Transitioning into Flexible Contracts: An Explanation for Persistent Earning Losses After Job Displacement.*

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Abstract

Flexible contracts have become increasingly prevalent in today's labor markets; however, little is known about the consequences of transitioning to flexible contracts after job displacement in terms of earning losses. Using Dutch data, we show that workers who transition to flexible contracts after job displacement experience earning losses of about 14%, while those who transition to permanent contracts experience significantly lower earning losses of around 1%. We find that these differences can be attributed to workers transitioning to low-paying firms through flexible contracts, with the loss of employer-specific wage premiums accounting for 83% of the earning losses experienced by flexible workers. Leveraging the easily observable nature of contract types, our results offer valuable insights for policy-makers in designing effective policies to address the adverse consequences of job displacement on workers.

Keywords: job displacement, flexible contracts, alternative work arrangements, earning losses, employer-specific wage premiums, income disparities, labor market.
JEL Codes: E32, J22, J31, J41, J63, R23

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1 Introduction

A growing body of literature shows that displaced workers suffer persistent employment and earning losses due to job displacement (Gulyas et al., 2019; Jarosch, 2021; Krolikowski, 2018; Lachowska et al., 2020b). A shortcoming of this literature is that most studies focus on workers with permanent types of jobs and thus do not explore the consequences of switching to flexible contracts after job displacement. We fill this important gap in the literature by studying the role of flexible contracts in explaining persistent earning losses due to job displacement. We make two important and novel contributions to the existing literature. First, we show that the leading explanation for larger earning losses after job displacement is the transition of workers to flexible contracts, resulting in significant losses of employer-specific wage premiums. Second, we document that a large number of workers shift to flexible contracts after job displacement, and many remain on such contracts for up to five years. This finding provides an explanation for the permanent employment and earning losses observed after job displacement.

In this paper, we study labor market outcomes of displaced workers in the Netherlands, using administrative data that provides us with detailed information about workers and firms. Specifically, our dataset includes information about the type of contract, as well as detailed data on labor earnings, worked hours, and household financial wealth. To study the labor market outcomes of displaced workers, we follow the literature and assume that when a firm is contracting by 30 percent or more (i.e., a mass layoff), the worker who separates from the firm does so because of distress at the firm (Gulyas et al., 2019; Jarosch, 2021; Krolikowski, 2018; Lachowska et al., 2020b). We then use propensity score matching, following the methodology utilized in Schmieder et al. (2022) and Bertheau et al. (2022), to identify a suitable non-displaced worker for each displaced worker. Next, we estimate the causal effect of job displacement on earnings by using Difference-in-Differences (DiD). Given the nature of job displacement, namely, multiple time periods, variation in treatment timing, and the potential heterogeneity of job displacement effects over the years, we adopt the approach developed by Callaway and Sant'Anna (2021). In contrast to the traditional dynamic two-way fixed effects (TWFE) regression employed for estimating treatment effects of job displacement, this method offers three distinct advantages: it facilitates cleaner comparisons between treated and untreated units, provides more accurate estimates of treatment effects, and computes the overall effect of job displacement across all groups defined by the year of displacement (Roth et al., 2022).

Our first main result is that, following job displacement, labor earnings of displaced workers decrease by 18% compared to their pre-displacement earnings. While some recovery occurs in the following years, earnings remain about 9% lower five years after displacement. These estimates are consistent with findings in other European countries, such as the study by Bertheau et al. (2022), which examines the consequences of job displacement on earnings across several European countries and reports a 10% loss in total earnings for Northern European countries five years after displacement. We also observe a large cross-group heterogeneity regarding the impact of job loss. We find that a worker displaced during the European Debt Crisis in 2013 experiences earnings losses of approximately 22%, while a worker displaced in 2017 suffers losses of about 3%. These results align with previous research by Schmieder et al. (2022), which highlights that earning losses after displacement are substantial, enduring, and sensitive to business cycles, with losses increasing by almost two-fold during economic downturns.

To understand the role of flexible contracts on persistent earning losses, we calculate the proportion of flexible workers before and after job displacement for the displaced and control group. Our second main result is that a large proportion of workers switch to flexible contracts after job displacement and stay on those contracts for up to five years, offering a novel explanation for the permanent nature of earning losses following job displacement. Specifically, we observe that the proportion of workers employed under flexible contracts increases from 14% at the time of job displacement to 35% in the first year after displacement. Although this transition to flexible contracts may be understood as a transition or as a stepping stone towards a better contract (Adermon and Hensvik, 2022), we find that the proportion of workers under flexible contracts remains high over time, going from 35% in the first year after displacement to 30% in the five years after displacement. Notably, we find that the proportion employed under flexible contracts in the control group remains consistently around 15%. We also show that the persistence of flexible contracts in the displaced group is not explained by gender, as suggested by Illing et al. (2021), or educational attainment, as suggested by Mas and Pallais (2020).

Our third main result is that the inability to secure a permanent contract is a significant source of earning losses for displaced workers. We find that workers that transit to permanent contracts experience earning losses of about 1%, while workers that transit to flexible contracts experience significantly higher earning losses of around 14%. Importantly, these numbers refer to workers that either move to permanent or flexible contracts after job displacement, and thus they represent the lower and upper bound of earning losses, as workers tend to change contract type several times after job displacement. We then use these estimates to calculate the earning losses associated to a larger group of workers under flexible contracts in the displaced group and we find that this change in the composition of contracts accounts for 22% of the total earning losses after 5 years of job displacement.

While the inability to secure a permanent contract is a significant source of earning losses for displaced workers, the leading explanation for earning losses after job displacement in European countries is the transition to worse-paying firms (Bertheau et al., 2022). To shed light on the relationship between flexible contracts and low-paying firms, we estimate the earning losses associated with the loss of employer-specific wage premiums for workers who transition to either permanent or flexible contracts after job displacement. We show that the large differences observed between permanent and flexible contracts can be attributed to the transitions of flexible workers to low-paying firms following job displacement. Specifically, we find that the change in employer-specific wage premiums explains 83% of earning losses for flexible workers.

Related Literature. This paper makes several key empirical contributions to the existing literature. First, the literature on job displacement and earning losses has documented large and long-lasting consequences of job loss and much of the recent literature have focused on understanding the sources of displaced's worker long term earning losses (Bertheau et al., 2022; Davis and Von Wachter, 2011; Gulyas et al., 2019; Jacobson et al., 1993; Jarosch, 2021; Krolikowski, 2018; Lachowska et al., 2020b). However, most studies have focused on permanent workers, ignoring the frequent transitions between different contracts after job displacement. In contrast, our paper is the first to systematically account the type of contract after job displacement as a complementary explanation of the persistent earning losses.

A second key contribution of this paper to quantify the earning losses associated to the transition to flexible contracts. For instance, Daruich et al. (2023) study the impact of 2001 Italian reform that lifted constraints on the employment of temporary contract workers and find that while the reform did increase the creation of temporary job, it also increased job destruction. Specifically, a large proportion of workers were trapped in a cycle of low-paid and fragile temporary jobs with reduced chances of transitioning to permanent jobs. In the same vein, Goos et al. (2022) study the impact of payrolling contracts on labor market outcomes for workers.[1] Using administrative data from the Netherlands, they find that even after three years of transit to payrolling, workers are 10 percentage points less likely than the control group to be on a permanent contract.

[1]Payrolled workers may be defined as workers hired by one firm that are placed on the payroll of another firm while continuing their duties at the original firm.

Like prior studies, our study shows that workers who are displaced from their jobs often transition to flexible contracts, but a higher share of them remain in such contracts five years later, suggesting that these arrangements may be dead ends for workers forced to choose between flexible contracts and unemployment (see, for example, Adermon and Hensvik, 2022). However, our contribution is novel in that we quantify how detrimental are the effects of transitioning to flexible contracts after job displacement.

A third key contribution of this paper is the estimation of job displacement effects. From a methodological point of view, we are close to Bertheau et al. (2022), Schmieder et al. (2022), and Illing et al. (2021). As them, we use similar baselines restrictions to choose the displaced workers and to build a suitable control group through a propensity score matching. However, while these studies employ a dynamic two-way fixed effects (TWFE) to estimate earning losses after job displacement, we adopt the alternative approaches developed by Callaway and Sant'Anna (2021) and Borusyak et al. (2022) to overcome the limitations of TWFEs in a setting with multiple time periods and heterogeneous treatment effects (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021). By advancing the estimation of job displacement effects on workers, we contribute to the development of more robust and reliable estimates of job displacement effects.

A final contribution of this paper is to document novel facts about flexible contracts. In many developed countries, flexible contracts have gained increasing popularity over the last decade, but we still know too little about the consequences of flexible contracts on labor market outcomes. Our paper addresses this gap by using a novel dataset that cover the entire Dutch labor market, which provide concrete and novel evidence on the impact of flexible contract on labor market outcomes and financial wealth. Unlike previous studies, we do not rely on survey data (Katz and Krueger, 2016, 2017; Mas and Pallais, 2020) or machine learning methods to identify flexible work arrangements (Adams-Prassl et al., 2020, 2023), but instead we use administrative data. We document that flexible workers face worse labor outcomes when compared to permanent workers: a lower hourly-wage, larger worked hour volatility, and are also more exposed to unemployment (Adams-Prassl et al., 2020; Goldschmidt and Schmieder, 2017; Lambert et al., 2014; Mas and Pallais, 2020; Scheer et al., 2022).[2] We also document that flexible workers are particularly vulnerable to unemployment.[3] Flexible workers are more much likely to be young, low-

[2]In a sample of early-career adults in the United States, Lambert et al. (2014) show that flexible workers are at high risk of all three dimensions of precarious work schedules: short notice, large fluctuation in worked hours, and little or no input into the timing of work.

[3]Flexible workers may self-sect into different types of contracts due to differences in risk aversion (Fuchs-Schündeln and Schündeln, 2005; Swanson, 2020). However, survey data from the Netherlands suggest that around 70% of workers under flex contracts did not have other choice in terms of the type

educated (also documented by Adams-Prassl et al. (2020); Mas and Pallais (2017)), and with a low financial wealth.

2 Flexible Contracts and Labor Market Outcomes

In this section, we show the large and negative effects on workers' labor market outcomes that result from transitioning to a flexible contract. Additionally, we show that flexible workers are particularly vulnerable to unemployment.

2.1 Data

The main administrative data we use is an integral worker-firm data set containing monthly wages and contract information (SPOLIS) for the Dutch labor market. The wage information includes the total decomposition of the salary (fixed wage, overtime wage, wage discounts, bonuses, etc.). The contract information includes information about the type of contract, weekly working time, and type of jobs. Information is also collected on the Standard Industrial Classification (SBI), the number of workers, and the municipality of the firm. The data is collected by firms and used to calculate the length and level of unemployment benefits by the government agency that pays out unemployment benefits. Since all workers (including workers in the public sector) are covered by unemployment insurance, the data is comprehensive for all legal employment. All workers and firms are anonymized, and Statistics Netherlands (CBS) provides identifiers to track workers and firms over time.

We define three types of flexible contracts (as used by Statistics Netherlands): on-call contracts (arrangements in which workers do not have guaranteed any hours of work), temporary-agency contracts (arrangements where the worker is employed by the agency but temporarily subcontracted to a client's firm), and fixed-term contracts and others (while this category include all others flexible contracts, it is mainly composed by arrangements that depends on the duration of a project or temporary replacement, which may include any type of job except on-call and temporary-agency workers).[4] We note that the Dutch distinction between flexible and permanent contracts is technically equivalent to the distinction between insecure and secure contracts for workers (see, for example, Wiengarten et al. (2021)), and thus, we include fixed-term contract in the category of

of contract (Trends in the Netherlands 2017, CBS).

[4]For example, payroll contracts are included in the category fixed-term contracts, although they are not necessarily fixed-terms contracts. We do this to focus in three largest types of flexible labor contracts.

flexible contracts.[5] We also note that on-call and temporary-agency jobs are usually called *alternative work arrangements* in the literature, as these contracts are mostly associated to nontraditional jobs (Katz and Krueger, 2017, 2019; Mas and Pallais, 2020).

To be able to work with this massive database, we calculate the total salary and worked hours over the year. As in Lachowska et al. (2020b), we focus on the hourly wage. We create two measures for the hourly wage: the fix hourly wage and the full hourly wage. The fix hourly wage corresponds to the sum of the fix wage (or basic wage) by the sum of the fix worked hours over the year. To incorporate the variable part of the salary to the fix part, the full hourly wage also considers bonuses, overtime salary, and any other item. Since a worker may have different contracts over time, we consider only the largest contract at the end of the year.

We complement this data set in three extends. First, we incorporate demographic information: age and gender. Second, we incorporate information about the highest education degree achieved by the worker by 2018, which we classified into two levels: low education and high education.[6] Third, we incorporate information about household wealth for the main earner (i.e., breadwinner). The data is provided to Statistics Netherlands by the Dutch Tax Authority (house value, stocks and bonds, outstanding mortgage loans, and considerable capital provision to companies) and banks (the sum of all checking and savings accounts). All values are provided at the end of the calendar year and aggregated at the level of the household.

We restrict our sample to workers between 25 and 55 years, who have at least 6 years of data, and financial wealth data. The resulting dataset contains $29,390,355$ worker-year observations covering the years $2006-2019$. Table 1 shows descriptive statistics. The share of flexible contracts is 18%, including 1% on-call contracts, 3% temporary-agency contracts, and 15% fixed-term contracts and others. The average fix- and full hourly wage are Euro 22.02 and 25.33 for permanent workers, respectively, compared to Euro 16.86 and

[5]In the Netherlands, firms pay lower unemployment insurance premiums for workers under flexible contracts, the firing rules are also weaker for these contracts, and firms are less liable in the event of long-term sick leaves of workers under flexible labor contracts.

[6]The two categories correspond to the following levels in the Dutch education system. "Low education" corresponds to primary education, practical education, VMBO (preparatory secondary vocational education), MBO (middle-level applied education) or any of these two streams of secondary education, VWO (senior general secondary education), and HAVO (university preparatory education), as the highest degree of education completed. "High education" includes "Bachelor's degree", "Master's degree", and "Ph.D.". "Bachelor's degree" corresponds to any of the two types of Bachelor's degrees, HBO (university of applied sciences) and WO (academic university education), as the highest degree of education completed. "Master's degree" corresponds to any of the two types of Master's degree, HBO and WO, as the highest degree of education completed. Finally, "Ph.D." corresponds to Doctor of Philosophy.

19.93 for flexible workers. These results are consistent with previous studies documenting the worse labor outcomes of workers under flexible contracts or alternative work arrangements (Adams-Prassl et al., 2020; Goos et al., 2022; Mas and Pallais, 2020). Average worker ages for permanent workers and flexible workers are 42.24 and 38.45. Because our sample focuses on breadwinners, the share of male workers is large. Specifically, the share of male workers for permanent workers and flexible workers are 0.76 and 0.71, which is consistent with female workers taking more flexible contracts (Illing et al., 2021; Mas and Pallais, 2020). The share of workers with low and high education in permanent contracts is 0.46 and 0.54 and they are 0.57 and 0.43 for workers in flexible contracts, confirming that flexible workers tends to be younger and less educated than workers in permanent contracts (Mas and Pallais, 2020). This also suggest that either that higher-educated workers may demand permanent contracts or that permanent contracts are cheaper for employers to provide in higher-skilled jobs. The average volatility of worked hours for permanent and flexible workers are 0.14 and 0.34, respectively, which is consistent with the flexible-hour nature of some flexible contracts (e.g., on-call contracts). We also observe that the unemployment dummy is much higher for flexible workers. While the unemployment dummy is 0.02 for permanent workers, this is 0.11 for flexible workers, highlighting the job insecurity of flexible contracts.

The average financial wealth for permanent workers and flexible workers are Euro $44,494$ and $15,982$. We analyze the components of financial wealth divided by total labor income. On the asset side, the share of risky assets, liquid assets, and other assets are 0.14, 0.52, 0.46 for permanent workers and they are 0.12, 0.50, and 0.12 for flexible workers. The share of risky assets and liquid assets are equivalents between permanent and flexible workers. However, we will see in the next subsection that workers under flexible contracts hold a larger share of financial wealth over total labor income. On the liability side, the share of other debt and student debt are 0.19 and 0.02 for permanent workers and they are 0.15 and 0.28 for flexible workers. This difference may be because flexible workers are younger than permanent workers and tend to have higher student debt. The low income of flexible workers may also explain the larger amount of student debt observed. We also document that real estate assets are Euro $215,759$ for permanent workers and $125,561$ for flexible workers. The share of workers with real estate assets is 75%, while the same number is 53% for flexible workers. Finally, the outstanding mortgage for permanent workers and flexible workers are Euro $157,433$ and $99,743$, respectively, which is consistent with the numbers shown above.

Table 1: Descriptive statistics.

	Observations	Mean	SD	p1th	p50th	p99th
Permanent contacts	29,390,355	0.82	0.39	0	1	1
Flexible contracts:						
-On-call contracts	29,390,355	0.01	0.11	0	0	1
-Temporary-agency workers	29,390,355	0.03	0.16	0	0	1
-Fixed-term contracts and others	29,390,355	0.15	0.35	0	0	1
PERMANENT WORKERS:						
Fix hourly wage (Euro)	23,977,131	22.02	10.03	9.19	19.52	64.01
Full hourly wage (Euro)	23,977,131	25.33	12.38	10.04	22.14	79.51
Age	23,977,131	42.24	7.79	26	43	55
Male worker	23,977,131	0.76	0.43	0	0	1
Low education	14,880,439	0.46	0.49	0	0	1
High education	14,880,439	0.54	0.49	0	1	1
Volatility of worked hours	23,977,131	0.14	0.19	0	0.11	0.80
Unemployment dummy (next year)	21,330,494	0.02	0.15	0	0	1
Financial wealth (Euro)	23,977,131	44,494	187,960	-113,440	13,245	925,754
Wealth measures to yearly gross wage:						
-Financial wealth	23,977,131	0.91	31.81	-1.88	0.23	12.10
-Risky assets	23,977,131	0.14	9.64	0	0	2.16
-Liquid assets	23,977,131	0.52	3.53	0	0.21	4.46
-Other assets	23,977,131	0.46	25.36	0	0	9.01
-Other debt	23,977,131	0.19	10.21	0	0	3.22
-Student debt	23,977,131	0.02	0.32	0	0	0.61
Real state assets (Euro)	23,977,131	215,759	317,839	0	194,957	982,633
Real state assets> 0	23,977,131	0.75	0.43	0	1	1
Mortgage(Euro)	23,977,131	157,433	170,419	0	146,800	724,084
FLEXIBLE WORKERS:						
Fix hourly wage (Euro)	5,413,194	16.86	7.57	7.38	15.02	46.67
Full hourly wage (Euro)	5,413,194	19.93	9.18	7.73	16.70	55.73
Age	5,413,194	38.45	8.35	25	38	55
Male worker	5,413,194	0.71	0.45	0	1	1
Low education	4,520,892	0.57	0.49	0	1	1
High education	4,520,892	0.43	0.49	0	0	1
Volatility of worked hours	5,413,194	0.34	0.32	0	0.23	1.30
Unemployment dummy (next year)	4,820,497	0.11	0.32	0	0	1
Financial wealth (Euro)	5,413,194	15,928	87,491	-86,612	3,796	263,061
Wealth measures to income:						
-Financial wealth	5,413,194	0.46	14.47	-3.83	0.10	7.72
-Risky assets	5,413,194	0.12	11.77	0	0	1.48
-Liquid assets	5,413,194	0.50	5.61	0	0.13	5.24
-Other assets	5,413,194	0.12	7.33	0	0	1.59
-Other debt	5,413,194	0.15	9.24	0	0	2.56
-Student debt	5,413,194	0.28	5.03	0	0	4.83
Real estate assets (Euro)	5,413,194	125,561	192,115	0	112,000	630,344
Real estate assets> 0	5,413,194	0.53	0.49	0	1	1
Mortgage (Euro)	5,413,194	99,743	125,553	0	50,000	481,000
Total observations (N×T)	29,390,355					

Notes: This table shows descriptive statistics. Permanent contracts are secure contracts for the worker's point of view. On-call contracts are arrangements in which workers do not have guaranteed any hours of work. Temporary-agency contracts are arrangements where the worker is employed by the agency but temporarily subcontracted to a client's firm. Fixed-term contracts and others include all others flexible contracts, but it is mainly composed by arrangements that depends on the duration of a project or temporary replacement, which may include any type of job except on-call and temporary-agency workers. Fix-hourly wage is the basic wage divided by basic hours. Full-hourly wage is the gross wage divided by paid hours (basic hours plus paid overtime hours). Age is worker age. Male worker is dummy if the worker is male. Low education denotes primary education, practical education, VMBO (preparatory secondary vocational education), MBO (middle-level applied education) or any of two levels of secondary education, VWO (pre-university secondary education), and HAVO (higher general secondary education). High education denotes completion of a Bachelor's degree, a Master's degree, or a PhD. Education is missing for about 35% of the workers. Volatility of worked hours is standard deviation of monthly worked hours within a year. Unemployment dummy is a dummy variable equal to 1 if the workers does not have employment. Financial wealth is defined as risky assets, liquid assets and other assets minus other debt and student debt. Income corresponds to yearly gross wage of the main earner's family.

2.2 Labor Market Outcomes for Flexible Workers

We describe the consequences of flexible contracts on labor market outcome compared to permanent contracts. To do that, we begin by regressing different measures of labor market outcomes on an indicator for flexible contract and on an indicator for the type of flexible contract: on-call contract, temporary-agency contract, and fixed-term and other contracts. All regressions control for worker and fixed effects, industry fixed effects, year fixed effects, a polynomial term on age, and the number of months under a flexible contract (within a year). Table 2 reports the estimates from these regressions. In Table 2 the general pattern is that flexible workers have a lower hourly wage, a larger volatility of worked hours, and a higher unemployment risk (as shown in Table 1). Column 1 and 2 show that flexible workers have 2.9% and 3.2% lower fix hourly wage and full hourly wage, respectively. Specifically, we find that on-call workers, temporary-agency workers, and fixed-term and other workers have a 3.1%, 3.1% and 2.9% lower fix hourly wage than permanent workers and the difference grows when considering variable compensation (column 2). These results are consistent with previous literature (Adams-Prassl et al., 2020; Goldschmidt and Schmieder, 2017; Wiengarten et al., 2021). For instance, Adams-Prassl et al. (2020) show for the U.K. that flexible arrangements are much more likely to be described in low-paid and non-salaried jobs and Goos et al. (2022) for the Netherlands show that workers that transit to payroll contracts, close to the temporary agency workers described here, have a 2% decline on hourly wages.

Flexible contracts are often considered insecure jobs because the uncertainty of working hours and job stability can result in earning volatility that negatively impacts workers and their families (Hosseini, 2018; Mas and Pallais, 2017; Wiengarten et al., 2021). In columns 3 and 4 of Table 2, we confirm these findings. In column 3, we measure the volatility of worked hours within a year. We calculate the standard deviation of monthly worked hours for each worker and assume zero worked hours for workers who are unemployed in a particular month. We find that flexible workers exhibit 0.153 larger volatility of worked hours compared to permanent workers. Specifically, on-call workers, temporary-agency workers, and fixed-term and other workers have 0.22, 0.27, and 0.15 higher volatility of worked hours than permanent workers, which may be due to the flexible-hour nature of on-call contracts and some part-time contracts or the prevalence of unemployment in these contracts. In column 4, we measure the unemployment risk of workers as the probability of not having a job next year. We observe that, on average, the unemployment risk for workers with flexible contracts is 1.6% compared to permanent contracts. Specifically, we find that the unemployment risk for on-call workers, temporary-agency workers, and fixed terms and other workers are 5.2%, 3.1%, and 1.4% higher than for workers under

Table 2: Relationship between flexible contracts and labor market outcomes.

	Log fix hourly wage (1)	Log full hourly wage (2)	Vol. worked hours (3)	Unemp (4)
Flexible contract	-0.0298***	-0.0321***	0.153***	0.0158***
	(0.000245)	(0.000267)	(0.000372)	(0.000358)
Disaggregated				
-On-call	-0.0308***	-0.0316***	0.224***	0.0523***
	(0.000784)	(0.000829)	(0.000976)	(0.000131)
-Temporary-agency	-0.0310***	-0.0360***	0.267***	0.0319***
	(0.000852)	(0.000908)	(0.000111)	(0.00143)
-Fixed-term and others	-0.0297***	-0.0320***	0.146***	0.0137***
	(0.000247)	(0.000269)	(0.000373)	(0.000358)
Mean y (permanent workers)	3.007	3.137	0.149	0.023
Observations	29,390,355	29,390,355	29,390,355	26,130,543

Notes: This table characterizes flexible contracts in terms of labor market outcomes. We run the following the regression $W_{i,t} = \phi Q_{i,t}^{Flex} + \boldsymbol{X}\boldsymbol{\beta} + \alpha_i + \psi_{J(i,t)} + \epsilon_{i,t}$, where $W_{i,t}$ may be any of the following variables: log of the fix hourly wage, log of the full hourly wage, volatility of worked hours within a year, and a dummy variable for being unemployed next year; $Q_{i,t}^{Flex}$ is either a dummy variable for having a flexible contract or a categorical variable for the type of flexible contract: permanent (baseline), on-call, temporary-agency, and fixed-term and others; $\boldsymbol{X}$ includes a polynomial term on age (normalized to 40 years old), number of months under a flexible contract within a year, and industry-year fixed effects; α_i are worker fixed effects; ψ_j are firm fixed effects. Finally, $\epsilon_{i,t}$ is the error term. I consider workers from 25 to 55 years old. I drop extreme values. Clustered standard errors at the worker level. t-statistics in parentheses.

permanent contracts.

2.3 Financial Wealth and Flexible Contracts

We have shown that flexible workers tend to experience worse labor market outcomes. Now, we show how vulnerable flexible workers are in terms of financial wealth. To estimate the relationship between flexible contracts and financial wealth, we regress different measures of financial wealth on either a dummy for having a flexible contract or an indicator for the type of flexible contract: on-call, temporary-agency, and fixed-term and other contracts. As with the previous regression, all regressions control for worker and fixed effects, industry fixed effects, year fixed effects, a polynomial term on age, and the number of months under a flexible contract within a year.

Table 3 reports the estimates from this regression. In column 1, we find that the financial wealth of flexible workers is, on average, Euro $29,566$ lower than that of workers under permanent contracts. This difference is even more pronounced for workers under temporary-agency or on-call contracts. However, in column 2, we show that the financial wealth-to-income ratio is 0.27 percentage points higher for flexible workers. On average, on-call workers, temporary-agency workers, and fixed-term and others have a financial

Table 3: Relationship between flexible contracts and financial wealth.

		Balance-sheet item to income:					
	Financial wealth (Euro)	Financial wealth	Risky assets	Liquid assets	Other assets	Other debt	Student debt
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Flexible contract	-29,566**	0.273***	0.0956***	0.321***	0.0881***	0.119***	0.113***
	(82.74)	(0.0361)	(0.0117)	(0.00445)	(0.0287)	(0.0122)	(0.00137)
Disaggregated							
-On-call	-31,626***	0.436***	0.180***	0.523***	0.104	0.198***	0.173***
	(301.2)	(0.0852)	(0.0275)	(0.0105)	(0.0676)	(0.0288)	(0.00323)
-Temporary-agency	-39,262***	0.353***	0.0850***	0.412***	0.131*	0.121***	0.155***
	(199.1)	(0.0963)	(0.0311)	(0.0119)	(0.0765)	(0.0326)	(0.00365)
-Fixed-term and others	-27,622***	0.263***	0.0922***	0.309***	0.0860***	0.115***	0.109***
	(91.17)	(0.0364)	(0.0118)	(0.00449)	(0.0289)	(0.0123)	(0.00138)
Mean y (permanent workers)	45,494	0.919	0.149	0.526	0.464	0.194	0.025
Controls:							
Industry × year FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Worker FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Polynomial term age	No	Yes	Yes	Yes	Yes	Yes	Yes
Firm municipality FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Gender × age FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29,390,355	29,390,355	29,390,355	29,390,355	29,390,355	29,390,355	29,390,355
R2	0.005	0.232	0.332	0.204	0.226	0.250	0.268

Notes: This table characterizes the financial wealth of flexible workers: on-call workers, temporary agency workers, and fixed-term and others. We run the following the regression $W_{i,t} = \phi Q_{it}^{Flex} + \boldsymbol{X\beta} + \alpha_i + \psi_{J(i,t)} + \epsilon_{i,t}$, where $W_{i,t}$ may be any of the following variables: financial wealth (Euro), financial wealth-to-income ratio, risky assets-to-income ratio, liquid assets-to-income ratio, other-to-income ratio, other debt-to-income ratio, and student-to-income ratio; $Q_{i,t}^{Flex}$ is either a dummy variable for having a flexible contract or a categorical variable for the type of flexible contract: permanent (baseline), on-call, temporary-agency contract, and other contract; $\boldsymbol{X}$ includes a polynomial term on age (normalized to 40 years old), number of months under a flexible labor contract within a year, and industry-year fixed effects; α_i are worker fixed effects; ψ_j are firm fixed effects. Finally, $\epsilon_{i,t}$ is the error term. I consider workers from 25 to 55 years old. I drop extreme values. Clustered standard errors at the worker level. t-statistics in parentheses.

wealth-to-income ratio that are 0.44, 0.35, and 0.26 percentage points higher than permanent workers (when compared to the mean). This result is mainly explained by the fact that flexible workers tend to told more liquid assets (column 4), which is broadly consistent with the buffer-stock saving model (Carroll, 2001; Carroll et al., 1992). On the liability side, we also observe that flexible workers tend to hold more debt, in particular, student debt.

Overall, Tables 1 and 2 show that flexible contracts face worse labor outcomes when compared to permanent workers. On top of that, Table 3 shows that flexible workers are particularly vulnerable to job displacement, in term of financial wealth.

3 Estimated Displacement Effects on Earnings

In this section, we study how job displacement affects labor earnings and specifically investigate the impact of flexible contracts on explaining persistent earning losses.

3.1 Construction of the Displaced Worker Analysis Sample

We denote the year prior displacement as d. We define a displaced worker by five criteria. First, a worker must have at least three years of job tenure with the same primary employer (i.e., we observe d, $d-1$, and $d-2$). Second, we define a worker as displaced if that worker separated from her primary employer within the same year in which the employer experienced a mass layoff (i.e., between d and $d+1$). An employer is counted as having a mass layoff in the year $d+1$ if employment dropped by 30 percent or more compared with d. We only consider an establishment with at least 30 employees (as standard in the literature). Third, after displacement, we require all workers to have at least one year with positive earnings to remain in the sample and we assume that a person is employed if they have any positive labor earnings during the year. If the person is non-employed in a given year, we impute zero earnings for that particular year (see, for example, Bertheau et al., 2022). Fourth, we follow the literature and restrict our sample to workers aged 25-55. Fifth, we restrict the main analysis to workers with financial information. This comes with the advantage that we can observe a large set of households variables for those workers (e.g., financial wealth, house ownership, number of family members, etc.). As a result, we restrict the analysis to breadwinners (to whom we can attach all household members). We identify $15,999$ displaced workers who are displaced in $2011-2018$, whose characteristics are observed in $2008-2018$.[7]

Contrary to Scheer et al. (2022), we include displaced workers who have unequal numbers of post-displacement years. For instance, while we observe five years after displacement for a worker displaced in 2014, we observe only year after displacement for worker displaced in 2018.[8] We do not restrict our displaced groups to have the same number of post-displacement years, as we also estimate earning losses by the year of displacement, which is known as group-specific effects (Callaway and Sant'Anna, 2021). We will provide a detailed explanation of this approach in the next subsection.

To match each displaced worker to one worker selected from the pool of potential control workers, we follow Schmieder et al. (2022) and Bertheau et al. (2022) and we divide the data by cells defined by year and gender. Within each cell or exact match, we then estimate the propensity score matching via probit model on the likelihood of being displaced. The model includes earning measured in $d-1$ and $d-2$, age, type of contract, tenure, industry, and employer size in d. We then apply a $1:1$ nearest neighbor matching algo-

[7] In the Appendix, we show the number of workers displaced by year (Figure A1).

[8] In the Appendix, we show the distribution of the number of years that a worker is observed after job displacement (Figure A2).

rithm without replacement to assign one control worker to each treated worker.

Our baseline restriction ensures that displaced worker and non-displaced workers are comparable before the mass layoff. However, they may still differ in many ways that will make it difficult to estimate the causal effect of displacement. For that reason, we also implement a data preprocessing method called entropy balancing over the pre-displacement value of covariates. The goal of entropy balancing is to adjust the covariate distribution of the control group data by reweighting or discarding units such that it becomes more similar to the covariate distribution in the treatment group (Hainmueller, 2012; Hainmueller and Xu, 2013).[9]

Table 4 displays descriptive statistics of variables for the displaced group, and the control group for both the unweighted and weighted sample. Comparing across groups, we observe that most variables are relatively balanced between treatment and control and similar to the baseline estimates from Table 1, which reports estimates for the overall sample with 29 million of observations. For instance, the share of permanent contracts is 0.85 for the displaced group and 0.84 for the control group, and 0.82 for the overall sample (Table 1). The fix hourly wage and full hourly wage are Euro 20.07 and 23.13 in the displaced group, respectively, compared to 19.94 and 22.96 in the control group. Average worker ages in the displaced group and the control group are 41.05 and 40.94 years, respectively. The proportion of male workers is 0.78 in both the displaced group and the control group. The low and high education share are 0.53 and 0.47 in the displaced group and 0.52 and 0.48 in the control group. In the displaced group, we observe that the volatility of worked hours is 0.19, compared 0.20 in the control group. Financial wealth in the displaced group and the control group are Euro $30,926$ and $31,241$, respectively.

However, we observe some differences between the displaced and control groups, such as the financial-wealth-to-income ratio, which is 0.62 in the displaced group and 0.60 in the control group. This difference is explained by the difference in the ratios of other asses and other debt to labor income, which are 0.13 and 0.07 in the displaced group and 0.14 and 0.09 in the control group. To address this potential issue, in Column (5)-(6), we report the descriptive statistics for the weighted control group. We observe that the displaced group and the weighted control group have even closer means and standard deviations for all variables considered in Table 4. This will allow us to run several robustness checks to confirm our results obtained from comparing the displaced group and the unweighted

[9]We will see later that the re-weighting makes no much of a difference in our results, which is also observed by Flaaen et al. (2019).

Table 4: Descriptive statistics of displaced workers and control workers before displacement.

	Displaced Group		Control Group			
			Unweighted		Weighted	
	Mean (1)	SD (2)	Mean (3)	SD (4)	Mean (5)	SD (6)
Permanent contacts	0.85	[0.31]	0.84	[0.31]	0.86	[0.30]
Flexible contracts:						
-On-call contracts	0.01	[0.06]	0.01	[0.08]	0.01	[0.06]
-Temporary-agency workers	0.02	[0.12	0.02	[0.11]	0.02	[0.10]
-Fixed-term contracts and others	0.12	[0.29]	0.13	[0.28]	0.12	[0.27]
Fix hourly wage (Euro)	20.07	[8.45]	19.94	[8.80]	20.07	[8.821]
Full hourly wage (Euro)	23.13	[10.71]	22.96	[11.04]	23.10	[11.03]
Age	41.05	[7.31]	40.94	[7.56]	41.05	[7.53]
Male worker	0.78	[0.42]	0.78	[0.42]	0.77	[0.42]
Low education	0.53	[0.49]	0.52	[0.49]	0.52	[0.49]
High education	0.47	[0.49]	0.48	[0.49]	0.48	[0.49]
Volatility of worked hours	0.19	[0.20]	0.20	[0.19]	0.19	[0.19]
Financial wealth (Euro)	30,926	[78,252]	31,241	[86,444]	30,931	[80,858]
Wealth measures to income:						
-Financial wealth	0.62	[5.83]	0.60	[5.01]	0.61	[4.30]
-Risky assets	0.11	[2.69]	0.11	[1.25]	0.11	[1.05]
-Liquid assets	0.48	[1.94]	0.47	[1.02]	0.47	[1.12]
-Other assets	0.13	[3.56]	0.14	[4.41]	0.11	[3.74]
-Other debt	0.07	[0.69]	0.09	[1.56]	0.06	[0.42]
-Student debt	0.02	[0.20]	0.03	[0.29]	0.02	[0.21]
Real state assets (Euro)	180,633	[158,331]	183,441	[165,341]	180,885	[156,943]
Real state assets>0	0.72	[0.43]	0.72	[0.43]	0.72	[0.43]
Mortgage (Euro)	135,571	[123,008]	135,814	[126,095]	135,783	[124,481]
Gross wage ($\times 1,000$):						
-Permanent worker	45.76	[22.20]	46.09	[23.08]	46.16	[22.99]
-Flexible worker	36.92	[19.02]	35.75	[19.31]	36.15	[19.44]
(difference)	(8.84)		(10.34)		(10.01)	
Number of workers	15,999		15,999		15,999	

Notes: This Table shows descriptive statistics for the displaced group and the control group. We report the mean and standard deviation (SD). In the control group, we consider the unweighted control group and the weighted control group. The weighted group adjusts the covariate distribution of the unweighted control group data by reweighting or discarding units such that it becomes more similar to the covariate distribution in the treatment group (Hainmueller, 2012; Hainmueller and Xu, 2013). Permanent contracts are secure contracts for the worker's point of view while flexible contracts are insecure contracts for workers. Flexible contracts can be divided on three categories: on-call contracts, temporary-agency contracts, and fixed-term contracts and others. On-call contracts are arrangements in which workers do not have guaranteed any hours of work. Temporary-agency contracts are arrangements where the worker is employed by the agency but temporarily subcontracted to a client's firm. Fixed-term contracts and others include all others flexible contracts, but it is mainly composed by arrangements that depends on the duration of a project or temporary replacement, which may include any type of job except on-call and temporary-agency workers. Fixed-hourly wage is the basic wage divided by basic hours. Full-hourly wage is the gross wage divided by paid hours (basic hours plus paid overtime hours). Age is worker age. Male worker is the proportion of male workers. Low education denotes primary education, practical education, VMBO (preparatory secondary vocational education), MBO (middle-level applied education) or any of two levels of secondary education, VWO (pre-university secondary education), and HAVO (higher general secondary education). High education denotes completion of a Bachelor's degree, a Master's degree, or a PhD. Education is missing for about 35% of the workers. Volatility of worked hour is the standard deviation of worked hour within a year. Financial wealth is defined as risky assets, liquid assets and other assets minus other debt and student debt. Income corresponds to yearly gross wage of the family related to the main earner.

control group.

3.2 Empirical Approach

We describe how we estimate earning losses and employment outcomes resulting from job displacement. We start by presenting the most common approach for estimating job displacement effects - the dynamic two-way fixed effects (TWFE) regression (Bertheau et al., 2022; Schmieder et al., 2022). The TWFE regression can be described as

$$Y_{itd} = c_i + \lambda_t + \sum_{k=-3}^{5} \theta_k \mathbf{1}\{t = d+k\} \times D_i + \sum_{k=-3}^{5} \delta_k \mathbf{1}\{t = d+k\} \; + \mathbf{X}\beta + e_{itd}, \quad (1)$$

where Y_{itd} is an employment outcome (earnings, employment status, or hourly wage) of worker i, with displacement year d observed in year t; c_i is a worker-specific fixed effect; λ_t is a vector of calendar year indicators; D_i is an indicator variable for whether worker i is a displaced worker or belongs to the control group. Under the assumption of parallel trends between the treated and control groups, the coefficients of interest, θ_k, capture the causal effect of job loss at the event time k, relative to the evolution of earnings among non-displaced workers (with θ_1 being the first year post-displacement). The coefficients $\{\theta\}$ are normalized relative to θ_{-3} (i.e., $\theta_{-3} = 0$).[10] Vector $\mathbf{X}$ consists of the characteristics of worker i's employer, worker's age and age squared, and a vector of gender interacted with the worker's age; e_{itd} are clustered standard errors at the worker level.

While Equation (1) represents the most common approach for calculating job displacement effects (Bertheau et al., 2022; Lachowska et al., 2020b), recent research suggests that using a dynamic TWFE approach with multiple time periods and heterogeneous treatment effects may have significant drawbacks, as this approach makes both clean comparisons between treated and not-yet-treated units as well as forbidden comparisons between units who are both already-treated (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021). To address these potential issues, we also adopt the alternative Difference-in-Difference (DiD) approach developed by Callaway and Sant'Anna (2021). This method has three advantages over the dynamic TWFE regressions: it allows for cleaner comparisons between treated and untreated units, it can provide more accurate estimates of treatment effects, and it calculates the overall effect of being job displaced across all groups, where groups are defined by the year of job displacement (Roth et al., 2022). Specifically, we estimate the average treatment effect at time t for the cohort job displaced in year g, denoted as $ATT(g, t)$, to measure the extent of treatment effects

[10] Like in Scheer et al. (2022), the TWFE regression also control for the "year relative to baseline year" fixed effects to control for any earning profile trend.

heterogeneity.[11] Additionally, we are interested in the "event-study" parameter, which gives the weighted average of the treatment effect d periods after job displacement across different job displaced cohorts. We express this parameter as

$$ATT_d^w = \sum_g w_g ATT(g, g+d), \tag{2}$$

where w_g is a weight assigned to different cohorts according to their frequency in the treated population. Therefore, ATT_d^w reports the average treatment effects by the length of exposure to the job displacement effect, where d indexes the length of exposure to the treatment. Note that ATT_d^w has the same *interpretation* as the coefficient θ_k from Equation (1), although the latter is likely incorrect in a staggered DiD setting.

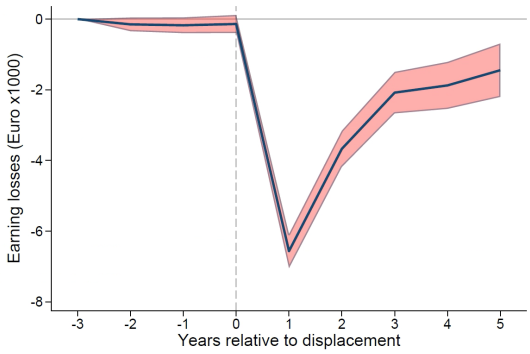
As previously stated, the approach developed by Callaway and Sant'Anna (2021) allows us to estimate the cohort-average treatment effects and their combinations. However, this method does not enable us to estimate the heterogeneity of job displacement by type of contract. To address this limitation, we employ an alternative estimator proposed by Borusyak et al. (2022). As Callaway and Sant'Anna (2021), they also propose an estimator for DiD designs with staggered treatment adoption and heterogeneous treatment effects. However, their approach does not require random sampling, which allows for more general estimands. Specifically, the framework developed by Borusyak et al. (2022) enables us to estimate the causal effect of job displacement by type of contract, which may be understood as an interactive term between the treatment status and type of contract in a TWFE regression. Whenever it is possible, we compare the treatment effects coming from the approaches of Callaway and Sant'Anna (2021) and Borusyak et al. (2022). The general conclusion is that both approaches provide similar estimates for the job displacement effects.

3.3 Estimated Earning Losses Due to Job Displacement

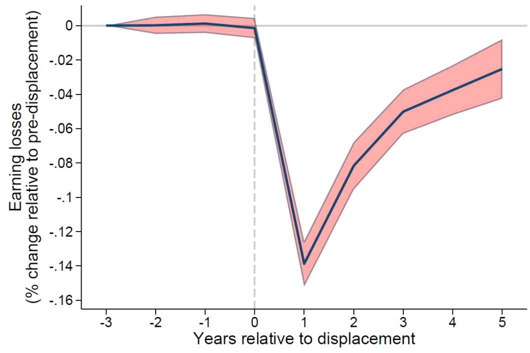
We star by presenting the estimated labor earning losses under the TWFE approach. Figure 1 (a) reports estimated effects of job displacement on earnings and employments over a period of 5 years. We get the figure by estimating Equation (1) and plotting the estimated θ_k, along with 95 percent confidence intervals. Panel (a) reports the effects on labor earnings and Panel (b) reports the effects on labor earning as percentage of earnings in the pre-displacement period. The vertical line marks the year prior to displacement, which is the last year in which a displaced worker is observed with earnings with the employer in the previous three years. Before displacement, we observe that worker's earnings

[11] See, for example, Callaway and Sant'Anna (2021) for more details.

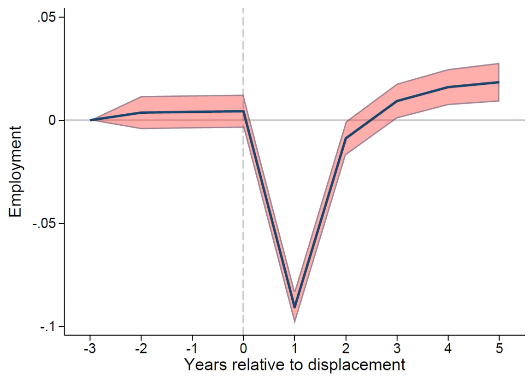
Figure 1: Estimated losses due to job-displacement.



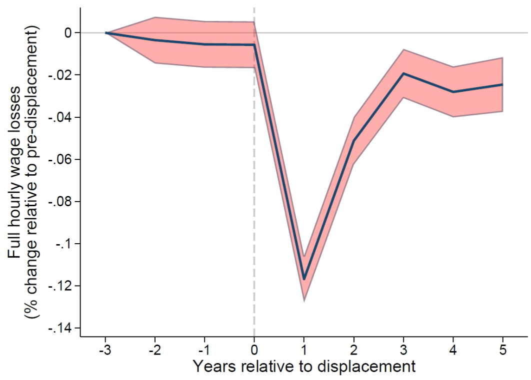
(a) Gross wage



(b) Percentage earning losses



(c) Employment



(d) Percentage hourly wage losses

Notes: The figure shows the estimated losses due to job-displacement. Panel (a) shows the labor income. Panel (b) shows the labor income as percentage of earnings in the pre-displacement period. Panel (c) shows employment. We use an indicator equal to one if a worker has a job during the corresponding year. Panel (d) shows the full hourly wage earnings as percentage of full hourly wages in the pre-displacement periods. These estimates are based on Equation (1). Shaded area denotes 95 percent confidence interval based on standard errors clustered by worker. The vertical lines denote the last year before displacement (i.e., $d-1$).

are similar to the ones of the control group, which is not surprising given the matching algorithm. In the first year following displacement, earnings decline by almost 14% relative to pre-displacement earnings (approximately €7,000 per year). There is some recovery in the following years, but five years after job displacement, earnings are still about 4% lower relative to the pre-displacement year. Panel (c) show that the earning losses are not driven by employment (extensive margin). Employment recovers to pre-displacement levels in the following two or three years after displacement. Panel (d) highlights that a larger part of the earning losses is explained by the losses on full hourly wages.

We compare the estimated earning losses reported by Panel (b) of Figure 1 with the alternative estimator proposed by Callaway and Sant'Anna (2021) and Borusyak et al. (2022). Table 5 reports the job displacement treatment effects on earning. The "$\widehat{ATT}$" row reports the weighted average (by group size) of all available group-time average treatment effects for two methods available in the literature that addresses the TWFE issues (Borusyak et al., 2022; Callaway and Sant'Anna, 2021) and for two samples: unweighted (baseline) and weighted sample. The 'Groups-specific affects (g)" row summarizes average treatment effects by the timing of the job the displacement, indexed by g (i.e., $\widehat{ATT}(g, t)$). The "Event study" row reports average treatment effects by the length of exposure to job displacement (i.e., $\widehat{ATT}_d^w$).[12]

Table 5 confirms the findings of Figure 1, which show that workers experience significant earnings losses following job displacement, with an estimated average treatment effect in the baseline sample ranging from 12%, based on the framework developed by Borusyak et al. (2022), to 13%, based on the framework developed by Callaway and Sant'Anna (2021).[13] However, there is considerable heterogeneity in these losses in terms of the year of job displacement (groups-specific effects estimates). For instance, workers who lost their jobs in 2013, during the European Crisis, experienced earning losses of approximately 21%, while those who lost their jobs in 2017 experienced only a 3% decrease in earnings. This result is largely consistent with Schmieder et al. (2022), where they show for Germany that losses in annual earnings after displacement are large, persistent, and highly cyclical, nearly doubling in size during downturns. The event study estimates also reveal interesting results. While the Panel (b) of Figure 1 shows that earning losses following job displacement recover to approximately 4% after five years, Table 5 shows that this is not the case. Specifically, we observe a drop on earnings of about 18% in the first year, and then in the following years, we observe that earnings losses stay around 9%. This difference may be partly explained by limitations of dynamics TWFE in the context of multiple time periods and heterogeneous treatment effects, as discussed in the empirical approach subsection.

Our findings on earnings losses align with those reported by other European countries. In a recent paper, Bertheau et al. (2022) investigate the consequences of job displacement on earnings for a range of European countries. They find that Northern Europeans countries experience a 10% earning loss in total earnings five years after displacement, whereas

[12]Contrary to Callaway and Sant'Anna (2021), we start d from 1 to match the interpretation of "years relative to displacement" of Figure 1. All estimates use double robust estimator, and we use age, gender, industry, and type of contract for the first step estimation of the generalized propensity score and outcome regression.

[13]In Table A1 of the Appendix, we repeat the exercise of Table 5, but using repeated crosssection estimators and we find similar results.

Table 5: Job displacement treatment effects on earnings.

	$\widehat{ATT}$				
Data:	Unweighted	Weighted			
Callaway and Sant'Anna (2021):	-0.131	-0.131			
	(0.00437)	(0.00448)			
Borusyak et al. (2022):	-0.115	-0.114			
	(0.00477)	(0.00428)			
Callaway and Sant'Anna (2021) - Unweighted sample:					
Groups-specific effects (g)	2010	2011	2012	2013	2014
	-0.120	-0.179	-0.110	-0.208	-0.135
	(0.01246)	(0.00757)	(0.00959)	(0.01109)	(0.01343)
	2015	2016	2017	2018	
	-0.117	-0.080	-0.031	0.042	
	(0.00841)	(0.01198)	(0.00947)	(0.00701)	
Event study (d)	$d = 1$	$d = 2$	$d = 3$	$d = 4$	$d = 5$
	-0.176	-0.138	-0.122	-0.106	-0.090
	(0.00365)	(0.00437)	(0.00568)	(0.00711)	(0.00831)
Observations	171,109				

Notes: This table reports aggregated treatment effects parameters. We consider two approaches: Callaway and Sant'Anna (2021) and Borusyak et al. (2022). Callaway and Sant'Anna (2021) reports the aggregated treatment effects parameter, when estimated with panel estimators. The control group considers never treated workers. All estimates use double robust estimator, and we use age, gender, industry, and type of contract for the first step estimation of the generalized propensity score and outcome regression. We cluster at worker level. Borusyak et al. (2022) reports the aggregated treatment effects parameters, using an imputation approach. We cluster at worker level. In the Table, the row $\widehat{ATT}$ reports the weighted average (by group size) of all available group-time average treatment effects for two DiD approaches and two samples: unweighted and weighted (i.e., entropy balancing). The row Groups-specific affects (g) summarizes average treatment effects by the timing of the job the displacement; here, g, indexes the year that a worker is first treated with job displacement. The row Event Study reports average treatment effects by the length of exposure to the job displacement. Contrary to Callaway and Sant'Anna (2021), we start d from 1 to match the interpretation of "years relative to displacement" of Figure 1.

their Southern European countries experience a 30% loss. Our findings are in line with the former. Workers in the Netherlands continue to experience a 9% loss in total earnings five years after displacement, as shown in Table 5. Our results are also consistent with the 8% loss reported by Gulyas et al. (2019) using Austrian data, the 10% loss identified by Fackler et al. (2017) using German data, and the 15% reported by Lachowska et al. (2020b) using U.S. data.[14]

[14] Note that this is a lower bound for traditional measures of earnings losses in the US (Krolikowski, 2018).

Table 6: Estimated earning losses due to job displacement, selected studies.

Study	Region	Period	Sample	Earning losses	
				First year	Mid-term
Lachowska et al. (2020a)	Washington	2002-2014	All UI claimants	49%	15%
Gulyas et al. (2019)	Austria	1984-2017	Social security records	26%	13%
Fackler et al. (2017)	Germany	2002-2014	Social security records	26%	9%
Bertheau et al. (2022)	North Europe (×3)	1999-2016	Social security records	18%	10%
	South Europe (×4)	1999-2016	Social security records	46%	30%
This paper	Netherlands	2007-2018	Social security records	18%	9%

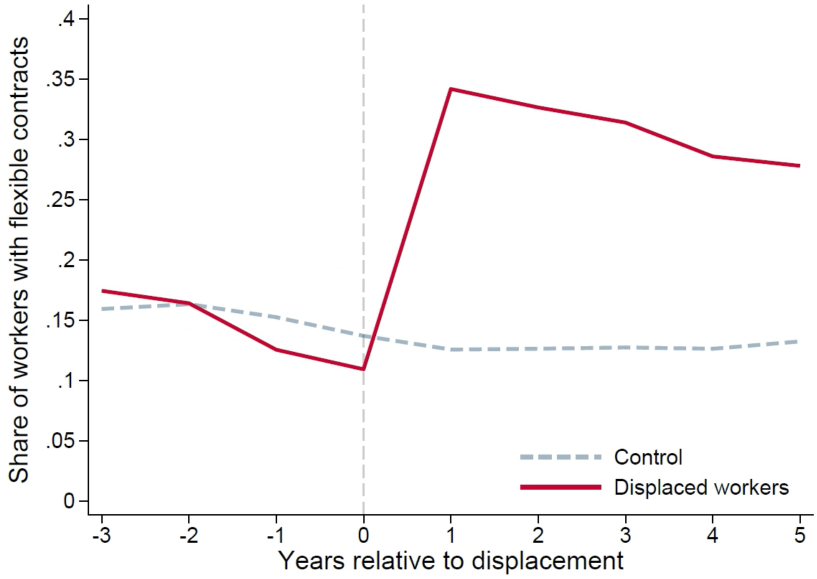
Notes: This table shows the earning losses estimates from selected studies. Lachowska et al. (2020a) estimates correspond to Table 2. UI stands for unemployment insurance. Gulyas et al. (2019) estimates correspond to Figure 1. Fackler et al. (2017) estimates of earning losses correspond to Figure 3 and Table 2 (first column). Bertheau et al. (2022) estimates correspond to Figure 1 and Table 2. Sample period corresponds to the year of job loss for France. North Europe includes to Denmark, Sweden, and Austria. South Europe includes to Italy, Spain, France, and Portugal.

3.4 The Role of Flexible Contracts on Earning Losses

Earnings losses after job displacement can be attributed to several reasons, such as transitioning to worse-paying firms, losing valuable worker-employer matches, and job insecurity. These factors have been identified as the most significant contributors to earnings losses after displacement (Gulyas et al., 2019; Jarosch, 2021; Lachowska et al., 2020b). However, the literature has paid less attention to the impact of the type of contract that workers switch to after displacement on explaining earning losses. To address this gap, we examine the share of workers on flexible contracts before and after job displacement in Figure 2. As we match displaced workers to similar workers in the pre-displacement period based on contracts and other variables, it is possible that the control and displaced groups do not have the same number of workers under flexible contracts before displacement. However, we find that the results are robust to an exact match on the type of contract in the pre-displacement period. Nonetheless, this reduces the sample size considerably.

Figure 2 presents compelling results about the impact of job displacement on worker's employment contracts. The figure shows that, in the pre-displacement period, the share of flexible workers is similar for both the control and displaced groups of workers, and even exhibits a slight downward trend due to the requirement in the Netherlands that firms offer permanent contracts after three years of tenure or three changes of contracts. However, following job displacement, we observe a striking increase in the number of

Figure 2: Share of workers with flexible contracts before and after job displacement.



Notes: The figure shows the share of workers with flexible contracts before and after job displacement. The vertical lines denote the last year before displacement (i.e., $d-1$).

workers on flexible contracts. In the first year after displacement, the share of workers with flexible contracts jumps from 11% to around 34%. Although the share of flexible contracts decreases over time, it remains 15 percentage points higher than that of the control group, providing critical evidence of the potential for flexible contracts to become a default employment arrangement for displaced workers.

The result shown in Figure 2 is consistent with recent evidence related to temporary contracts (Broughton et al., 2016; Daruich et al., 2023; Goos et al., 2022). For instance, Daruich et al. (2023) examine the impact of 2001 Italian reform that lifted constraints on the employment of temporary contract workers while maintaining rigid employment protection regulations for employees hired under permanent contracts. They find that while the reform did increase the creation of temporary job, it also increased job destruction. Specifically, more workers were trapped in cycle of low-paid and fragile temporary jobs with substantial likelihood of transitioning from temporary to permanent jobs. These results are nicely illustrated in Figure 2.

To gain further insight into the results of Figure 2, we divide workers by education attainment and gender in Figure 3. Panels (a)-(b) divide workers in either low educated workers (less than Bachelor Degree) or high educated workers (more than a Bachelor Degree), respectively. Since low educated workers are more likely to hold flexible contracts and receive them after job displacement, it is possible that the results shown in Figure 2 are driven by low-educated workers being trapped in flexible contracts after displacement (Josten and Vlasbom, 2018; Mas and Pallais, 2017). Surprisingly, we find similar trends for both low- and high-educated workers. The prevalence of flexible contracts increases for both groups after job displacement and remains high even five years after displacement. Nonetheless, the prevalence of flexible contracts is 10 percentage points higher for low-educated workers, consistent with the evidence that they are more likely to work under flexible contracts.

Panels (c)-(d) divide workers in either male workers or female workers, respectively. We observe that the prevalence of flexible contracts increases for both male and female workers. In particular, the prevalence of flexible contracts increases for both groups after job displacement and remains high even five years after displacement. As a result, our findings suggest that flexible contracts are prevalent among all groups of workers, regardless of their education level or gender.

3.5 Estimated Earning Losses by Type of Contract

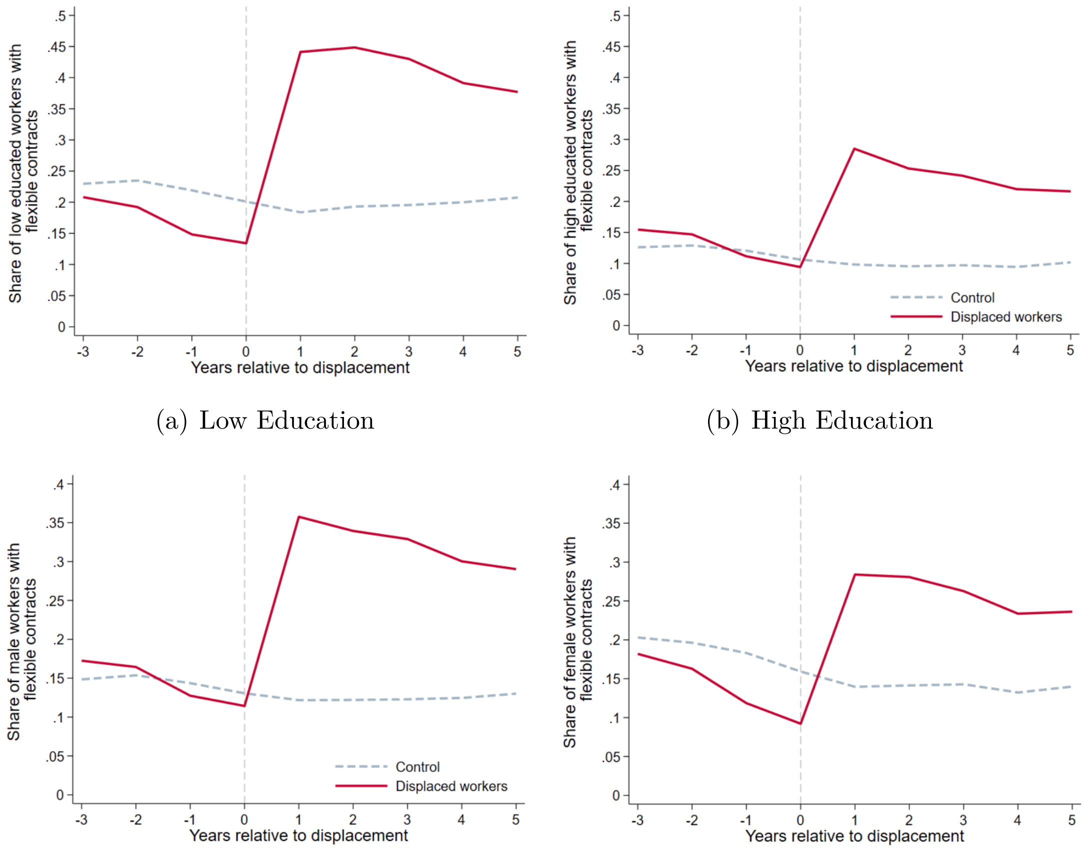
Our findings in Tables 1, 2, and 3 and Figures 1, 2 and 3 suggest then that the type of contract is part of the explanation of job losses after displacement, since flexible workers face worse labor outcomes compared to permanent workers: a lower hourly-wage, larger worked hour volatility, and are also more exposed to unemployment.

We use the approach proposed by Borusyak et al. (2022) to estimate the causal effect of job displacement by type of contract. This approach *is like* including an interactive term between the treatment status and type of contract in a TWFE regression. Table 7 presents the estimated effects of job displacement by type of contract. Our findings indicate that the earnings losses are primarily driven by workers transitioning into flexible contracts. While the earnings losses associated with permanent contracts amount to 1 percent, the losses for flexible contracts reach 14 percent.[15] It is important to note that these numbers refer to workers that either move permanently to permanent or flexible contracts after job displacement, and thus do not represent the reality of the majority of workers who change contracts type after job displacement.

We use the estimates from Table 7 to calculate implications of a larger share of flexible workers in the job displaced group on earning losses. In Figure 3, we have shown that

[15] As a robustness check, in the Appendix, we estimate the earnings due to job displacement by type of contract in a dynamic TWFE setting and confirm the results shown in Table 7. The transition to flexible contracts after job displacement is leading source of earning losses for displaced workers.

Figure 3: Share of workers with flexible contracts by education level and gender.



(a) Low Education (b) High Education

(c) Male (d) Female

Notes: The figure shows the share of workers with flexible contracts before and after job displacement. Panel (a) includes workers with low education (less than a Bachelor Degree). Panel (b) includes workers with at least a Bachelor Degree. Panel (c) includes male workers. Panel (d) includes female workers. The vertical lines denote the last year before displacement (i.e., $d-1$).

the share of flexible contracts remains 15% higher than of the control even after 5 years of displacement. In Table 7, we have shown that the earning losses of workers under flexible contracts are 13% larger compared to workers under permanent contracts (i.e., 14% vs. 1%). Based on these assumptions, we estimate that having a larger group of workers under flexible contracts in the displaced group leads to earning losses of 0.0195 ($= 0.15 \times 0.13$). Since the total earning losses are 0.090 after five years of job displacement (as shown in Table 5), the earning losses associated exclusively to a larger share of flexible workers in the displaced group accounts for 22% of the total earnings losses.

We also show the magnitude of the impact of job displacement on workers, who are already flexible before job displacement, in terms of labor income inequality. In the bottom part of Table 4, we present an overview of the average gross wages during the pre-displacement period for both permanent and flexible workers within the job displaced group, amounting to Euro $46,000$ and Euro $37,000$, respectively. This reveals a difference of approximately Euro $9,000$ between the two worker groups prior job displacement. Referring to Table 7, our findings indicate that workers transitioning to permanent contracts experience earning losses of approximately Euro 900, whereas those transitioning to flexible contracts encounter earning losses of around Euro $6,700$. Consequently, the initial earnings disparity of Euro $9,000$ escalates to a considerable extent, reaching nearly Euro $15,000$, signifying an amplified increase of almost 40%.

To demonstrate the significance of our findings in explaining earnings losses, we also assess the job displacement effects by gender, which is an important predictor of earning losses after job displacement. We observe that women experience earning losses of 17%, compared to an average of around 10% for men. In a recent paper, Illing et al. (2021) show that women's earning losses are approximately 35% higher than men's, and this gap persists even five years after job displacement.[16] Illing et al. (2021) argue that disparity is partly attributed to the higher likelihood of women taking up marginal employment following job loss. Our results corroborate these findings and highlight that the type of contract, beyond gender, plays a significant role in determining the extent of earning losses.

3.6 Employer-specific Wage Premium

We have shown that the inability to secure a permanent contract is a significant source of earning losses for displaced workers, however, the leading explanation of earning losses after job displacement, in European countries, is the transition to worse-paying firms (Bertheau et al., 2022). To better understand the impact of employer-specific wage premiums and flexible contracts on earnings losses, and to determine the extent to which each of these factors are related, we estimate the role of employer-specific on earning losses.

We follow Bertheau et al. (2022) and Lachowska et al. (2020b), and we calculate the employer-specific wage premiums from an AKM regression (Abowd et al., 1999). In particular, we run the following regression

$$logY_{it} = \alpha_i + \psi_{J(i,t)} + \lambda_t + \mathbf{X}\beta + e_{it}, \tag{3}$$

[16] We observe that women experience earnings losses approximately 70 percent higher than men, in comparison to the 35 percent gender gap identified by Illing et al. (2021) in the German context. This substantial disparity may stem from our sample predominantly composed of male breadwinners. Moreover, we do not reweigh our sample to account for the composition of male and female workers, which appears to be crucial in understanding the earnings loss gap.

Table 7: Job displacement treatment effects on earnings by type of contract and gender.

	Earnings (1)		Gross wage (×1000) (2)	
By contract:				
Permanent	-0.011	(0.00244)	-0.904	(0.16007)
Flexible	-0.145	(0.00641)	-6.765	(0.16246)
By gender:				
Male	-0.096	(0.00461)	-5.049	(0.19455)
Female	-0.173	(0.00763)	-5.793	(0.27860)
Observations	252,566			

Notes: This table reports estimates for the causal effect of job displacement by type of contract and gender, as estimated by Borusyak et al. (2022). Column 1 reports the normalized earnings. Column 2 reports the yearly gross wage ($\times 1,000$). We cluster at worker level.

where Y_{it} denotes earnings, or the hourly wage of worker i in year t; α_i are worker fixed effects; $\psi_{J(i,t)}$ are firm fixed effect, where $J(i,t)$ is the main employer of worker i in year t; λ_t are year fixed effects; $\mathbf{X}$ is cubic polynomial in age; e_{it} are clustered standard error at the worker level. We run this regression on the sample that we use in Section 2 to characterize flexible workers. Our focus is $\psi_{J(i,t)}$, which capture the time-invariant wage policy component for a given employer, which we denote as the employer-specific wage premium (Card et al., 2018; Song et al., 2019). After running regression (3), we calculate $\hat{\psi}_{J(i,t)}$ and we run Equation (1) by using $\hat{\psi}_{J(i,t)}$ as an outcome variable.[17] This allows us to calculate the change in the employer-specific wage premiums for displaced workers relative to their matched control workers, d-years following displacement. Following the standard approach in the literature, we take the ratio of job displacement effect on the employer-specific wage premium relative to the overall job displacement effect on the log of the full hourly wage. This gives a measure of the share of earning losses explained by changes in the employer-specific wage premiums.

[17] Contrary to original regression, we do include a dummy variable for having a flexible contracts in the post-displacement period. The dummy is 1 if the worker has a flexible contract and 0 otherwise. Since we have missing data for the years where the workers were unemployed after job displacement, we complete it with 0 and we create an additional dummy that control for years with missing data.

Table 8: Loss of employer-specific wage premiums 5 years after job displacement.

Panel A: Callaway and Sant'Anna (2021)

	Earnings (1)		AKM fixed effects (2)		Ratio (2)/(1) (3)
$d = 5$	-0.090	(0.00840)	-0.055	(0.00216)	0.61

Panel B: Borusyak et al. (2022)

$d = 5$	-0.083	(0.00754)	-0.054	(0.00221)	0.65

Panel C: Borusyak et al. (2022)

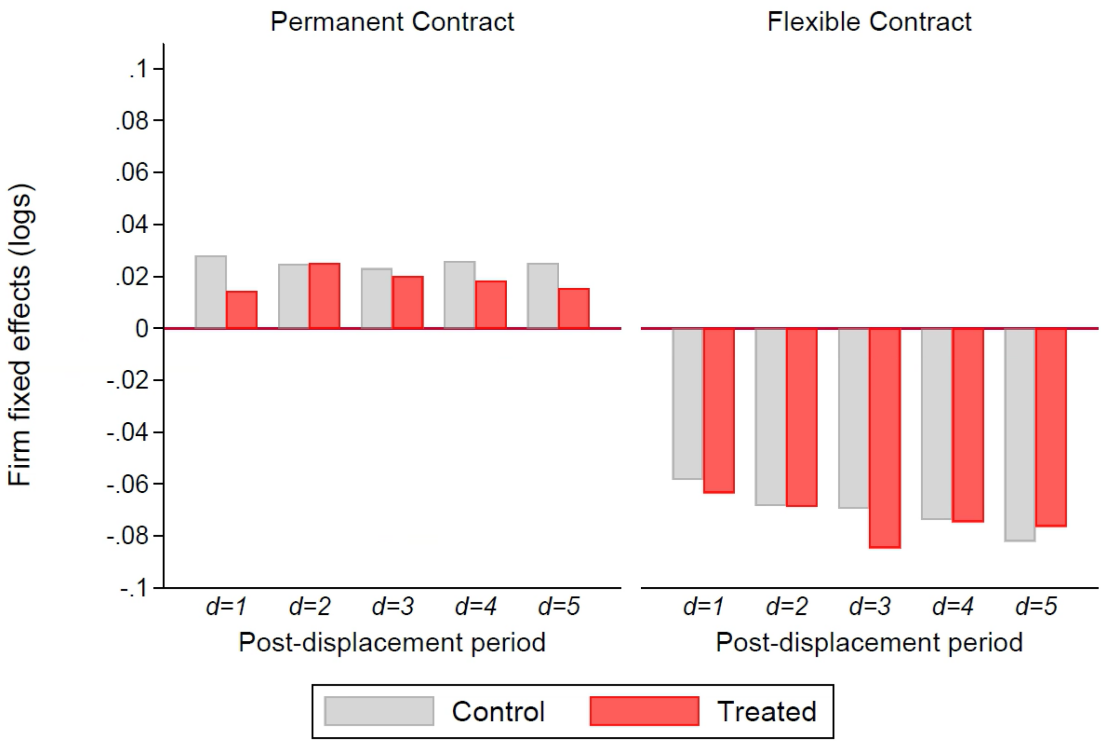
By type of contract:

Permanent	-0.010	(0.00616)	-0.032	(0.00210)	3.20
Flexible	-0.172	(0.01076)	-0.147	(0.00626)	0.83

Notes: This table reports estimates from the event study model as estimated by Callaway and Sant'Anna (2021) (Panel A) and Borusyak et al. (2022) (Panel B and Panel C). Column 1 reports results for normalized earnings. Column 2 reports results where the AKM employer fixed effects is used as independent variable. AKM stands for a regression like Equation (3), which is associated to these authors Abowd et al. (1999). Column 3 reports the share the share of losses in earnings due to losses in employer-specific wage premiums. In Panel A, all estimates use double robust estimator, and we use age, gender, industry and type of contract for the first step estimation of the generalized propensity score and outcome regression. We cluster at worker level in all panels.

Table 8 presents the estimated loss of employer-specific wage premiums for earnings after 5 years of job displacement ($d = 5$). Panel A reports the estimates from Callaway and Sant'Anna (2021) approach, while Panel B reports the estimates from Borusyak et al. (2022) approach. In Column 1, we report the total job loss effect on earnings (same as in Table 5). In Column 2, we report the loss on employer-specific wage premiums and in Column 3 we report the resulting share of earning losses explained by the employer-specific wage premiums. In Panel A, we find that the employer-specific wage premiums are the leading explanation for earning losses after job displacement. Specifically, five years after displacement ($d = 5$), the change in employer-specific premiums explains 61% of earning losses. Similarly, in Panel B, we find that the change in employer-specific premiums explain 65% of earning losses. The disparities between approaches primarily arise from variations in how the treatment effects are aggregated over different groups and time periods. Notably, we find that the loss of employer-specific wage premiums remains

Figure 4: Relationship between job displacement, employer-specific wage premiums, and flexible contracts in the post-displacement period.



Notes: The figure shows the relationship between job displacement, the average employer-specific wage premium (also called firm fixed effects), and flexible contracts in the post-displacement period. Firm fixed effects stands for employer-specific wage premiums in logs, based on Equation (3) (Abowd et al., 1999).

consistent between the two approaches, with a value of -0.055 and -0.054 in Panel A and B, respectively. This consistency aligns with the observation that the loss of employer-specific wage premiums tends to be similar across groups and relatively stable over time (see, for example, Lachowska et al., 2020b). We remain agnostic here, so we consider that change in employer-specific premiums explains between 61% and 65% of earning losses. Bertheau et al. (2022) reports similar numbers for a large group of European countries. Bertheau et al. (2022) show that five years after displacement, the change in employer-specific premiums explains between 35% and 98% of earning losses in Europe: Spain (35%), Denmark (46%), Italy (47%), Sweden (52%), Austria (57%), France (68%), and Portugal (98%).

3.7 Flexible Contracts and Employer-Specific Wage Premiums

We have shown that the transition of displaced worker to worse-paying employers as well as the transition to flexible contracts are import factors in explaining earning losses due to job displacement. We now focus on the relationship between employer-specific wage premiums and type of contract.

To motivate the relationship between employer-specific wage premiums and type of contract, we present Figure 4, which shows the average employer-specific wage premium for each year after displacement, broken down by contract and group of workers. Panel (a) shows the average employer-specific wage premium for workers who transitioned to permanent contracts after displacement, while Panel (b) shows the average employer-specific wage premium for workers who transitioned to flexible contracts.[18] Figure 4 reveals important insights. First, there is a large difference in employer-specific wage premiums between permanent and flexible workers. While permanent workers exhibit employer-specific wage premiums of about 2%, flexible workers exhibit much lower employer-specific wage premiums of about -8%. This result suggests that the large difference in earning losses between type of contracts, as shown in Table 7, could potentially explained by the large losses of employer-specific wage premiums. Second, we find that loss of employer-specific wage premiums for flexible workers in the job displaced group is similar in magnitude to the losses observed for the control group. This is an important result as it confirms that the change of the composition of permanent and flexible workers, as shown in Figure 2, is an important source of earning losses for the displaced group.

To formalize the results shown in Figure 4, we use Borusyak et al. (2022) approach for breaking down earnings losses and employer-specific wage premiums by type of contract. Panel C of Table 7 show the results of this exercise. We find that earning losses are largely explained by the type of contract. Specifically, we find that after 5 years of job displacement, the losses associated to flexible contract are around 17%, compared to earning losses of 1% for permanent contracts.[19] When we estimate the loss of employer-specific by type of contract, we find interesting results. We find that the change in employer-specific premiums explains 83% of earning losses for flexible workers. This result show that the type of contract largely explains earning losses because it predicts the transit of workers into low-paying firms. Regarding permanent contracts, we find that loss of employer-specific premiums is larger than the final earning losses, suggesting that permanent worker can overcome these losses after 5 years of job displacement.

[18]Note that workers move between type of contracts over the post-displacement period, so the number of workers for each bar is not fixed over time.

[19]These results are different in term of magnitude when compared to the values shown in Table 7 as in this Table we focus in 5 year after displacement, instead of the average treatment effect of all periods. Therefore, the job displaced groups considered in the calculation is different, and thus the estimates.

4 Concluding remarks

In this paper, we use administrative employer-employee data from the Netherlands to investigate how the cost of job loss differs between workers under permanent and flexible contracts. Whereas existing research from both the U.S. and Europe has shown that displaced workers suffer larger and persistent earnings losses, evidence for the transition into different types of contracts is scarce. The main contribution of this paper is to compare workers under flexible and permanent contracts who are displaced from comparable jobs with similar pre-displacement careers. This distinction is important for understanding the impact of job losses.

We make two important and novel contributions to the existing literature. First, we show that the leading explanation for larger earning losses after job displacement is the transition of workers to flexible contracts, resulting in significant losses of employer-specific wage premiums. Second, we document that a large number of workers shift to flexible contracts after job displacement, and many remain on such contracts for up to five years. This finding provides an explanation for the permanent employment and earning losses observed after job displacement.

Overall, our study highlights the detrimental effects of flexible contracts on the economic outcomes of displaced workers and emphasizes the need for policies that mitigate the negative impact of job displacement on workers' welfare. One possible recommendation is to provide greater protection and benefits to flexible workers, such as training and education programs and job security provisions. Another approach is to incentivize employers to offer more stable employment opportunities by providing tax breaks or subsidies for creating permanent positions or investing in their workforce's skills. Such measures can reduce the cost of flexible contracts on workers, promote financial security and stability, and help reduce wage disparities between permanent and flexible workers. While these policies may not consider the general equilibrium effects of flexible contracts in the economy, a companion paper by Carreño (2023) show that contractual flexibility is welfare-improving up to a certain extent and that protecting workers in such contracts is the only way to conceive of a labor market with a higher share of flexible contracts.

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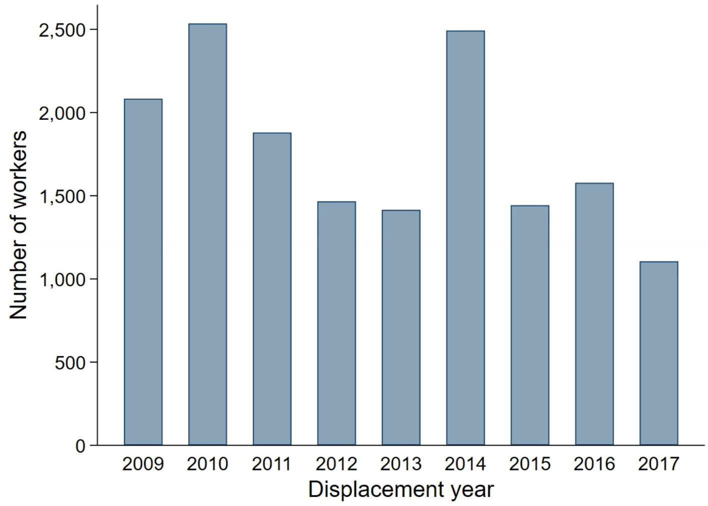
APPENDIX

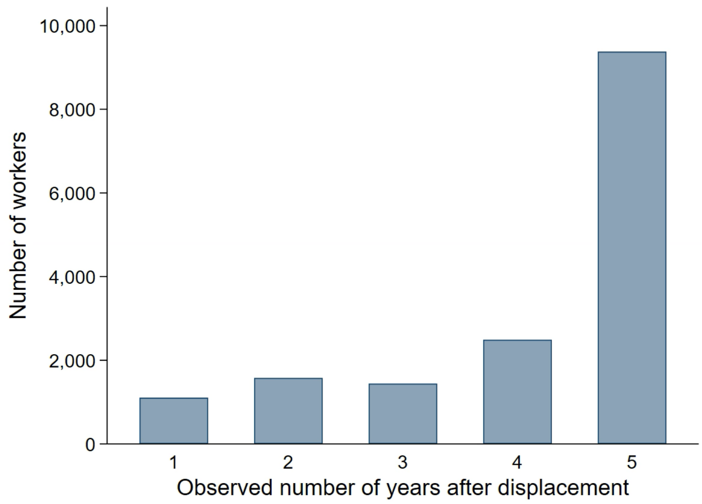
A Figures and Tables

Figure A1: Distribution of job displacement year.



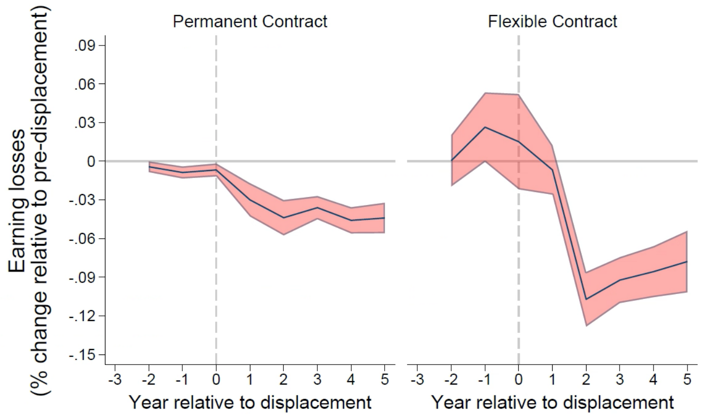
Notes: The figure shows the number of workers by displacement year. The total number of workers is 15,999.

Figure A2: Distribution of the number of years that a worker is observed after job displacement.



Notes: The figure shows the number of workers by observed year after job displacement. The total number of workers is 15,999.

Figure A3: Estimated earning losses due to job-displacement for worker under permanent and flexible contracts.



Notes: The figure shows the estimated earning losses due to job-displacement for permanent and flexible workers. Shaded area denotes 95 percent confidence interval based on standard errors clustered by worker. The vertical lines denote the last year before displacement (i.e., $d-1$).

Table A1: Job displacement treatment effects on earnings (with repeated crosssection estimators).

Reporting measures as Callaway and Sant'Anna (8):					
$\widehat{ATT}$	-0.137				
	(0.00485)				
Groups-specific effects (g)	2010	2011	2012	2013	2014
	-0.103	-0.174	-0.097	-0.219	-0.162
	(0.01828)	(0.00788)	(0.00962)	(0.01148)	(0.01458)
	2015	2016	2017	2018	
	-0.142	-0.090	-0.059	0.022	
	(0.00868)	(0.01233)	(0.00951)	(0.00762)	
Event study (d)	$d = 1$	$d = 2$	$d = 3$	$d = 4$	$d = 5$
	-0.176	-0.136	-0.123	-0.123	-0.106
	(0.00353)	(0.00462)	(0.00607)	(0.00751)	(0.01095)
Observations	252,566				

Notes: This table reports aggregated treatment effects parameters, when estimated with repeated crosssection estimators. The control group considers never treated workers. We report treatment effects on earnings. The row $\widehat{ATT}$ reports the weighted average (by group size) of all available group-time average treatment effects. The row Groups-specific affects (g) summarizes average treatment effects by the timing of the job the displacement; here, g, indexes the year that a worker is first treated with job displacement. The row Event Study reports average treatment effects by the length of exposure to the job displacement. Contrary to Callaway and Sant'Anna (8), we start d from 1 to match the interpretation of "years relative to displacement" of Figure 1. All estimates use double robust estimator, and we use age, gender, industry, and type of contract for the first step estimation of the generalized propensity score and outcome regression. We cluster at worker level.