitions from employment to unemployment, but that they come with very different subsequent labor market outcomes. In particular, we find that subsequent earnings outcomes are less negative and less long-lived compared to those of the involuntarily unemployed. Finally, we use a stylized structural model to show that these patterns are in fact consistent with a framework in which workers and firms gradually search for high-quality matches.

While our model is too stylized for a careful quantitative analysis of existing policy settings, it does offer qualitative insights. We believe that a richer model – including on the job search and a more realistic modeling of worker and firm heterogeneity – would be well suited to analyze existing and new policies and as such is a fruitful avenue for future research.

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A HILDA summary statistics

For our event study specification we use the HILDA survey, while for our description of labor market flows we rely on the larger Longditudinal Labour Force Survey (LLFS).

The reason for doing using these two surveys was that i) we believe the LLFS is a more representative survey for considering labo market outcomes ii) the HILDA survey has well reported income measures and a longer panel for observed individuals.

In this section we outline the summary statistics associated with the HILDA survey to show its relative comparability.

Unlike the LLFS, we focus only on a sample of individuals that i) remain in the same job, ii) are involuntarily unemployed, or iii) are strict voluntarily unemployed. All other individuals are dropped

A.1 Relative treatment

For our sample we restrict the age range for individuals to be between 25 and 50 at treatment. As a result, pre-treatment ages have to be between 24 and 49. As a result, although the involuntary group is slightly older the relative ages are less dispersed than in the labo force data.

In our sample 60% of involuntary displacements are male, while 54% of voluntary displacements are female.

B Subsequent labor market outcomes

One potential important distinction between labor market transitions is the labor market state the individuals end up in following the transition. In Table 7, we report the fractions of individuals in employment, unemployment, and not in the labor force (NILF) one year after a voluntary and involuntary transition into unemployment.

In the US data, individuals who leave their job to unemployment voluntarily are slightly more likely to be reemployed or in NILF one year later.

A year after the EU transition, 37% of involuntarily unemployed individuals remain out of work compared to 34% of voluntarily unemployed individuals. However, 21% of involuntarily unemployed individuals remain unemployed compared to only 15% of voluntarily unemployed individuals.

C Alternative Event Study specifications

C.1 Pre-employment assumptions

In the main specification, the displaced individual is observed as employed in the current year and but they may have been a new entrant to the labo market. This fits with our description of voluntary transitions reflecting an observed mismatch between the employer and the employee which leads the individual to exit in search of a better match.

Our unbalanced results are sensitive to this assumption. Consistent with Coates and Ballantyne (2022) we find that two-years of employment leads to similar wage trajectories for the voluntary and involuntary groups.

However, the differences depending on prior employment disappear when we use a balanced panel as outlined below. This indicates that the driver of changes from varying pre-employment assumptions stems from the dropping of individuals with missing values, not the dropping of individuals who are observed and record zero income.

C.2 Stacked balanced panel

The main estimates use the unbalanced HILDA panel to estimate the income penalty associated with forms of job loss. Using an unbalance panel involves implicitly imputing that missing values move with observed values, which would be problematic if non-response was correlated with income shocks.

A key reason why we do not use the full 19 year panel to estimate our results is that this is seen as an especially selected sample of individuals. Estimating income penalties from this data would drop all individuals who were added in the top-up survey in 2011 and individuals who came into the sample due to movement into households or through birth. Furthermore, it only includes individuals who were contentious enough to report to the survey each year for each year.

When using this fully balanced panel our sample of treated units falls to 479 people while our sample of untreated units falls to 1747 individuals.

Another approach that weakens the response requirements instead uses a balanced panel for a shorter period of time. This involves taking individuals who are observed for a shorter number of consecutive years. For treated individuals we take individuals who are observed for that many periods centred on the event time, while for untreated individuals we take each individual who is available for at least that many periods, cut their observations into overlapping periods, and stack these observations.

For example, if we set the event study period to 9, then treated individuals will be those who are observed 4 periods prior to treatment and 4 periods after treatment. An untreated individual who is observed for 11 consecutive periods will then be taken for periods 1-9, 2-10, and 3-11, and each of these will be stacked with the same individual ID.

Below we produce comparable event study results to those in the main paper using the balanced sample and estimating the same event study with errors clustered at the individual ID level.

Figure 4: Relative wage profile by displacement type

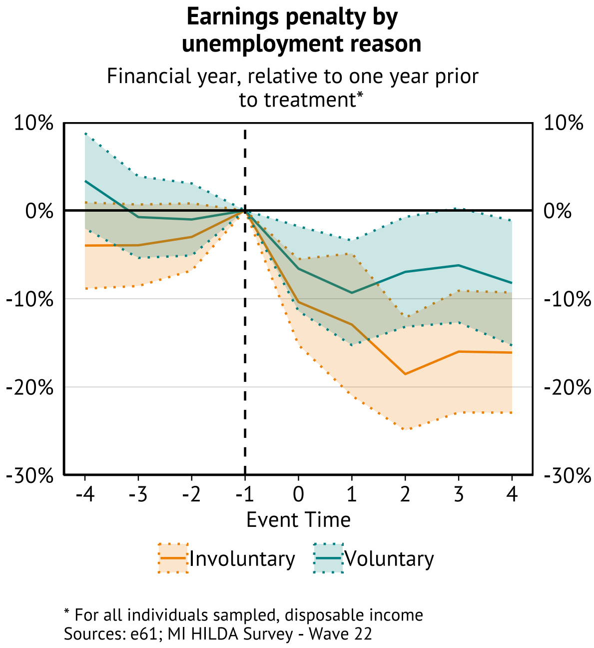
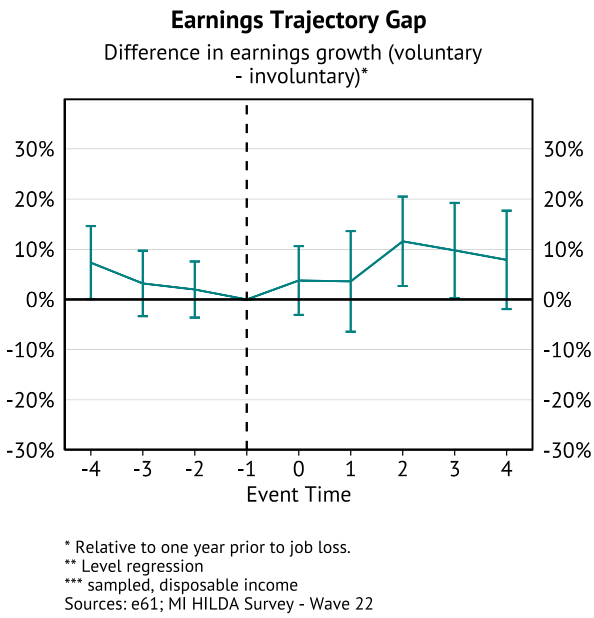


Figure 5: Difference between voluntary and involuntary job loss

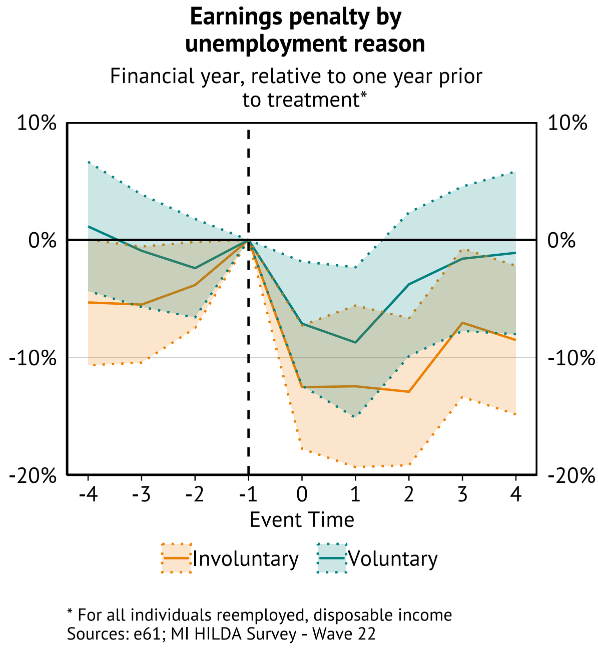


C.3 Income concept

In the primary event study we focused on reflects the disposable income of the individual. This is chosen as it most closely reflects the purchasing outcomes faced by individuals following the shock, and matches the scarring we wish to understand in our structural model.

In the wage scarring literature, which is related to the form of our event study, it is common to focus only on gross labo market earnings - as this reflects the direct penalty to wage earnings

Figure 6: Relative wage profile for those reemployed within two-years



that occur due to the event.

The relative wage scarring results are produced below.

D SIPP Summary Data

Categorising the Reasons To preserve comparability with our own estimates of reasons for separation we aggregate the detailed reasons into 4 categories.

- Involuntary
- Voluntary
- Voluntary Loose
- Other

These are similar to the categorisations found in Simmons (2023) but importantly we exclude those who leave employment for caring responsibilities and education as not voluntarily seperated as these are transitions of a different kind. This does not make a large difference as we are also mostly interested in E to U transitions opposed to separations into NILF which absorb a substantial fraction of such cases.

D.1 Summary Statistics

We begin by presenting summary statistics for the unimputed sample of the SIPP (Table 8).

Table 5: Updated Summary of Involuntary, Voluntary, total treated, and Non-movers across years

Year	Involuntary	Voluntary	Total unemployed	Non-movers
2002	34	44	78	6,250
2003	39	40	79	6,213
2004	22	34	56	6,220
2005	16	40	56	6,322
2006	17	34	51	6,356
2007	12	28	40	6,436
2008	11	27	38	6,501
2009	48	30	78	6,549
2010	20	38	58	6,559
2011	24	23	47	6,602
2012	30	47	77	6,661
2013	37	57	94	6,727
2014	24	65	89	6,790
2015	43	30	73	6,838
2016	31	40	71	6,883
2017	38	47	81	6,952
2018	24	47	71	7,058
2019	22	40	62	7,147
Total	492	707	1,199	-

Note: Raw count of the number of separations in each category within each year. Relative to the size of the non-mover control group.

Table 6: Summary Statistics for year prior to treatment

Statistic	Age	Real Disposable Income (000s)	Real Wage Income (000s)
Voluntarily Unemployed			
1st Qu.	31.0	34.93	20.59
Median	36.0	46.96	51.34
Mean	36.6	50.65	51.98
3rd Qu.	43.0	64.12	67.93
Involuntarily Unemployed			
1st Qu.	33.0	38.41	19.32
Median	37.0	51.31	51.34
Mean	36.8	62.40	72.98
3rd Qu.	43.0	78.09	95.00

Note: Distribution of HILDA income measures by separation type in the year prior to separations.

Table 7: One-year transition probabilities conditional on EU transition

	SIPP			HILDA		
	Involuntary	Voluntary	All	Involuntary	Voluntary	All
Reemployed	0.63	0.67	0.64	0.74	0.66	0.70
Unemployed	0.21	0.15	0.19	0.15	0.11	0.13
NILF	0.16	0.19	0.18	0.10	0.23	0.17

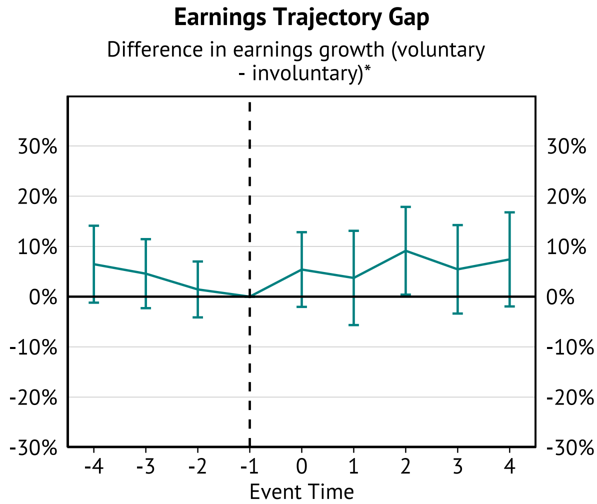
Note: Left column (SIPP), the proportion of workers reporting an employment to unemployment transition will be in a particular labor market state in 12 months time by reason for separation and conditional on remaining in the sample. Right column (HILDA), proportion of workers reporting a job loss in the previous year that then report a employment in the next reporting period.

Table 8: SIPP Full Sample Transition Probabilities

	EU	**EN**	**UE**	**UN**	**NE**	**NU**
Rates	0.0098	0.0132	0.1809	0.0972	0.0399	0.0192

Note: Monthly transition probabilities calculated as $s_t = \frac{EU_t}{E_{t-1}}$.

Figure 7: Difference for those reemployed within two-years



* Relative to one year prior to job loss.
** Level regression
*** reemployed, disposable income
Sources: e61; MI HILDA Survey - Wave 22

E Where do Separators end up?

One issue that might upwardly bias the estimates of the wage scar is if the voluntary separators are more likely to end up in a position that is either not in employment or NILF than the involuntary separators. We can check this in two ways, by including those with zero income in the estimates of the wage scar, and simply by checking the 1 year transition probabilities of each group. We can see that the voluntary separators in the SIPP and in HILDA are more likely to be employed after a year (Table 9). We also find little difference in our wage scar results when subsequent NILF transitions are included.

Table 9: HILDA Two year transition probabilities conditional on EU transition

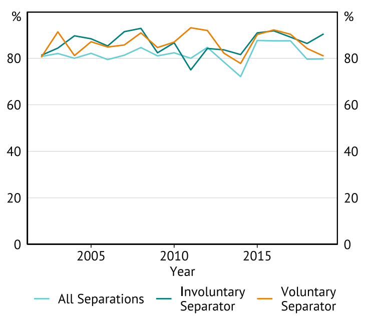
	Involuntary	Voluntary	All
Reemployed	0.52	0.65	0.59
Unemployed	0.14	0.06	0.098
NILF	0.09	0.15	0.12

Note: HILDA labor market transition states 2 years after the an unemployment to employment transition. Columns do not sum to 1 as this includes attrition of the sample.

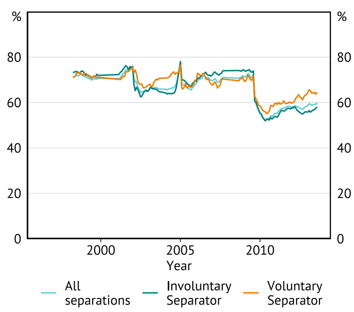
We do observe that there is a cyclical pattern in the variation of the one year reemployment rates for each of the 3 groups (Figure 8). The years where the voluntary reemployment rate is highest (relative to the involuntary group) are also the years when there are high **levels** of involuntary separations. particularly in the period after the financial crisis. This is a further advantage of the SIPP as the monthly observations allow us to construct a higher frequency time series of reemployment.

Figure 8: Reemployment Probabilities

(a) One year reemployment probabilities-HILDA



(b) One year reemployment probabilities-SIPP



F Flow decompositions

To show the relative importance of the Employment to Unemployment transitions we can show the relative importance of the reasons for unemployment and their behavior over the cycle. We can see clearly that there is a cyclical aspect to separations overall. Voluntary separations tend to be positively correlated with involuntary separations (Figure 9) but the relative shares tend to be negatively correlated over time Figure 10. One avenue of future research is to understand the how these flows vary over the cycle, whether the wage scars vary over the cycle and whether this is due to the composition of the workers or changes in reporting during recessions.

Figure 9: SIPP EU contributions

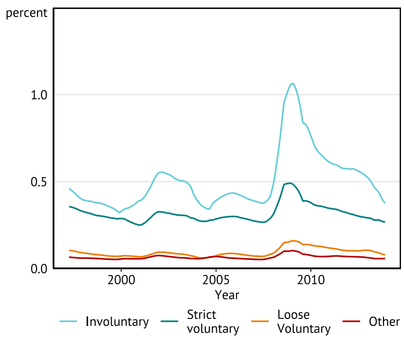
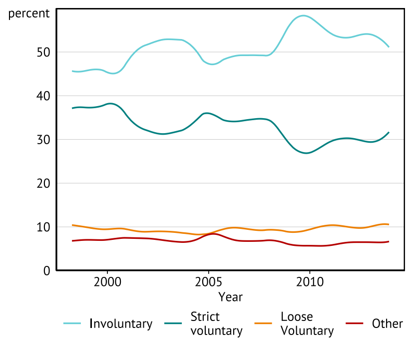


Figure 10: SIPP EU shares



F.1 How well does the steady state decomposition track unemployment?

One of the issues with the above breakdown of entrance into unemployment is that we implicitly assume that the three state decomposition of unemployment is an effective proxy for observed unemployment in Australia. And in general this is true (see Figure 11).The labo market of the US adjusts much faster than most other countries (Corseuil, Foguel, and Moreira 2023). In general however, the steady state rate tends to overestimate the unemployment rate, leading to a systematic level difference. For this reason adjustment is necessary.

$$u_t^* = \frac{\lambda_t^{EN} \times \lambda_t^{NU} + \lambda_t^{NE} \times \lambda_t^{EU} + \lambda_t^{NU} \times \lambda_t^{EU}}{\lambda_t^{EN} \times \lambda_t^{NU} + \lambda_t^{NE} \times \lambda_t^{EU} + \lambda_t^{UN} \times \lambda_t^{NE} + \lambda_t^{NE} \times \lambda_t^{UE} + \lambda_t^{NU} \times \lambda_t^{UE}} \tag{23}$$

It's unclear why this steady state level difference occurs as overall, the time aggregation problem diagnosed in the USA by Shimer (2012) is not as acute in Australia. For this reason in the main text we restrict much of our conceptual thinking to a two state model of the labo market. This is surprising given the sheer volume of job seekers who enter employment from NILF in each

Figure 11: Australian Steady State and Observed unemployment

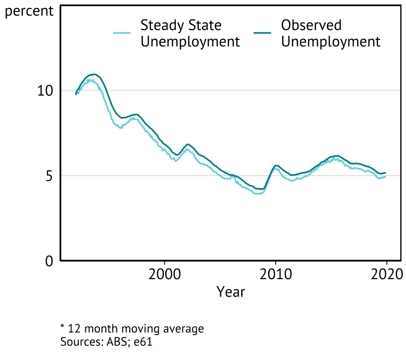
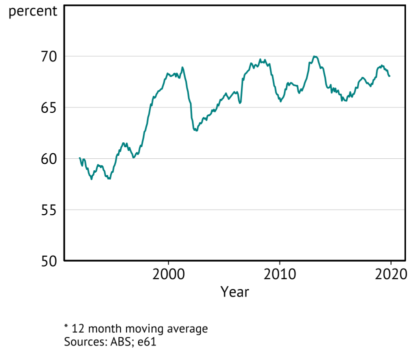


Figure 12: Share of NILF to Employment



month (See Figure 12). Despite this they contribute little to overall variation in the rate of unemployment.

F.2 Relative flows in non-participation

The main focus of our paper is people who enter into unemployment for voluntary reasons. However, theoretically we have little to say about the distinction between unemployment and NILF. The main value of focusing on unemployment is largely because of the job search requirement. Searchers from non-participation are another potentially important group but harder to distinguish from those who do not search. However, as a proportion of total separations out of employment voluntary and involuntary separations into unemployment account for very similar shares compared to the share that exit the labo force.

Table 10: SIPP Share of total separations by reason

Category	**EU**	**EN**
Involuntary	22.8	21.2
Voluntary	14.7	19.7
Loose Voluntary	4.3	5.0
Other	3.0	12.7

Note: Reasons for separation are defined as in table 1 and split by initial destination of separation.

Further the pattern of separations is quite different compared to separations into unemployment and the relative importance of voluntary separations is less than in the unemployment flows (see the raw data in Figure 13).

Importantly for our present investigation there is very little cyclical variation in the share of the voluntary separations into non-employment. This is at odds with the behaviour pf those in in unemployment. Rather involuntary separations and 'Other' appear to drive these results to a much greater extent.

Figure 13: Separations to NILF by reason