Theodoropoulos, Nikolaos; Voucharas, Georgios

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Firm Closures and Labor Market Policies in Europe: Evidence from Retrospective Longitudinal Data*

Nikolaos Theodoropoulos **Georgios Voucharas**

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Abstract

We examine the impact of active and passive labor market policies expenditures on the probability of re-employment, re-employment duration, unemployment duration, and re-employment wages in the case of job displacements due to firm closures. We use retrospective homogeneous longitudinal data from the Survey of Health, Ageing and Retirement in Europe and OECD data for 24 countries over the period 1985-2017 and we operate within alternative econometric frameworks. Our findings suggest that, in contrast to passive labor market policies, investing in active labor market policies increases the re-employment probability and the re-employment duration, reduces the risk of staying unemployed, and leads to higher wages at the lower end of the conditional wage distribution. Passive labor market policies estimates offset active labor market estimates and their interaction effect is always negative, but complementarities effects are found for Northern countries. By breaking down active and passive labor market policies into eight subcomponents, our results indicate that they have significant heterogeneous effects within and across labor market outcomes. Further, expenditures on labor market policies vary substantially across regions. For instance, active labor market policies have a stronger impact for Eastern countries, whereas passive labor market policies such as out-of-work income has a positive impact for Southern countries. Further, females are found to benefit more from active labor market policies in terms of re-employment probability, duration of re-employment, and risk of unemployment, but not in terms of wages, compared to males. Policymakers may consider the importance of implementing diverse reforms tailored to different countries and groups to enhance the effectiveness of labor market policies.

Keywords: Labor market policies; plant closures; job loss; re-employment probability; unemployment duration; re-employment wages;

JEL Classification Codes: C21; E24; J08; J65

This paper uses data from SHARE Waves 3 and 7. (DOIs: 10.6103/SHARE.w3.800, 10.6103/SHARE.w7.800), see Börsch-Supan et al. (2013) for methodological details. This paper uses data from the generated Job Episodes Panel (DOI: 10.6103/SHARE.jep.800), see Brugiavini et al. (2019) for methodological details. The Job Episodes Panel release 8.0.0 is based on SHARE Waves 3 and 7 (DOIs: 10.6103/SHARE.w3.800, 10.6103/SHARE.w7.800). See also Bergmann et al. (2019), Börsch-Supan, A. (2022a), Börsch-Supan, A. (2022b) and Brugiavini et al. (2022). The SHARE data collection has been funded by the European Commission, DG RTD through FP5 (QLK6-CT-2001-00360), FP6 (SHARE-I3: RII-CT-2006-062193, COMPARE: CIT5-CT-2005-028857, SHARELIFE: CIT4-CT-2006-028812), FP7 (SHARE-PREP: GA N°211909, SHARE-LEAP: GA N°227822, SHARE M4: GA N°261982, DASISH: GA N°283646) and Horizon 2020 (SHARE-DEV3: GA N°676536, SHARE-COHESION: GA N°870628, SERISS: GA N°654221, SSHOC: GA N°823782, SHARE-COVID19: GA N°101015924) and by DG Employment, Social Affairs & Inclusion through VS 2015/0195, VS 2016/0135, VS 2018/0285, VS 2019/0332, and VS 2020/0313. Additional funding from the German Ministry of Education and Research, the Max Planck Society for the Advancement of Science, the U.S. National Institute on Aging (U01_AG09740-13S2, P01_AG005842, P01_AG08291, P30_AG12815, R21_AG025169, Y1-AG-4553-01, IAG_BSR06-11, OGHA_04-064, HHSN271201300071C, RAG052527A) and from various national funding sources is gratefully acknowledged (see www.share-project.org).

* Contact information: Theodoropoulos: Department of Economics, University of Cyprus, P.O. Box 20537, Nicosia CY-1678, Cyprus, email: n.theodoropoulos@ucy.ac.cy: Voucharas: Economics Research Centre, University of Cyprus, P.O. Box 20537, Nicosia CY-1678, Cyprus, email: gvouch01@ucy.ac.cy. We would like to thank conference participants at the 7th SHARE User Conference in Bled, Slovenia (2022).

1. Introduction

We examine the impact of active and passive labor market policies expenditures (henceforth, ALMPs and PLMPs) on the probability of re-employment, on re-employment duration, on unemployment duration, and on re-employment wages when workers lose their jobs due to firm closures. There are many reasons through which firm closures can happen: recessions, pandemics, creative destruction, globalization, transition to a market economy, mergers and acquisitions, offshoring, and bad firm management. Involuntary job loss due to firm closures or mass layoffs is a common phenomenon (Bertheau et al., 2023; Gathmann et al., 2020; Hyslop et al., 2021; Huttunen et al., 2011) and can affect a worker's welfare and career opportunities not only in the short- but also in the long-run (Schwerdt et al., 2009). In addition, job loss has negative and consequential effects running from the individual level (Couch and Placzek, 2010; Couch et al., 2011), to the family level (Doiron and Mendolia, 2012; Jolly and Phelan, 2017) and to the society as a whole (Raphael and Winter-Ebmer, 2001; Kuhn et al., 2009). Further, given that in recessions workers' skills can be deteriorated (Ljungqvist and Sargent, 1998), then even temporary economic shocks can create unemployment persistence due to thin labor markets (Pissarides, 1992). Thus, a major and current public policy issue is what policies can be implemented in order to ameliorate the aforementioned negative and consequential effects that arise when workers lose their jobs due to exogenous events such as firm closures (Scarpetta et al., 2021).

To meet the above challenges, ALMPs and PLMPs have been in operation for many years across Europe since their inception in the 1950s in Sweden (Martin 2015).[1] Data from Eurostat suggest that in the aftermath of the Great Recession (i.e., in 2011), the EU member states with the financial assistance of the European Social Fund (ESF) spent a total of 205 billion Euros on labor market interventions. In relative terms and on average, the above number represents about 2 percent of the combined Gross Domestic Product (GDP) of member states.[2] [3] These expenses have significantly

[1] For a comparison of European and U.S. ALMPs as well as for a discussion on the evaluation of ALMPs between the two continents, see Kluve and Schmidt (2002).
[2] Source: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Archive:Labour_market_policy_expenditure
[3] Israel in 2012 spent about 2.5 billion Shekel on income support benefits. Part of this expenditure was allocated to ALMPs. However, this amount compares relatively low to other European countries. Source:https://www.etf.europa.eu/sites/default/files/m/C42F878FF524B3C4C1257DEA00558C22_Employment%20policies_Israel.pdf. Also, Figure 1 in Section 4 below reveals that Israel less to ALMPs compared to European countries.

increased relative to the late 1980s in Europe which amounted to 0.7 percent of the GDP (Jackman et al., 1990).

To capture job loss due to firm closures and to construct labor market histories of workers we use retrospective and homogeneous longitudinal data from the third and seventh waves of the Survey of Health, Aging and Retirement in Europe (henceforth, SHARELIFE) which collects information on the entire job histories and wages of workers aged fifty plus. In this way, we are able to construct complete work histories at the individual level, a feature missing in most studies estimating the effect of labor market policies on job loss. To capture expenses on ALMPs and PLMPs we use data from the Labor Market Programs Database as provided by the Organization for Economic Cooperation and Development in 2022 (henceforth, OECD).

By using homogeneous longitudinal data for 23 European countries and Israel over the period 1985-2017 and by employing different econometric approaches, we make the following contributions to the literature: First, we jointly examine the aggregate effect of ALMPs and PLMPs expenses as well as the disaggregated effect of their eight sub-components respectively on four labor market outcomes. Second, unlike previous studies that focus on employment effects, we also examine quality measures, such as the impact of ALMPS and PLMPs on re-employment duration and on re-employment wages. Third, we examine complementarity effects of ALMPs and PLMPs. Fourth, we investigate the potential heterogeneity of the effectiveness of LMPs across regions and genders.

Our results suggest that ALMPs expenditures have positive effects on the re-employment probability, on employment duration and at the lower end of the wage distribution, whereas they have a negative impact on the unemployment duration and at the upper end of the wage distribution. However, the aggregate ALMP expenses mask considerable component heterogeneity. For instance, expenses on supported employment and start-up incentives have positive and significant effects on the re-employment probability and on decreasing unemployment duration, whereas expenses on public sector employment subsidies and administration increase employment duration. In contrast, PLMPs have negative effects on all labor market outcomes and offset the positive ALMPs effects. Interaction effects suggest that more expenditures on both LMP programs have a negative effect on all labor market outcomes. However, some complementarity effects are found for Northern countries. Further, the heterogeneity results uncover significant differences in ALMPs across regions and gender. For instance, ALMPs have a stronger impact for Eastern countries, whereas passive labor market policies such us out-of-work income has a positive impact for Southern countries. Also, ALMPs have a positive and significant impact only for females.

Theoretically, institutions such as ALMPs and PLMPs can be thought as endogenous processes (Arpaia and Mourre, 2012). Further, spending on these two policies depends on labor market conditions, thus making these two policies also empirically endogenous. Although we acknowledge the endogeneity problem we do not attempt to tackle it here as the literature has shown that instrument validity is often problematic (Lehmann and Muravyev, 2012). Another reason that we do not tackle the endogeneity problem is that we disaggregate ALMPs and PLMPs to their eight sub-components and this suggests that we would need at least as many instruments.

Thus, our estimates are reduced form in nature. However, as in Andrews et al. (2019) to reduce the potential endogeneity of labor market policies with respect to labor market outcomes we use an exogenous measure of job loss, that is job loss due to firm closures. Also, following Andrews et al. (2019), we average the two LMPs over five-year non-overlapping periods instead of using the current annual variation which is affected by the business cycle. Further, we use expenditure on the two LMPs as a percentage of the GDP instead of using expenditure per-unemployed worker. The expenditure per unemployed worker measure may overstate the impact of ALMP on re-employment. Thus, scaling expenditures on the two LMPs by GDP provides lower bound estimates.

The remainder of the paper proceeds as follows. Section 2 provides a theoretical discussion on ALMPs and PLMPs. Section 3 reviews the relevant literature from both the macroeconomics and microeconomics literatures. Section 4 presents the data and provides descriptive statistics. Section 5 outlines the empirical methodology, while Section 6 reports and discusses the findings. Section 7 concludes.

2. Theoretical background

The main goal of ALMPs is to improve the performance of labor markets by increasing labor mobility and adjustment (Boeri and Van Ours, 2013). ALMPs aim to facilitate the re-employment of workers and enhance human capital through training. They also try to keep steady the labor force participation rate, sustain the employability of participants and match the competition for available jobs. They do this by facilitating active job search behavior and improving the efficiency of the job-matching process. ALMPs also function as a screening mechanism because they can substitute for regular work experience. This helps to reduce employer uncertainty about the employability of job applicants as well as it provides a signal about the worker's unobserved ability (Boeri and Van Ours, 2013). Finally, placements in ALMPs test the willingness to work as individuals who are not willing to work will prefer to lose registration to an ALMP rather than participate in that program (Van den Berg et al., 2004).

Nonetheless, ALMPs have not escaped criticism in terms of their effectiveness (Lechner and Wunsch, 2009). First, an adverse side effect of ALMPs is that workers are locked into training and job creation programs and because of their participation they reduce their job search intensity (Van Ours, 2004). Second, according to Calmers (1994), ALMPs may have displacement effects because jobs created by an AMLP may replace jobs created by another ALMP.[4] Third, there are deadweight loss effects because labor market programs subsidize hiring that would have occurred anyway in the absence of the program (Martin, 2000). Fourth, there are substitution effects because jobs created for a certain category of workers displace jobs created for other categories as wage relativities change (Crepon et al., 2013). Fifth, there are fiscal substitution effects as taxes that are required to finance AMLPs may affect the behavior of other people in society (Brown and Koettl, 2015). Thus, even if ALMPs do increase inflows from unemployment to employment, this does not necessarily imply an improvement in labor market conditions. Indeed, as we outline in the next section, the evidence is mixed.

Another objective of ALMPs is to counterbalance market failures arising from PLMPs such as generous unemployment insurance benefits or incentives for early retirement. PLMPs create moral hazard problems for the workers as insured workers might be indifferent between keeping their job and

[4] Evidence from Sweden (Dahlberg and Forslund, 2005) suggests that ALMPs have displacement effects as high as 65 percent in case of subsidized employment, but not in case of training.

becoming unemployed. Thus, they incentivize workers to decrease job search intensity as well as they reduce the willingness of the unemployed to accept a job offer. In other words, PLMPs lower the economic costs of unemployment and increase the reservation wage, thus increasing unemployment. Despite the fact that PLMPs may create disincentives to work, they are important because they allow the unemployed to pool their risks, and compensate them for economic deprivation especially if getting unemployed is through an unintended effect, such as business closure. They also help to smooth consumption despite liquidity constraints (Browning and Crossley, 2008) and reduce poverty and inequity (Brown and Koetll, 2015). But, at the same time, PLMPs may increase the effectiveness of the matching process and improve labor market performance through spending more time searching for jobs (Caliendo et al., 2013).

Thus, although ALMPs and PLMPs may provide opposite labor market incentives they are important programs in their own right as they serve different purposes. In this paper, we examine not only the own effect of ALMPs and PLMPs and their complementarity effects on various labor market outcomes, but also, we examine the contribution of their various components that constitute them.

3. Literature review

At the macroeconomics level, the literature has mainly focussed on examining the impact of ALMPs on unemployment. For instance, Boone and Van Ours (2009) construct a theoretical model based on the search and matching framework and examine three active labor market policies: labor market training, public employment and subsidized jobs. They then test the model on macro-level data from 20 OECD countries. In line with their theoretical findings, their empirical results suggest that in contrast to public employment and subsidized jobs, higher expenditures on labor market training reduce unemployment. Pignatti and Van Belle (2021) examine the macroeconomic impact of public expenditure on ALMPs and PLMPs on unemployment, employment and labor force participation for 121 developed, developing and emerging economies. They uncover important interactions between ALMPs and PLMPs as the effect of spending in either of the two policies is more favorable the more is spent on the other. They suggest that this complementarity is important for developing and emerging economies but not for developed economies. Escudero (2018) looks at the effect of spending on ALMPs in 31 developed countries and reports that ALMPs can improve employment outcomes, especially for low-skilled individuals.

Another strand of the macroeconomic literature looks at the effects of labor market institutions and reforms of which ALMPs and unemployment insurance (UI) are two important components. For instance, Blanchard and Wolfers (2000) focus on 20 OECD countries over the period 1960-1995 and examine the interaction between ALMPs and adverse economic shocks. They find that higher expenditures on ALMPs reduce the effects of adverse economic shocks on unemployment. Bassanini and Duval (2009) use data for 20 OECD countries and find that the adverse effect of the generosity of UI is lower in countries that spend more on ALMPs. Elmeskov et al. (1998) using data for 19 OECD countries, find a negative and marginally statistically effect of ALMPs on unemployment that becomes much higher in magnitude and statistical significance when Sweden is removed from the sample.

At the micro-level, the literature examines the effectiveness of specific labor market programs on participants. For instance, Card et al. (2018) present a meta-research assessment from 207 studies on ALMPs and find mixed evidence.[5] They report that ALMPs have small average effects on employment in the short run, but larger average effects in the medium and long run. They also find significant heterogeneity in the time profile between the different ALMPs. Specifically, they note that job search assistance (JSA) programs have similar impacts in the short and long run, whereas training has negative and small effects in the short run but larger positive effects in the medium or long run.[6] In contrast, subsidized public sector employment programs are relatively ineffective or even have negative average effects over time.[7] Finally, they reveal heterogeneous effects with respect to gender, duration of unemployment and age. Precisely, they report larger average effects for females and for the long-term unemployed, and smaller average effects for older and younger workers. Again, they uncover

[5] Other contributions include meta-analysis papers by Kluve (2010), Card et al. (2010) and Escudero et al. (2019). For a comprehensive literature review of both the observational and experimental studies on ALMPs see chapter 12 in Boeri and Van Ours (2013), and for a review of the economic and econometric literature on active labor market programs see Heckman et al. (1999).

[6] For a comparison of short-run, medium-run and long run effectiveness of different ALMPs for Austria see Lechner et al. (2011), and for the Netherlands see Lammers and Kok (2021).

[7] Eichhorst and Zimmermann (2007) review evaluation reports of the famous Hartz labor market reforms in Germany and suggest that training programs, wage subsidies, business start-up grants and placement vouchers are the most helpful programs in improving individual re-employment probabilities. Lalive et al. (2008) using a random sample of Swiss administrative data on unemployed, they find that the subsidized jobs program is the most promising in having positive effects on the transition rate from unemployment back to jobs. However, once they allow for selectivity into ALMPs this positive effect disappears.

significant heterogeneity for the different ALMPs with JSA programs to be more successful for disadvantaged groups, and training and private sector employment subsidies to have larger effects for the long-term unemployed. Overall, they find that ALMPs are more effective in recessionary periods that are short-lived (see also Forslund et al., 2011).

Another recent meta-research study by Vooren et al. (2019) utilises published research on ALMPs from 57 experimental and quasi-experimental studies. Their results differ from the above study by Card et al. (2018) mainly due to the different research protocols of their meta-analysis. For instance, in contrast to the Card et al. results with respect to training as described above, the Vooren et al. study finds positive but not statistically significant effects of training programs on re-employment. Another interesting result that emerge from Vooren et al. study is that public employment and subsidized labor programs have negative short-run effects, but the effects of subsidized labor programs turn positive faster than those of the public employment programs. Further, they find that enhanced services such as JSA programs have positive effects in the short run that become ineffective in the long run.

In a series of papers based on a field experiment in Denmark, Graversen and Van Ours (2008a, 2008b) find that those individuals who were randomly allocated to an activation program (treatment group) based on their date of birth were 30% more likely to find a job compared to the control group. They attribute this much higher probability for the treatment group to work through a threat effect at the start of the program, as well as on intensive monitoring and counselling.[8] In a follow-up paper, Graversen and Van Ours (2011) using the same dataset and extend it with location data on individual addresses as well as on public employment offices, they find that unemployed people living far away (25 kilometres plus) from their activation program find a job faster. However, when examining the quality of the new job through the length of post-employment spells and wages they do not find an effect by geographical distance, suggesting that is mainly the compulsory effect that generates the positive effects of the activation program.

[8] Other papers for Denmark include Rosholm and Svarer (2008) who find that the threat effect decreases the average unemployment duration for men by two and a half weeks. Geerdsen (2006) highlights the importance of the threat effect in lowering unemployment duration, and Ahmad et al. (2019) note the importance of benefit sanctions and employment subsidies in lowering unemployment duration. For a paper that finds differences in threat effects across natives and immigrants in Germany, see Bergemann et al. (2011).

Van den Berg et al. (2009) set up a search model and then test it using German micro data of unemployed workers. They find that active labor market programs affect the behavior of unemployed individuals prior to participation in the program, suggesting that the German ALMP system generates a negative ex-ante effect on the reservation wage of the unemployed workers and a positive effect on the job search effort. The authors suggest that their results are in line with individuals disliking participation in the program. Thus, in order to avoid participation in the program they accept lower job search offers, or alternatively, they search harder than would have done in the absence of the program.

A new strand of the literature looks at the impact of specific interventions that target the demand side of the labor market as opposed to the supply side. For instance, Algan et al. (2022) set up randomized experiments in collaboration with the French Public Employment Services office and examine what happens to the labor demand and hiring if randomly chosen small and medium size firms are provided with help prior to screening and hiring. They find that treated firms are more likely to increase labor demand suggesting that when firms are offered free recruitment services that improve the firm-worker matching, they hire more.

The literature that studies the effect of PLMPs on labor market outcomes, such as the impact of UI on labor market outcomes also provides mixed results. Although there is a consensus that the longer the time period of offered UI is, the longer the unemployment duration is (Tatsiramos 2009)[9], there is no consensus about the effect of unemployment benefits on job quality (Tatsiramos 2014). For instance, Lalive (2007) using administrative data from Austria finds that extended unemployment benefits do not affect the duration of a successful job search and that changes in benefit duration do not affect the quality of jobs after unemployment ends. Moreover, Van Ours and Vodopivec (2008) using administrative data from a natural experiment in Slovenia examine whether shortening the duration of unemployment benefits affects the quality of jobs after unemployment episodes. They do not find evidence that shortening the duration of unemployment benefits leads workers to accept lower-quality jobs, temporary and low-pay jobs. Nekoei and Weber (2017) using Austrian data and taking advantage of a discontinuous change in benefit eligibility in the UI system find a positive effect of benefit duration

[9] For a literature review on the effects of unemployment insurance design on labour market outcomes see Tatsiramos and Van Ours (2014).

on re-employment wages. Also, Caliendo et al. (2013) use a sharp discontinuity design based on labor market reforms in Germany, find that German men who stay longer on unemployment insurance find jobs that last longer and pay higher wages.

In terms of wages, a recent paper by Bertheau et al. (2023) using harmonized matched employed-employee data for seven European countries finds significant heterogeneity in earnings losses after job displacement due to a mass layoff or workplace shutdown. However, they find heterogeneous effects not only across but also within countries. Moreover, they find that earnings losses and differences in workers' characteristics do not explain much of the differences in earnings losses across countries, but what explains most of the cross-country earnings differences is how active labor market policies work across countries.

It becomes evident that the literature on the effectiveness of LMPs on labour market outcomes is voluminous and, in several cases, mixed results emerge. We aim to fill this gap in the literature and advance our understanding of the topic. To our knowledge, our study is the first one to provide an international comparison between 23 European countries and Israel on the impact of ALMPs and PLMPs expenditures on various labor market outcomes drawing on a novel retrospective dataset. In fact, we build upon the paper of Andrews et al. (2019) that utilizes SHARELIFE and OECD data to investigate the impact of LMPs two on the re-employment probability and re-employment duration.

Our paper differs from Andrews et al. (2019) along several important dimensions. First, we incorporate more recent data by utilizing two SHARELIFE waves instead of one. In what follows, we extend the sample to 24 countries (instead of 13) over the period 1985 to 2017 (instead of 1985-2008), allowing us to investigate in total 4,565 job displacements due to firm closure.[10] Second, we assess the impact of LMPs on two additional important labour market outcomes, that is, the unemployment hazard and re-employment wages. Third, we explore the cross-regional and cross-gender dimensions. Overall,

[10] Andrews et al. (2021) have the following 13 countries in their sample: Austria, Belgium, Czech Republic, Denmark, France, Germany, Greece, Italy, the Netherlands, Poland, Spain, Sweden and Switzerland. On top of the above countries we add the following countries: Estonia, Finland, Hungary, Ireland, Israel, Latvia, Lithuania, Luxembourg, Portugal, Slovakia, Slovenia. Thus, we have 24 countries in our sample. The use of more recent data and the addition of the extra countries allow for a more recent and broader picture of active and passive labor market policies to be drawn for Europe. The OECD dataset does not provide information for labor market policies for Bulgaria, Croatia, Cyprus, Malta, Romania. Thus, we do not merge these countries to the SHARELIFE data.

by doing so, we aim for a more comprehensive examination of the topic which will provide further insights into the role of LMPs in shaping labour market outcomes and thus provide a bigger picture.

4. Data

We utilize data from two sources. As a starting point, we employ retrospective data on labor market trajectories drawn from SHARELIFE and specifically from the Jobs Episodes Panel dataset (henceforth, JEP). The latter is generated using life-course data obtained from SHARELIFE Wave 3 and SHARELIFE Wave 7.[11] Respondents in the JEP dataset answered questions relevant to their employment status, job characteristics, the reason for job displacement, and wages throughout their working life cycle. The JEP dataset also includes other individual-level information such as demographics as well as family and human capital characteristics. Expenses on ALMPs and PLMPs as a share of the GDP are obtained from the OECD.

The analysis covers the period 1985-2017 and includes individual-level data for 23 European countries plus Israel.[12] [13] Eligible individuals in our analysis are individuals between the ages of 19 and 64 that lost their jobs due to business closure which is considered an exogenous shock.[14] In total, we have 3,700 individuals and 4,565 observations.[15] The JEP dataset details the reason the individual lost their job in seven categories: "I resigned", "I was laid off", "by mutual agreement", "my plant or office closed down", "a temporary job had been completed", "I retired" and "other reason". Table A1 in the Appendix provides the distribution of responses for each one of the above outcomes suggesting that "my plant or office closed down" is the fourth more populous response and makes up 8.84% of the answers. Thus, the fact that job loss due to firm closure is a widespread phenomenon, as well as an

[11] Description and methodological details can be found in Brugiavini et al. (2019) and Antonova et al. (2014).
[12] OECD reports labor market data from 1985 onwards, hence, this is starting observation year. Similarly, the JPE dataset provides employment histories until 2017, which is the last year of our sampled period.
[13] In some cases, (i.e., Eastern European countries) the OECD data start after 1985. Table A2 in the Appendix reports the list of countries and their time horizon in our analysis.
[14] Individuals are either employed in the public or private sector. Self-employed individuals are dropped from the sample as closing down your business is not a purely exogenous decision (781 observations).
[15] We allow individuals to be displaced more than once during their work lifecycle. We report qualitative similar results when we keep only the first occurrence of displacement.

exogenous event that has individual, family and society repercussions, it makes it an important topic to be studied with respect to labor market policies.

Table 1 reports summary statistics. We start by briefly presenting descriptive statistics for the individual level variables and then in the following sub-sections we present descriptive statistics for the aggregate labor market policy variables and their components. Around 54% of the individuals are females and the average age is approximately 46 years. Almost 80% of the respondents are married, the average number of children in the household is around two, and 61% of the respondents report excellent or very good childhood health. On average, at the time of displacement, individuals have 15 years of tenure and have completed 14 years of education. In addition, 60% of the individuals found a job one year after displacement, while the average duration an individual stayed employed in the job following displacement is approximately 8 years and the average years of unemployment is almost 3 years.

<< Table 1 here>>

4.1 Labour Market Policies and Expenditures

As we outlined in Section 2 above, ALMPs describe demand- and supply-side interventions that aim to integrate individuals into the labor market or prevent them from losing their jobs. In terms of expenses, the OECD groups them into six categories: i) "*Public Employment Services and Administration"* (hereafter *PES*) refers to services that connect employers with jobseekers; ii) "*Training"* describes training programs aiming at providing individuals with the right skills before they apply for a job; iii) "*Employment Incentives"* includes recruitment and employment maintenance incentives as well as targeted schemes for job rotation and sharing; iv) "*Sheltered and supported employment and Rehabilitation"* (hereafter *Supported Employment*) provides financial support and vocational rehabilitation to individuals with reduced working capacity; v) "*Direct job creation*" refers to interventions targeting the creation of additional jobs and vi) "*Start-up incentives"* refers to programs that encourage entrepreneurial activities aspiring to motivate individuals to initiate their own business. On the other hand, PLMPs aim to compensate unemployed individuals and the OECD splits them into two main categories: i) "*Out-of-work income maintenance and support*" (hereafter *Out-of-work income)* relates to unemployment insurance and assistance as well as to benefits and compensations to out-of-work individuals and ii) "*Early retirement"* includes policies concerning the early retirement of older individuals that either might have lower possibilities of finding a job or/and its retirement will give the chance to a relevant jobseeker to take their place.[16]

<< Figure 1 here>>

We summarize the OECD data through graphical analysis. **Figure 1** illustrates the levels of ALMPs and PLMPs expenditures expressed as a percentage of the GDP for each country in our sample. Public spending on labor market policies reveals substantial heterogeneity across countries. Except in the Czech Republic, Lithuania and Sweden, expenditures on ALMPs are lower than expenditures on PLMPs. On average, expenditures on ALMPs range from 0.17% in Israel to 1.6% in Denmark. The top three countries in ALMPs expenses are the Netherlands, Sweden and Denmark and the bottom three countries are Greece, Estonia and Israel. Expenditures on PLMPs range from 0.21% in the Czech Republic to 2.74% in Denmark. The top three countries in terms of PLMPs expenses are Spain, Belgium and Denmark and the bottom three are Greece, Lithuania and Czech Republic.

<< Figure 2 here>>

Figure 2 shows the association between ALMPs and PLMPs. There is a linear and positive relationship between the two variables suggesting that countries that spend more on one policy also spend more on the other. The raw correlation coefficient between ALMPs and PLMPs is 0.66.[17] Almost all the countries are located around the 45 degrees linear line, but there are some outliers. For instance, Sweden spends considerably more on ALMPs compared to PLMPs, whereas Belgium and Spain do the opposite. Denmark spends more on both than any other country.

<< Figure 3 here>>

[16] More information on the coverage and classification of the Labor Market Programs is provided by OECD (2015) in this link: https://www.oecd.org/els/emp/Coverage-and-classification-of-OECD-data-2015.pdf
[17] The correlation coefficients between the aggregate and the disaggregate LMPs are provided in Table A3 in the Appendix.

Figure 3 shows two-time series lines, one for ALMPs and one for PLMPs and suggests (as also shown in Figure 1) that expenses on PLMPs are always higher than expenses on ALMPs. It further shows that the PLMP series is more volatile in recessions. For instance, during the early 1990s crisis as well as during the Great Recession the PLMP line shows a spike relative to a smoother adjustment of the ALMPs line. There is some convergence between the two time-series after 2000. This captures the changing preferences of governments to support labor market activation programs as opposed to passively supporting the unemployed (Hujer and Caliendo, 2001).

<< Figure 4 here>>

Figure 4 depicts the evolution of ALMP expenditures over time and by category. In terms of time variation, it shows that ALMP expenses per category vary significantly over time and also depicts that the highest share of the ALMPs expenditures goes to training and the lowest to start-up incentives. The more volatile time series lines are those of *Training* and *Direct job creation*.

<< Figure 5 here>>

Figure 5 breaks down PLMPs by category and presents their evolution of their corresponding expenditure over time. It shows that expenses on PLMPS are driven primarily by *Out-of-work income* as opposed to *Early retirement* which its evolution remains very low and almost constant over time.

<< Figure 6 here>>

Figure 6 illustrates the share of individuals that lost their jobs due to business closure over time as a share of the total job losses (SHARE data). As expected, the job loss time series line peaks in the early 1990s crisis as well as during the Great Recession and flattens out before and after these two events.

5. Econometric framework

The three dependent variables we analyze differ in their unit of measurement. Thus, we employ alternative econometric estimators. In what follows, we initiate our analysis by estimating the re-employment probability using a probit regression model. We continue our analysis by employing an

OLS regression model to estimate the effect of LMPs on employment duration after displacement. Finally, we investigate the duration and risk of unemployment using a Weibull parametric regression survival-time model.

5.1 Re-employment probability

The general form of the estimated equation used is given by the following equation:

$$Reemployment_{ict} = \beta_0 + \beta_1' \boldsymbol{X}_{ict} + \sum_j \beta_2' LMP_{ct}^j + \gamma_c + \gamma_t + \gamma_d + \varepsilon_{ict} \qquad (1)$$

where $Reemployment_{ict}$ takes the value of 1 if the individual *i*, in country *c*, lost their job due to business closure in a given year *t* and found a job within the next year, zero otherwise. *X* is a vector of individual-level controls which controls for gender, age and its quadratic term divided by 100, years of education, years of job tenure, marital status, number of children, and an indicator of health status.

LMP is a set of labor market policy expenses (j) which vary at the country level *c* and over time *t*. These labor market policies enter the equation at the aggregate level as ALMPs or PLMPs or at the disaggregate level as separate categories (six categories for ALMPs and two categories for PLMPs). We use the log of these policies.[18] Country fixed effects are denoted by γ_c, time (year) fixed effects by γ_t, and industry fixed effects by γ_d.[19]

5.2 Duration of re-employment

The dependent variable, $DurationEmpl_{ict}$ captures the number of years in employment (i.e., the first employment following displacement) for an individual *i*, in country *c*, after re-employment. This equation is estimated using a linear probability model and takes the following form:

$$DurationEmpl_{ict} = \beta_0 + \beta_1' \boldsymbol{X}_{ict} + \sum_j \beta_2' LMP_{ct}^j + \gamma_c + \gamma_t + \gamma_d + \varepsilon_{ict} \qquad (2)$$

[18] This is another difference of our paper compared to the Andrews et al. (2019), who they enter LMPs linearly.

[19] In a robustness check exercise, we also included variables at the macroeconomic level such as the growth rate of the GDP per capita, and the unemployment rate as well as variables that capture other labor market institutions as the strictness of employment protection legislation (EPL). The findings are in line with the baseline estimates and the results are available upon request.

5.3 Duration and risk of unemployment

To quantify the risk of an individual staying unemployed following job displacement, we estimate a Weibull parametric regression survival-time model. Defining λ and α as the scale and location parameters, respectively, the hazard and survivor functions have the following forms:

$$S(t) = exp(-\lambda t^{\alpha}) \quad \text{(3a)}$$

$$h(t) = \alpha\lambda t^{(\alpha-1)} \quad \text{(3b)}$$

Under this specification, the outcome (i.e., duration) variable, *DurationUnempl* measures the number of years an individual remained unemployed following job displacement. In other words, it captures the amount of time it takes until a certain event (that is, being re-employed) occurs.[20]

6. Results

6.1 Baseline estimates

Consistent with the econometric framework presented in the previous section, we report the main findings of our analysis in **Table 2,** which consists of the above three regression models. More precisely, model (1) consists of the prospects of re-employment one year after displacement, model (2) quantifies the effect of LMPs on the duration of the new job found after displacement, and model (3) assesses the risk of an individual staying unemployed following an unemployment spell. Overall, we find strong evidence that ALMPs expenses lessen the impact of unemployment in all specifications, while PLMPs expenses have disincentive effects for entering employment.

<< Table 2 here>>

Column 1 shows that higher expenditure in ALMPs is linked with a higher probability of re-employment one year after displacement. For instance, the estimated parameter of the ALMPs suggests that a 100% increase in ALMPs expenditures increases the probability of re-employment by 8.87 percentage points. In contrast, higher expenditure in PLMPs decreases the probability for a displaced worker to find a job one year after the unemployment spell occurred. In the same vein, a 100% increase

[20] There are some cases where the individual either retired after displacement or we stop observing him in the sample data. We drop these cases as the minimum unemployment duration we allow in our sample under this specification is set to 1 year.

in PLMPs expenditures decreases the probability of re-employment by 15.1 percentage points. Thus, the estimated negative effect of PLMPs offsets the positive effect of ALMPs.[21] Other results from Column 1 suggest that displaced female workers are less likely to find a new job compared to males, while younger and more educated individuals are more likely to find a new job following a job displacement.[22] The length of time (tenure) an individual has worked in his previous job is negatively associated with the probability of finding a new job suggesting some evidence of firm-specific human capital.

Column 2 shows that ALMPs expenses are positively associated with longer re-employment duration. For instance, the estimated coefficient of the ALMPs variable suggests that a 100% increase in ALMPs expenditures increases the duration of employment by 13.4 years. This is a large effect given that the average years of employment in our sample is 8 years. In contrast, the same percentage increase in PLMP expenditures leads to a 22.1 decrease in years of employment.[23] Although we observe differences in terms of magnitude that might be attributed to different sample sizes, different time periods as well as different model specifications, overall, these results are in accordance with the findings reported by Andrews et al. (2019). Further, females as well as individuals who are relatively older, with lower job tenure, with worse health, and with children are more likely to experience a shorter employment duration.

Finally, column 3 shows that the higher the investment in ALMPs is, the faster individuals get out of unemployment.[24] In other words, ALMPs lower the risk of staying unemployed. Higher expenditures in PLMPs are associated with higher unemployment duration, and thus individuals will terminate unemployment at a slower pace. As in Columns 1 and 2 above, the estimated effect of the PLMP estimate offsets the ALMP estimated effect.[25]

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[21] As expected the two coefficients are statistically significant from each other given their opposite sign and high precision they are estimated [chi2(2)=40.07, p.val=0.0000].

[22] As individuals get older, the effect of age is lessened.

[23] The negative estimated effect of PLMPs offsets the positive effect of ALMPs and the two estimates are statistically different from each other [F(2,131)=8.98, p.val=0.0002].

[24] A positive (negative) coefficient is connected to lower (higher) unemployment duration or in other words, unemployment will be terminated faster (slower).

[25] Again, the two effects are statistically different from each other [chi2(2) = 27.34, p.val = 0.0000].

There are many empirical papers pointing in the direction of our results. For instance, de Serres et al. (2012) and Gal and Theising (2015) find that higher spending in ALMPs boosts employment while investing in PLMPs affects employment rates negatively. In the same vein, Andrews et al. (2019) point out the benefits of investing in ALMPs in increasing re-employment prospects and employment duration, and at the same time highlights the impact of investing in PLMPs on unemployment duration.

6.2 Interaction Effects

As we have argued above, PLMPs can delay the unemployed to get back to employment through searching longer for a job, re-applying for benefit extension, or even withdrawing from the labor market completely. On the other hand, ALMPs aim to incentivise the unemployed to get back to work. Although ALMPs and PLMPs may serve different purposes, they target the same group and are often co-ordinated. Thus, they can be thought as complementary policies (Boeri and Van Ours, 2013). Thus, in this sub-section we examine the complementarity effects of ALMPs and PLMPs by adding their interaction term as an additional explanatory variable in our baseline specification.

Table 3 presents the results and shows that the interaction term between ALMPs and PLMPs is negative and statistically significant across all specifications. This suggests that increasing both LPM expenditures leads to a negative effect on all labor market outcomes. Possibly this happens because as we saw in Table 2, the negative PLMPs estimates always offset the positive ALMPs estimates. Column 1 suggests that if the expenditures on PLMPs are zero, then ALMPs have a positive and significant effect on the re-employment probability. By the same argument, if the expenditures on ALMPs are zero, then PLMPs have a negative and significant effect on the re-employment probability. The interpretation of their interaction term is the effectiveness of ALMPs (PLMPs) on the re-employment probability for a percentage change in PLMP (ALMPs) expenditures. The results in Column 1 suggest that the higher the increase in PLMP expenditures the lower the effectiveness of the ALMPs. For instance, a 100% increase in the PLMPs expenditures decreases the effectiveness of the ALMPs on the re-employment probability by 5.10 percentage points. Also, the total effect of both LMPs on the re-employment probability is negative if we assign to ALMPs and PLMPs their mean values (-0.040). However, this total effect is lower in magnitude than what the addition of the separate coefficients of ALMPs and PLMPs would suggest from Table 2 (-0.123).

<< Table 3 here>>

6.3 Empirical findings: LMPs Categories

The previous section provides clear evidence about the role of the aggregate measures of Active and Passive LMPs expenses in shaping labor market outcomes. However, the aggregate expenditure on labor market policies could mask significant heterogeneity between the sub-components of the two LMPs. Thus, it could be meaningful for policymakers to know which labor market programs have the most significant impact on the labor market outcomes we study. For this reason, we replicate the analysis presented in Section 6.1, but, this time, we split LMPs into their corresponding components.

<< Table 4 here>>

Table 4 summarizes the findings which are quite revealing across many dimensions. In terms of ALMP expenses the results reveal significant heterogeneity across the six components. In particular, the policies of *Supported employment* and *Start-up incentives* increase the re-employment prospect (Column 1) and, at the same time, are associated with a lower risk of staying unemployed (Column 3). The latter result is also confirmed by Caliendo and Künn (2011), which state that *Start-up subsidies* can be of major importance. In addition, spending in *PES* is found to make the labor market more efficient, leading to higher employment duration (Column 2). This finding complements the existing literature supporting the effectiveness of *PES,* such as in Boone and Van Ours (2009) and Bassanini and Duval (2006).

Not all the ALMPs components contribute to reducing unemployment. Surprisingly, spending on *Employment incentives* seems to have an inverse effect on the re-employment probability, and it also increases the risk of unemployment duration. Although there is little scientific understanding of the negative effect of employment maintenance incentives and job rotation policies on creating work disincentives, one could attribute the latter to inappropriate management and implementation of these policies (Escudero, 2018). In terms of the two PLMPs components, it is *Out-of-work income* that affects negative all three labor market outcomes. Early retirement has a negative but not statistically significant effect across all three columns.

6.4 Regional Heterogeneity

Having assessed the impact of Active and Passive LMP expenses on labor market outcomes, we now turn our interest to whether the findings are driven by institutional differences across countries. For this reason, we follow the existing literature (Trevisan and Zantomio, 2016; Jolly and Theodoropoulos, 2023) and we divide countries into four homogeneous groups: Eastern (Czech Republic, Slovenia, Slovakia, Poland, Hungary, Estonia, Latvia, Lithuania), Northern (Finland, Sweden, Denmark, Netherlands), Western (France, Luxemburg, Switzerland, Austria, Belgium, Germany, Ireland), and Southern (Greece, Italy, Portugal, Spain and Israel).

Before presenting the results from the multivariate analysis, we present the Kaplan-Meier estimates comparing unemployment duration across the four regions. The vertical axis of Figure 7 shows the proportion of individuals surviving (that is, the proportion of individuals exiting unemployment), and the horizontal axis represents time in years. The separate stepped curves show that workers in Southern countries face a significantly higher risk of staying unemployed compared to workers from the other three regions.[26]

<< Figure 7 here>>

<< Table 5 here>>

Table 5 reports the results using the aggregate LMPs measures for each region. Panel A shows that higher expenditures in ALMPs are associated with a higher probability of re-employment one year after displacement and this is mainly driven by Eastern countries. In contrast, PLMPs significantly decrease the probability of re-employment in Eastern and Northern regions.

Our results for the Eastern region are in line with a series of papers based on transition of Eastern or Central European countries. For instance, Boeri and Burda (1996) use quarterly data for the

[26] Testing the equality of the survivor functions using a log-rank test shows that all four survivor functions are independent from each other [chi2(3)=191.32, p.val=0.0000)].

Czech Republic and find a small but statistically significant effect of ALMP expenditures from unemployment into employment. They argue that this positive effect works through more intensive supervision by PES offices suggesting more careful screening of vacancies and job seekers and better placements. Evidence from Romania suggests that training and retraining, self-employment assistance, and public employment and relocation services had success in improving employment outcomes. In contrast, public employment was found detrimental to the employment prospects of its participants (Rodríquez-Planas and Benus, 2010). Also, for Romania Rodríquez-Planas (2010) presents evidence of a 20 percent increase in the employment probability due to job search assistance in Romania. Van Ours (2001) reports that hiring subsidies in Slovakia seem the most efficient active labor market policy. Another paper for Slovakia by Lubyova and Van Ours (1999) finds that unemployed workers who accept temporary ALMP jobs (publicly useful jobs) or follow re-training programs are immensely more likely to obtain regular jobs after participating in these two programs. Evidence from Hungary shows that training increases the probability of re-employment and job duration but does not increase earnings, whereas public service employment does not increase the employment probability and can reduce re-employment earnings (O'Leary, 1997). Kluve et al. (2008) using micro data from the Polish Labor Force survey, find that training has a positive treatment effect on employment probabilities whereas subsidized employment (i.e., wage subsidy schemes) have negative treatment effect. Vodopivec (1999) using data from Slovenia finds that public work programs (i.e., jobs for the unemployed in public or non-profit organizations) increase the employment probability in the short-run, but decrease it in the long-run.[27]

Panel B shows that ALMPS significantly increase the probability of employment duration in Eastern and Western regions. In the case of the Eastern region the positive effect of ALMPs by more than offsets the negative effect of PLMPs.[28] Expenses on PLMPs have a negative and significant effect in Eastern and Northern regions. Panel C shows that ALMPs significantly reduce the risk of unemployment duration for the Eastern region only. Again, the magnitude of the coefficient of ALMPs

[27] A recent paper for Slovenia by Burger et al. (2022) studies four labor market outcomes in Slovenia (institutional training, on-the-job training, wage subsidies and public works) and finds that all four programs have a positive effect on employment probability and job quality and that except public works all programs are cost effective.
[28] The difference is statistically significant [F(2,37)=5.55, p.val=0.0078].

is higher than the estimated magnitude of the PLMPs.[29] Again, PLMPs significantly increase the risk of unemployment duration for the Eastern and the Northern regions.

Notably, the findings above suggest that the effectiveness of ALPMs and PLMPs vary across regions. Although Eastern countries report relatively low expenditures in LMPs as we show in Figure 1, their effectiveness is more profound compared to the other countries. One interpretation of this finding could be that since the Eastern countries went through or still undertake a number of structural reforms, then one Euro invested in the labor market of an Eastern (transition) country has a bigger impact than a Euro invested in the labor market of a non-transition country.

6.5 Regional Heterogeneity - Interactions

Turning our interest to **Table 6** where the cross-regional analysis with the interaction effect is presented, we observe a number of different patterns. In Panel A (re-employment probability) we see that the cross-interaction term is positive but not significant for Northern countries and negative and highly significant for the Western countries. For Eastern and Southern countries, the interaction effect is negative but not significant. For Panel B (employment duration), the cross-interaction term is positive and highly significant for Northern countries. This new result in the literature with respect to employment duration suggests that spending more on both policies increases the employment duration. If we give the two LMPs their mean values, then we see that the total effect is positive (0.242). An alternative interpretation of the above results is that the adverse impact of PLMPs employment duration is lower in countries that spend more on ALMPs.[30] As shown in Figure 1, this is indeed the case for the Netherlands, Finland, Sweden and Denmark. Again, the interaction term is negative and significant for the Western countries. When examining unemployment duration in Panel C, then we again see that the interaction term is negative and significant for the Western countries only.

Overall, these findings highlight the importance of the ALMPs in ameliorating the employment prospects of unemployed people and in mitigating the negative effects of PLMPs. In addition, they

[29] The differences between the respective coefficients of ALMPs and PLMPs are statistically significant in Eastern and Northern countries. The relevant equality tests are available upon request.
[30] This result is in line with Bassanini and Duval (2006) who in another setting find that the positive effect of unemployment benefits on unemployment is lower in countries that spend more on ALMPs.

highlight how differently the interaction of ALMPs and PLMPs work across Europe and suggest evidence of complementarities between the two policies only for the Northern countries.

<< Table 6 here>>

6.6 Regional Heterogeneity: LMPs Categories

The aggregate estimates mask considerable heterogeneity among the different components of the two LMPs. In what follows, **Table 7** reports findings for each component of the ALMPs and PLMPs. Panel A and column 1 show that for Eastern countries, training, and supported employment have a positive and statistically significant effect in increasing the re-employment probability. As Column 2 shows, in Northern countries, *PES*, *Employment incentives* and *Start-up incentives* have positive and significant effects in increasing the re-employment probability. In contrast, *Supported employment* has a negative and statistically significant effect in reducing the re-employment probability. As Column 3 presents, in Southern countries *Supported employment* has a positive and statistically significant effect whereas *Direct job creation* has a negative and statistically significant effect. The magnitudes of the coefficients of these two estimates as well as their associated standard errors are high suggesting that they are estimated on a smaller sub-sample.

Interestingly and in sharp contrast to the other regions as well as to the results above, *Out-of-work income* has a positive and statistically significant effect in increasing the re-employment probability. Consistent with Tatsiramos and van Ours (2014), well-designed unemployment insurance schemes could create incentives to find a job, and thus, increase the re-employment probability. Column 4 shows that *Direct job creation* significantly increases the probability of re-employment in Western regions, whereas *Employment incentives* significantly reduce it. These two effects seem to offset each other and their estimated effects are not statistically different from each other.

Panel B shows that PES, *Direct job creation* and *Start-up incentives* significantly increase employment duration in Eastern countries. Column 2 shows that for Northern countries *Employment incentives* increase the duration of employment, whereas *Direct job creation* reduces it. Column 3 shows that for the Southern countries, none of the separate components of ALMPs or the PLMPs has a significant effect on employment duration. Column 4, shows for the Western countries that *Employment* *incentives* significantly reduce employment duration. This finding is in sharp contrast to the Northern countries (Column 2) which shows a positive and significant effect of *Employment incentives* in increasing employment duration.

Column 1 of Panel C shows that for Eastern countries *Supported employment* significantly reduces the risk of staying unemployed. Column 2 shows that for Northern countries *PES* and *Start-up incentives* significantly reduce the risk of staying unemployed. Column 3 shows that *Supported employment* significantly decreases the risk of staying unemployed in Southern countries, whereas column 4 suggests that *Employment incentives* significantly increase the risk of staying unemployed in Western countries. *Out-of-work income* is negative and statistically significant for Eastern and Northern countries only suggesting higher risk of unemployment duration.

<< Table 7 here>>

6.7 Gender analysis

In this sub-section we replicate the baseline analysis, focusing separately on females and males. In what follows, we present **Table 8**. Columns 1 and 2 show the results for the re-employment probability and suggest that the ALMPs coefficient is positive and statistically significant only for females. This higher effect remains true when looking at the duration of employment (Columns 3 and 4) as well as when looking at the risk unemployment duration (Columns 5 and 6). This finding corroborates previous literature that has found that ALMPs have positive and larger effects on women rather than on men. For instance, our results are in line with the results presented by Bergemann and Van den Berg (2008) who review sixteen individual level studies across Europe and find that many ALMPs have positive effects on employment outcomes for women especially in countries with low female labor force participation rate. Lechner and Wiehler (2011) examine gender differentials across ALMPs in Austria and suggest that the positive effect of ALMPs for women is working through the unintended effect of ALMPs in reducing or postponing pregnancies for women as well as by reducing parental leave. In other words, they find that ALMPs increase labor force participation for women. Caliendo and Künn (2015) using German administrative and survey data examine the impact of two start-up ALMPs (bridging allowance and start-up subsidy) on bringing women back to work through establishing their own business. Their results suggest that in the long run both programs were very successful in integrating women back to work and that their effect was about four times higher than other ALMPs programs offered to women. Also, in contrast to Lechner and Wiehler (2011) they find no penalized effect on fertility due to participating in the program. Their results suggest that helping women to choose self-employment as opposed to paid-employed allows a higher degree of flexibility in allocating their time to work in the market place and in the household and family thus enhancing their employment chances. Bergemann et al. (2017) using micro data from an East German examine the impact of job creation schemes on job search outcomes after the re-unification of the East with the West Germany. They find that female and skilled individuals have a higher probability of leaving unemployment faster than men. This finding suggest that skilled women benefit more from participation in job creation schemes.

<< Table 8 here>>

Table 9 shows the results by gender for each sub-component of the ALMPs and PLMPs. For females, *Supported employment* significantly increases the probability of re-employment as well as it reduces the risk of unemployment duration. Also, *Start-up incentives* significantly increase the duration of employment for females. For males, we find a positive and statistically significant effect for *Start-up incentives* in increasing the re-employment probability and for *PES* in increasing employment stability. However, *Employment incentives* significantly decrease the re-employment probability and increase the risk of unemployment for males. Finally, as above we observe that *Out-of-work income* has negative effects for both males and females and for all three labor market outcomes.

These results are in line with previous literature. For instance, Terrell and Sorm (1999) use micro data from the Czech Republic and find that women are more likely than men to exit unemployment through a district labor office job than to exit unemployment through a job they find on their own suggesting that labor offices are more likely to target women. This is further supported by their finding that women were more likely to receive help from local labor offices at any time compared to men with the same characteristics. Kluve et al. (1999) using quarterly labor force data from Poland focus on three ALMP schemes: training and retraining, subsidized employment, and direct public employment. They find that training of men and women has a positive effect on the employment probability. For men, subsidized employment and direct public employment have negative treatment effects, while participation in subsidized employment does not affect women's employment probabilities. They attribute the negative treatment effects for men to benefit churning rather than to stigmatization of intervention and public works participants. However, Lubyova and Van Ours (1999) use data from Slovakia and find stronger effects for males than for females in finding a regular job after participating in ALMP jobs and in re-training programs.

<< Table 9 here>>

6.8 Wages before and after displacement

The last part of our empirical framework refers to the association between LMPs and the level of re-employment wages. For this reason, we define *wagepct* to be the percentage change between the initial wage (i.e., the wage of the last job before displacement) and the final wage (i.e., the wage of the first job after displacement).[31]

While labor market policies' responses to re-employment wages are of particular interest, this approach has to be seen in light of some limitations arising from the nature of our data. Although the starting wage for each job of each respondent is available, this is not always the case with the final wage which is only available for the main job of each respondent.[32] Given the latter, in such cases, we assume that for each job spell, the starting wage equals the final wage. In this specification, our sample consists of 21 countries and 1,274 observations. Greece, Ireland and Israel were dropped from the sample due to insufficient information on wages. Although on average, re-employment wages are found to have increased by 1.84 times, significant cross-country variation does exist. More specifically, in Poland, on average re-employment wages are decreased by approximately 24.9%, while in Slovenia and Latvia are increased by 10.7% and 22.3%, respectively. The higher increase is recorded in Austria, the Czech

[31] To correct for price differences across countries we use the PPP exchange rates as provided by OECD and we express wages in terms of national currency per US dollar. See here: https://data.oecd.org/conversion/purchasing-power-parities-ppp.htm

[32] Even if we had information on the final wage for all the observation that would also be problematic as according to Jacobson et al. (1993) using the last wage in our set-up is problematic because of anticipatory wage effects due to firm closure.

Republic and Hungary were reemployment wages are on average 2.45, 2.35 and 3.14 times higher than the pre-employment ones, respectively.

In what follows, we employ a quantile regression approach with country-fixed effects proposed by Canay (2011) to quantify the effect of LMPs on the whole conditional distribution of wages. We rely on a quantile regression model for two reasons. First, it allows us to quantify the effects of LMPs on wages by focusing on the entire conditional distribution of wages rather than estimating only conditional means. This could be quite informative as one could expect that labor market policies would aim to recover the level of re-employment wages of the most affected displaced workers. Thus, investigating the behavior at the tails of the distribution of wages offers a comprehensive picture of the relationship. Second, quantile regression performs well in the presence of non-normally distributed variables such as wages with possible outliers. As we can see in Figure A1 in the Appendix the distribution of *wagepct* is right-skewed, giving us confidence towards the chosen methodology.[33]

More precisely, the quantile regression approach proposed by Canay (2011) involves two steps. In the first step, we estimate Equation (4) using a fixed effects regression technique. In the second step, we capture the country fixed effects (γ_c) and subtract them from *wagespct* (i.e., our dependent variable). The so-called "two-step estimator" is obtained by estimating Equation (4) using a standard quantile regression approach (but setting the dependent variable equal to $\hat{y} = log(wagepct) - \gamma_c$).

$$\log\,(wagepct_{ict}) = \beta_0 + \beta_1' \boldsymbol{X}_{ict} + \sum_j \beta_2' LMP_{ct}^{j} + \gamma_c + \gamma_t + \gamma_d + \varepsilon_{ict} \quad (4)$$

<< Table 10 here>>

Table 10 presents the results from the quantile regression for the full sample (columns 1-2), for females (columns 3-4) and for males (columns 5-6). In the last row, for reasons of comparison, we also report the conditional mean estimates from a country fixed effects regression model. In all specifications, and as in the previous equations, demographic controls, time and industry dummies as well as a constant term is included. We report only the coefficients of the variables of interest are presented.

[33] We drop extreme cases where the *wagepct* is higher than 10 (that is, cases where the wage of the new job is 10 times higher than the initial one).

Columns 1 and 2 suggest that ALMPs show a positive and statistically significant effect at the bottom two deciles, but a negative and statistically significant effect at the median and at higher level deciles of the conditional distribution of wages. This result could suggest that although ALMPs increase the probability of re-employment as well as the employment duration, they do not lead to high status jobs. In contrast, PLMPs show a negative and statistically significant effect at all deciles below the median.

Columns 3 and 5 suggest that ALMPs have positive and statistically significant effects at the bottom end of the of the conditional distribution of wages for both males and females. However, the magnitude of the effect of ALMPs in the female sample is approximately twice as high to that in the male sample and more precisely estimated despite the female sample having almost the same number of observations as the male sample.

While the fixed effects estimates fail to support the role of LMPs in shaping re-employment wages at the conditional mean as all estimates are insignificant, this is not the case for quantile regression that shows further insights into the relationship of interest. We illustrate the coefficients of ALMPs (PLMPs) across quantiles of the conditional distribution of wages in Figures 8 (9) respectively. The shaded areas correspond to the confidence interval at the 90% level. The dashed lines represent the corresponding coefficients at the conditional means.

7. Conclusions

We study the effects of ALMPs and PLMPs expenditures on labor market outcomes following an exogenous reason for job loss, that is firm closures. Using harmonized and retrospective longitudinal data across 23 European countries and Israel our results suggest that spending on ALMPs is significantly associated with higher probabilities of re-employment, lower unemployment duration, higher employment duration and relatively higher earnings for low-wage workers based on the conditional distribution of wages. When we disaggregate ALMPs and PLMPs to eight sub-components, we find that different components impact differently not only within labor market outcomes, but also across the labor market outcomes we study. For instance, expenses on *Supported employment* and *Start-up incentives* have positive and significant effects on the re-employment probability and on decreasing unemployment duration, whereas expenses on *PES* increase employment duration. In contrast, PLMPs have negative effects on all labor market outcomes and offset the positive ALMPs effects. The negative effect of PLMP works through of *Out-of-work income*. Interaction effects suggest that more expenditures on both LMP programs have a negative effect on all labor market outcomes.

The heterogeneity results uncover significant differences in ALMPs across regions. For instance, ALMPs have a stronger impact for Eastern countries, whereas PLMPs such us out-of-work income has a positive impact for Southern countries. Also, complementarity effects between ALMPs and PLMPs are found for Northern countries only. Thus, our results uncover significant regional heterogeneity suggesting that labor market institutions in some regions have the potential for mitigating involuntary job losses (Belot and Van Ours, 2004) and that labor markets work differently across Europe (Boeri, 2011). With respect to gender the results reveal that ALMPs favour more women as opposed to men and that PLMPs have almost the same negative effects across both genders.

Overall, our findings suggest that economic incentives do affect individual labor market behavior. At the same time our results suggest that one-size-fits all policy cannot impact the same across countries and across groups. This suggests that policymakers should first consider the existing policy framework they operate in before investing in different institutions in order to combat unemployment, return the unemployed back to work and offer them stable employment and earnings.

References

Ahmad, N., Svaver, M. and Naveed, A. (2019). The effect of active labour market programmes and benefit sanctions on reducing unemployment duration. Journal of Labor Research 40, 202-229.

Algan, Y., Crépon, B. and Glover, D. (2022). Are active labor market policies directed at firms effective? Evidence from a randomized evaluation with local employment. Working Paper. Available from: https://drive.google.com/file/d/1vevIcORw-pqxtDfX4mn_cX721OgnJ4E7/view

Andrews, D., Ferrari, I. and Saia, A. (2019). The costs of firm exit and labour market policies: New evidence from Europe. The B.E. Journal of Economic Analysis & Policy 20170211.

Antonova, L., Aranda, L., Pasini, G., and Trevisan, E. (2014). Migration, family history and pension: the second release of the SHARE Job Episodes Panel. Working Paper Series, 18.

Arpaia, A. and Mourre, G. (2012). Institutions and performance in European labour markets: Taking a fresh look at evidence. Journal of Economic Surveys 26 (1), 1-41.

Bassanini, A. and R. Duval. (2006). The determinants of unemployment across OECD countries. OECD Economic Studies 1, 7-86.

Bassanini, A. and Duval, R. (2009). Unemployment, institutions, and reform complementarities: Re-assessing the aggregate evidence for OECD countries. Oxford Review of Economic Policy 25 (1), 40-59.

Belot, M. and Van Ours, J.C. (2004). Does the recent success of some OECD countries in lowering their unemployment rates lie in the clever design of their labor market reforms? Oxford Economic Papers 56, 621-642.

Bergemann, A. and Van den Berg, G. (2008). Active labor market policy effects for women in Europe – A survey. Annales d'Économie et de Statistique No. 91/92, 385-408.

Bergemann, A., Caliendo, M, Van den Berg, G.J, and Zimmermann, K.F. (2011). The threat effect of participation in labor market programs on job search behavior of migrants in migrants in Germany. International Journal of Manpower 32 (7), 777-795.

Bergemann, A., Pohlan, L. and Uhlendorff, A. (2017). The impact of participation in job creation schemes in turbulent times. Labour Economics 47, 182-201.

Bergmann, M., T. Kneip, G. De Luca, and A. Scherpenzeel (2019). Survey participation in the Survey of Health, Ageing and Retirement in Europe (SHARE), Wave 1-7. Based on Release 7.0.0. SHARE Working Paper Series 41-2019. Munich: MEA, Max Planck Institute for Social Law and Social Policy.

Bertheau, A., Acabbi, E., Barceló, C., Gulyas, A., Lombardi, S. and Saggio, R. (2023). The unequal cost of job loss across countries. American Economic Review: Insights forthcoming.

Brugiavini, A., C. E. Orso, M. G. Genie, R. Naci, G. Pasini (2019). Combining the retrospective interviews of wave 3 and wave 7: the third release of the SHARE Job Episodes Panel. SHARE Working Paper Series (36-2019). Munich: MEA, Max Planck Institute for Social Law and Social Policy.

Brugiavini, A., C. E. Orso, M. G. Genie, R. Naci, G. Pasini (2022). SHARE Job Episodes Panel. Release version: 8.0.0. SHARE-ERIC. Data set. DOI:10.6103/SHARE.jep.800

Boeri, T. (2011). Institutional reforms and dualism in European labor markets. Handbook of Labor Economics 4 Part B, 1173-1236.

Boeri, T. and Burda, M.C. (1996). Active labor market policies, job matching and the Czech miracle. European Economic Review 40, 805-817.

Boeri, T. and Van Ours, J.C. (2013). The economics of imperfect labor markets (2nd edition). Princeton University Press: Princeton and Oxford.

Boone, J. and Van Ours, J.C. (2009). Bringing unemployed back to work: Effective active labor market policies. De Economist 157, 293-13.

Börsch-Supan, A., M. Brandt, C. Hunkler, T. Kneip, J. Korbmacher, F. Malter, B. Schaan, S. Stuck, S. Zuber (2013). Data Resource Profile: The Survey of Health, Ageing and Retirement in Europe (SHARE). International Journal of Epidemiology. DOI: 10.1093/ije/dyt088.

Börsch-Supan, A. (2022a). Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 3 – SHARELIFE. Release version: 8.0.0. SHARE-ERIC. Data set. DOI: 10.6103/SHARE.w3.800

Börsch-Supan, A. (2022b). Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 7. Release version: 8.0.0. SHARE-ERIC. Data set. DOI: 10.6103/SHARE.w7.800

Börsch-Supan, A., Brandt, M., Hank, K. and Schröder, M. (Eds.) (2011). The individual and the welfare state: Life histories in Europe. Springer, Heidelberg.

Brown, A.J.G. and Koettl, J. (2015). Active labor market programs – employment gain or fiscal drain? IZA Journal of Labor Economics 4: 12.

Browning, M. and Heinesen, E. (2012). Effect of job loss due to plant closure on mortality and hospitalization. Journal of Health Economics 31, 599-616.

Brugiavini, A., Orso, C. E., Genie, M. G., Naci, R. and Pasini, G. (2019). Combining the retrospective interviews of wave 3 and wave 7: the third release of the SHARE Job Episodes Panel. Munich Center for the Economics of Aging (MEA), Munich, SHARE Working Paper Series, 36-2019.

Burger, A., Kluve, J., Vodopivec, M. and Vodopivec, M. (2022). A comprehensive impact evaluation of active labour market programmes in Slovenia. Empirical Economics 62, 3015-3039.

Caliendo, M., and Künn, S. (2011). Start-up subsidies for the unemployed: Long-term evidence and effect heterogeneity. Journal of Public Economics 95(3-4), 311-331.

Caliendo, M. and Künn, S. (2015). Getting back into the labor market: the effects of start-up subsidies for unemployed females. Journal of Population Economics 28, 1005-1043.

Caliendo, M., Tatsiramos, K. and Uhlendorff, A. (2013). Benefit duration, unemployment duration and job match quality: A regression-discontinuity approach. Journal of Applied Econometrics 28 (4), 604-627.

Canay, I.A. (2011). A simple approach to quantile regression for panel data. Econometrics Journal 14, 368-386.

Card, D. Kluve, J. and Weber, A. (2010). Active labor market policy evaluations: A meta-analysis. Economic Journal 120, 452-477.

Card, D. Kluve, J. and Weber, A. (2018). What works? A meta-analysis of recent active labor market program evaluations. Journal of the European Economic Association 16 (3), 894-931.

Couch, K. and Placzek, D.W. (2010). Earnings losses of displaced workers revisited. American Economic Review 100 (1), 572-589.

Couch, K., Jolly, N. and Placzek, D.W. (2011). Earnings losses of displaced workers and the business cycle: An analysis with administrative data. Economics Letters 111 (1), 16-19.

Dahlberg, M. and Forslund. A. (2005). Direct displacement effects of labour market programmes. Scandinavian Journal of Economics 107 (3), 475-494.

De Serres, A., Murtin, F. and de La Maisonneuve, C. (2012). Policies to facilitate the return to work. Comparative Economic Studies 54 (1), 5–42.

Doiron, D. and Mendolia, S. (2012). The impact of job loss on family dissolution. Journal of Population Economics 25, 367-398.

Eichhorst, W. and Zimmermann, K.F. (2007). And then there were four… How many (and which) measures of active labor market policy do we still need? Applied Economics Quarterly 53, 243-272.

Elmeskov, J., Martin, J.P. and Scarpetta, S. (1998). Key lessons for labour market reforms: Evidence from OECD countries' experiences. Swedish Economic Policy Review 5, 205-252.

Escudero, V. (2018). Are active labor market policies effective in activating and integrating low-skilled individuals? An international comparison. IZA Journal of Labor Policy 7 (1), 4.

Escudero, V., Kluve, J., Lopez Mourelo, E. and Pignatti, C. (2019). Active labour market programmes in Latin America and the Caribbean: Evidence from a meta-analysis. The Journal of Development Studies 55 (12), 2644-2661.

Forslund, A., Fredriksson, P. and Vikstrom, J. (2011). What active labor market works in a recession? Nordic Economic Policy Review, 172-201.

Gal, P. and Theising, A. (2015). The macroeconomic impact of structural policies on labour market outcomes in OECD countries: A reassessment. OECD Economics Department Working Papers No. 1271.

Gathmann, C., Helm, I. and Schönberg, U. (2020). Spillover effects of mass layoffs. Journal of the European Economic Association 18 (1), 427-468.

Geerdsen, L.P. (2006). Is there a threat effect of labour market programmes? A study of ALMP in the Danish UI system. Economic Journal 116, 738-750.

Graversen, B.K and Van Ours, J.C. (2008a). How to help unemployed find jobs quickly: Experimental evidence from a mandatory activation program. Journal of Public Economics 92, 2020-2035.

Graversen, B.K and Van Ours, J.C. (2008b). Activating unemployed workers works; Experimental evidence from Denmark. Economics Letters 100, 308-310.

Graversen, B.K and Van Ours, J.C. (2011). An activation program as a stick to job finding. LABOUR 25 (2), 167-181.

Heckman, J.J., Lalonde, J. and Smith, J.A. (1999). The economics and econometrics of active labor market programs. In Handbook of labor economics, ed. O. Ashenfelter and D. Card. Amsterdam: Elsiever.

Hujer, R. and Caliendo, M. (2001). Evaluation of Active Labour Market Policy - Methodological Concepts and Empirical Estimates, in: Becker, I., Ott, N. and Rolf, G. (Eds.): Soziale Sicherung in einer dynamischen Gesellschaft, Campus-Verlag, Frankfurt, 583-617.

Huttunen, K., Møen, J. and Salvanes, K.G. (2011). How destructive is creative destruction? Effects of job loss on job mobility, withdrawal and income. Journal of the European Economic Association 9 (5), 840-870.

Hyslop, D., Maré, D., Noy, S. and Sin, I. (2021). Involuntary job loss: Welfare effects, earnings impacts and policy options. Motu Working Paper 21-06.

Jackman, R., Pissarides, C., Savouri, S., Kapteyn, A. and Lambert, J.P. (1990). Labour market policies and unemployment in the OECD. Economic Policy 5 (11), 449-490.

Jacobson, L.S., Lalonde, R.J. and Sullivan, D.G. (1993). Earnings losses of displaced workers. American Economic Review 83 (4), 685-709.

Jolly, N. and Theodoropoulos, N. (2023). Health shocks and spousal labor supply: An International perspective. Journal of Population Economics 36 (2), 973-1004.

Jolly, N. and Phelan, B.J. (2017). The long-run effects of job displacement on sources of health insurance coverage. Journal of Labor Research 38, 187-205.

Kluve, J. (2010). The effectiveness of European active labor market programs. Labour Economics 17, 904-918.

Kluve, J., Lehmann, H. and Schmidt, C.M. (1999). Active labor market policies in Poland: Human capital enhancement, stigmatization, or benefit churning? Journal of Comparative Economics 27, 61-89.

Kluve, J., Lehmann, H. and Schmidt, C.M. (2008). Disentangling treatment effects of active labor market policies: The role of labor force status sequences. Labour Economics 15, 1270-1295.

Kluve, J. and Schmidt, C.M. (2002). Can training and employment subsidies combat European unemployment? Economic Policy 35, 411-448.

Kuhn, A., Lalive, R. and Zweimüller, J. (2009). The public health costs of job loss. Journal of Health Economics 28, 1099-1115.

Lalive, R. (2007). Unemployment benefits, unemployment duration, and post-unemployment jobs: A regression discontinuity approach. American Economic Review 97, 108-112.

Lalive, R. Van Ours, J. and Zweimüller, J. (2008). The impact of active labour market programmes on the duration of unemployment in Switzerland. Economic Journal 118, 235-257.

Lammers, M. and Kok, L. (2021). Are active labor market policies (cost-)effective in the long run? Evidence from the Netherlands. Empirical Economics 60, 1710-1746.

Lechner, M., Miquel, R. and Wunsch, C. (2011). Long-run effects of public sector sponsored training in West Germany. Journal of the European Economic Association 9 (4), 742-784.

Lechner, M. and Winhler, S. (2011). Kids or courses? Gender differences in the effects of active labor market policies. Journal of Population Economics 24, 783-812.

Lechner, M. and Wunsch, C. (2009). Active labour market policy in East Germany. Waiting for the economy to take off. Economics of Transition 17 (4), 661-702.

Lehmann, H. and Muravyev, A. (2012). Labour market institutions and labour marker performance. What can we learn from transition countries? Economics of Transition 20 (2), 235-269.

Ljungqvist, L. and Sargent, T.J. (1998). The European unemployment dilemma. Journal of Political Economy 106, 514-550.

Lubyova, M. and Van Ours, J.C. (1999). Effects of active labor market programs on the transition rate from unemployment into regular jobs in the Slovak Republic. Journal of Comparative Economics 27, 90-112.

Martin, J.P. (2000). What works among active labor market policies: Evidence from OECD countries' experiences. OECD Economic Studies 30. Paris: OECD.

Martin, J.P. (2015). Activation and active labour market policies in OECD countries: Stylised facts and evidence on their effectiveness. IZA Journal of Labor Policy 4 (1), 4.

Nekoei, A. and Weber, A. (2017). Does extending unemployment benefits improve job quality? American Economic Review 107 (2), 527-561.

OECD (2022). Public spending on labour markets (indicator). DOI: 10.1787/911b8753-en (Accessed on June 2022).

O'Leary, C.J. (1997). A net impact analysis of active labour programmes in Hungary. Economics of Transition 5 (2), 453-484.

Pignatti, C. and Van Belle, E. (2021). Better together: Active and passive labor market policies in developed and developing economies. IZA Journal of Development and Migration 12:09.

Pissarides, C. (1992). Loss of skill during unemployment and the persistence of employment shocks. Quarterly Journal of Economics 107 (4), 1371-1391.

Raphael, S. and Winter-Ebmer R. (2001). Identifying the effect of unemployment on crime. Journal of Law and Economics 44 (1), 259-283.

Rodríquez-Planas, N. (2010). Channels through which public employment services and small business assistance programmes work. Oxford Bulletin of Economics and Statistics 72 (4), 458-485.

Rodríquez-Planas, N. and Benus, J. (2010). Evaluating active labor market programs in Romania. Empirical Economics 38, 65-84.

Scarpetta, S., Keese, M., Butler, S., Langenbucher, C. Lauringson, A and Xenogiani, T. (2021). Designing active labour market policies for the recovery. OECD Report. Available from: https://read.oecd-ilibrary.org/view/?ref=1100_1100299-wthqhe00pu&title=Designing-active-labour-market-policies-for-the-recovery

Schwerdt, G., Ichino, A., Ruf, O., Winter-Ebmer, R. and Zweimüller, J. (2010). Does the color of the collar matter? Employment and earnings after plant closure. Economics Letters 108 (3), 137-140.

Tatsiramos, K. (2009). Unemployment insurance in Europe: Unemployment duration and subsequent employment stability. Journal of the European Economic Association 7, 1125-1260.

Tatsiramos, K. (2014). Unemployment benefits and job match quality. IZA World of Labor: 44.

Tatsiramos, K. and Van Ours, J.C. (2014). Labor market effects of unemployment insurance design. Journal of Economic Surveys 28 (2), 284-311.

Terrell, K. and Sorm, V. (1999). Labor market policies and unemployment in the Czech Republic. Journal of Comparative Economics 27, 33-60.

Trevisan, E. and Zantomio, F. (2016). The impact of acute health shocks on the labour supply of older workers. Evidence from sixteen European countries. Labour Economics 43, 171-185.

Van den Berg, G.J., Bergemman, A.H., and Caliendo, M. (2009). The effect of active labor market programs on the not-yet treated unemployed individuals. Journal of the European Economic Association (Papers and Proceedings) 7(2/3), 606-616.

Van den Berg, G.J., Van der Klauuw, B. and Van Ours, J.C. (2004). Punitive sanctions and the transition rate from welfare to work. Journal of Labor Economics 22 (1), 211-241.

Van Ours, J.C. (2004). The locking-in effect of subsidized jobs. Journal of Comparative Economics 32 (1), 37-52.

Van Ours, J.C. (2011). Do active labor market policies help unemployed workers to find and keep regular jobs? in: Lechner, M. and Pfeiffer, F. (Eds.), Econometric Evaluation of Labour Market Policies, Physica-Verlag, 125-152, 2001.

Van Ours, J.C. and Vodopivec, M. (2008). Does reducing unemployment insurance generosity reduce job match quality? Journal of Public Economics 92 (3-4), 684-695.

Vodopivec, M. (1999). Does the Slovenian public work program increase participants' chances to find a job? Journal of Comparative Economics 27, 113-130.

Vooren, M., Haelemans, C., Groot, W. and Maasen Van den Brink, H. (2019). The effectiveness of active labor market policies: A meta-analysis. Journal of Economic Surveys 33 (1), 125-149.

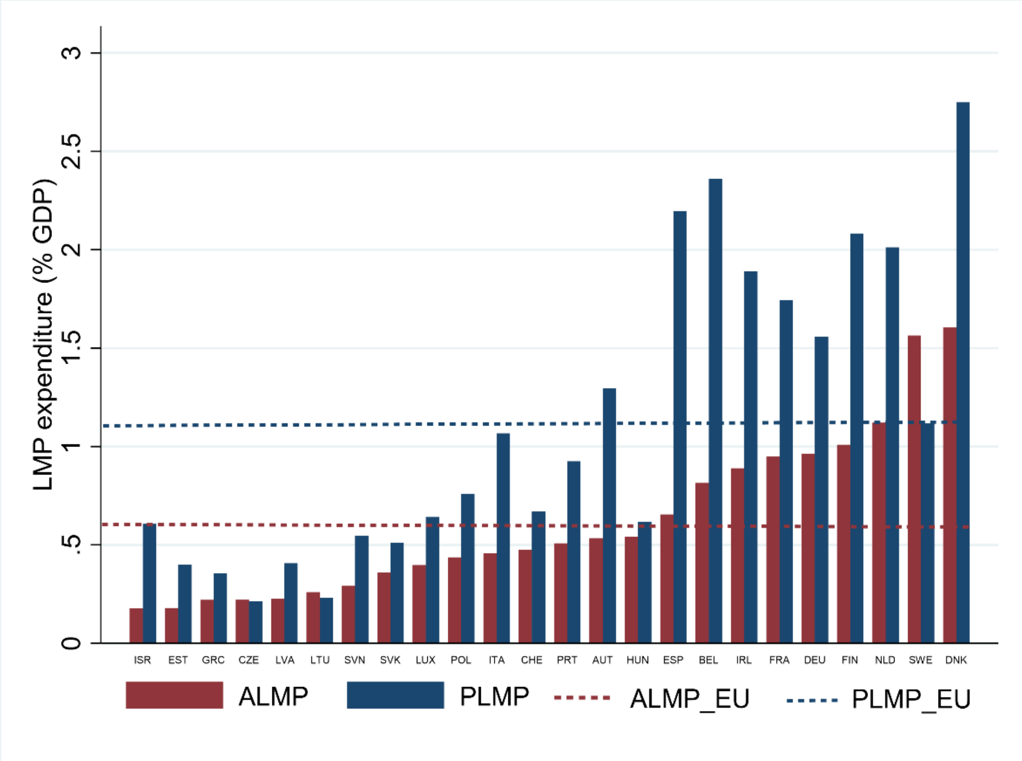

Figure 1. ALMP and PLMP expenses as a percentage of GDP across Europe and Israel. OECD sample (2022).

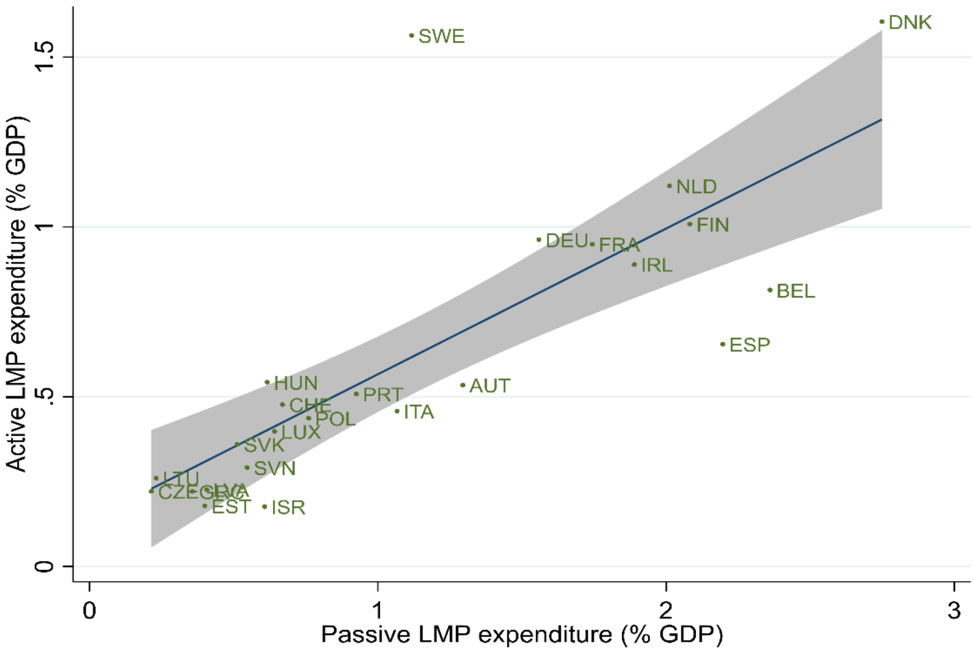

Figure 2. The relationship between ALMPs and PLMPs (OECD sample).

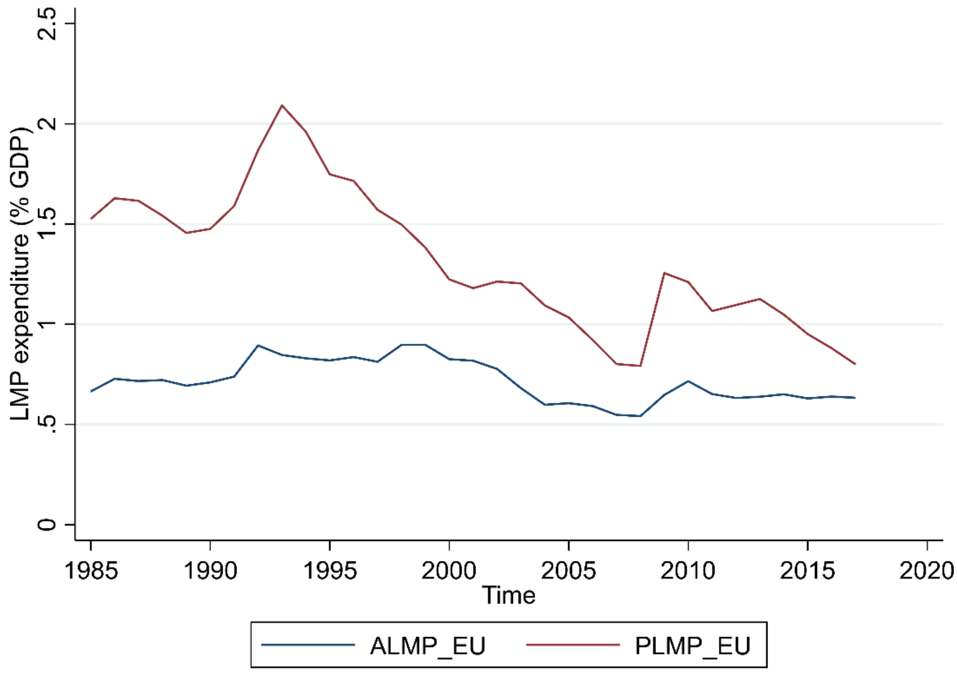

Figure 3. OECD sample.

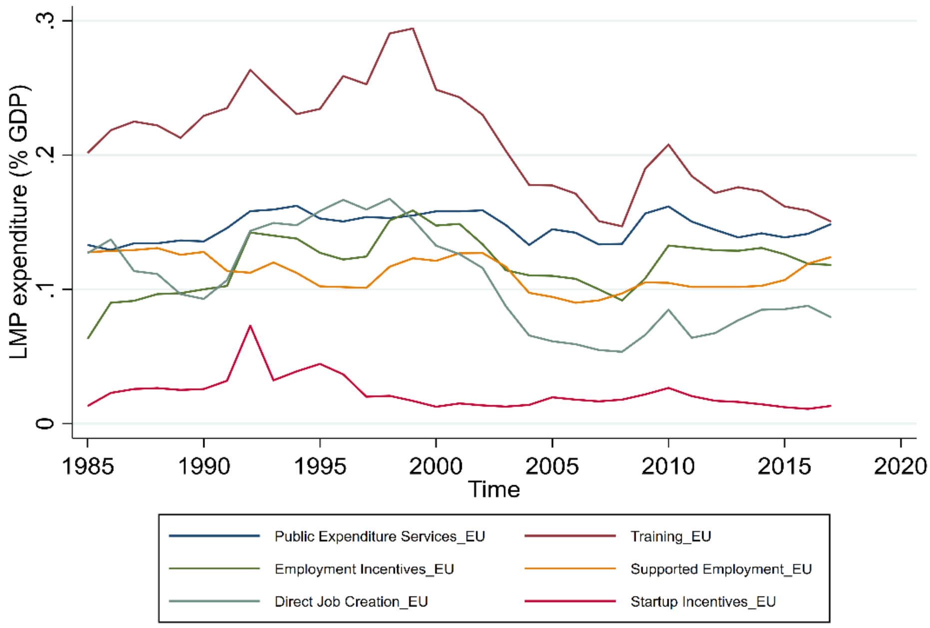

Figure 4. OECD sample.

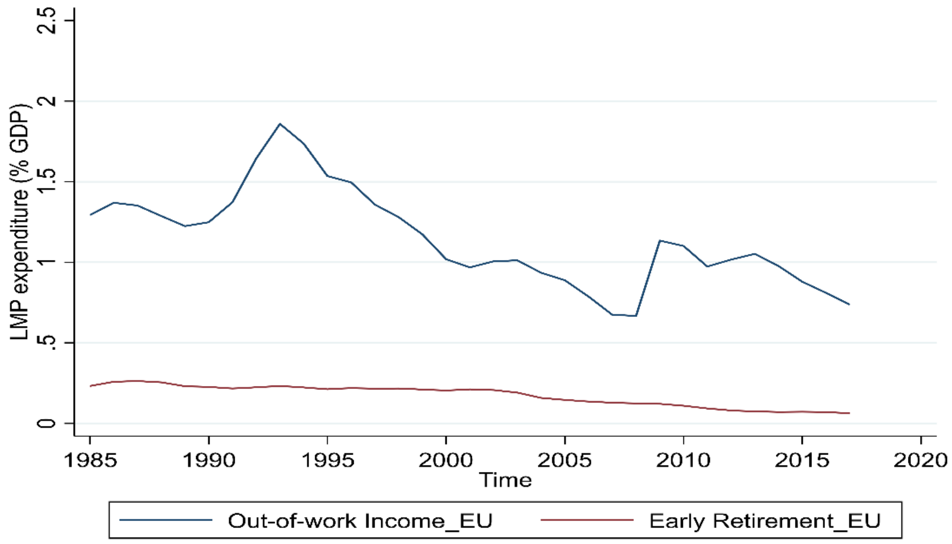

Figure 5. OECD sample.

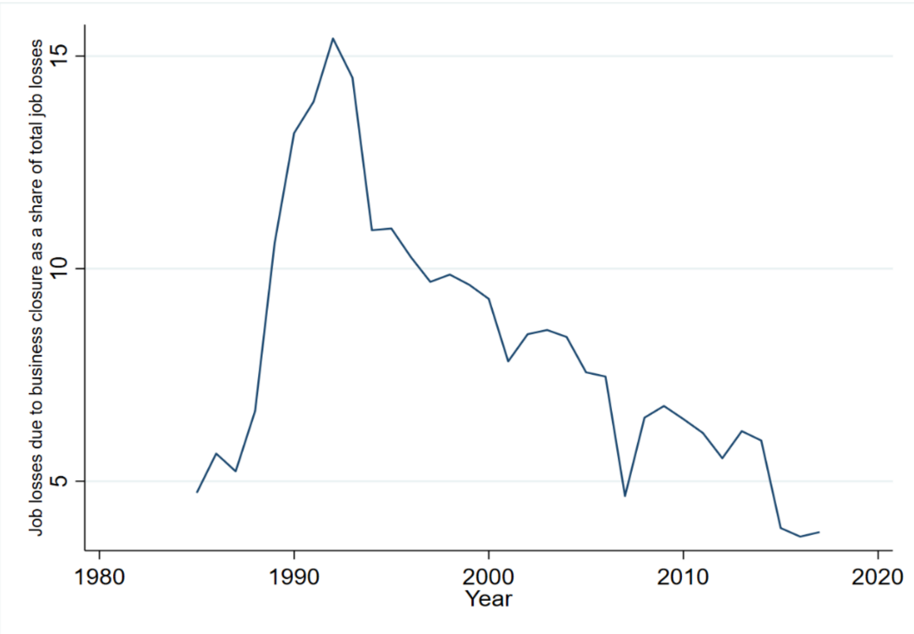

Figure 6. Job loss due to firm closure over time 1985-2017 (SHARELIFE sample).

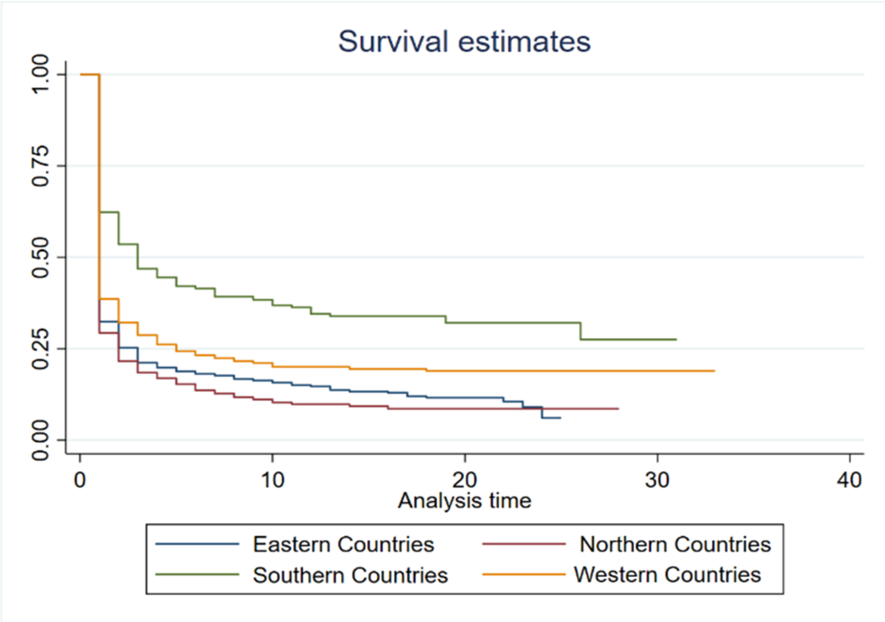

Figure 7. Kaplan-Meier curves comparing unemployment duration across the four regions (SHARELIFE sample).

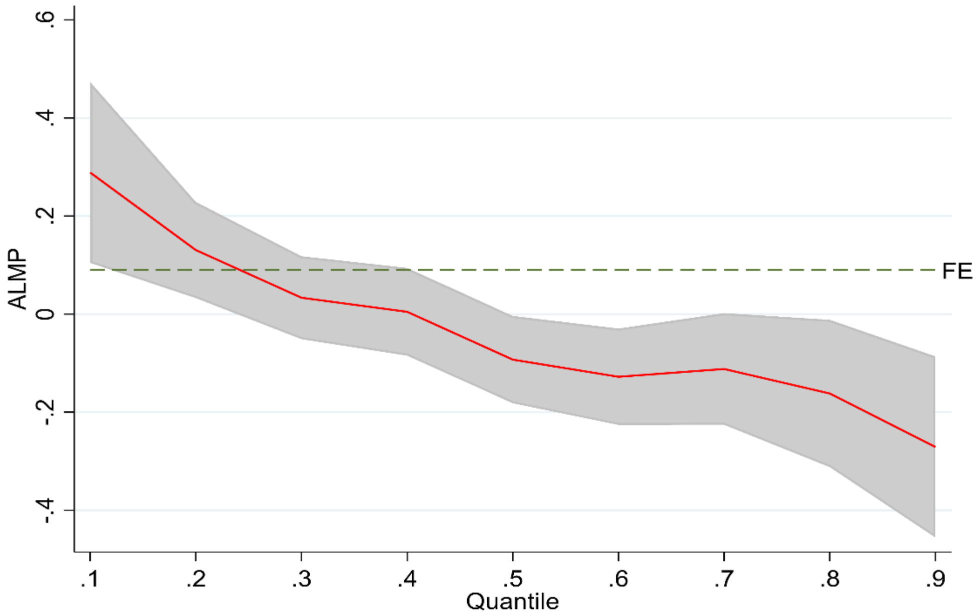

Figure 8. The effect of ALMPs on wages across deciles (SHARELIFE sample).

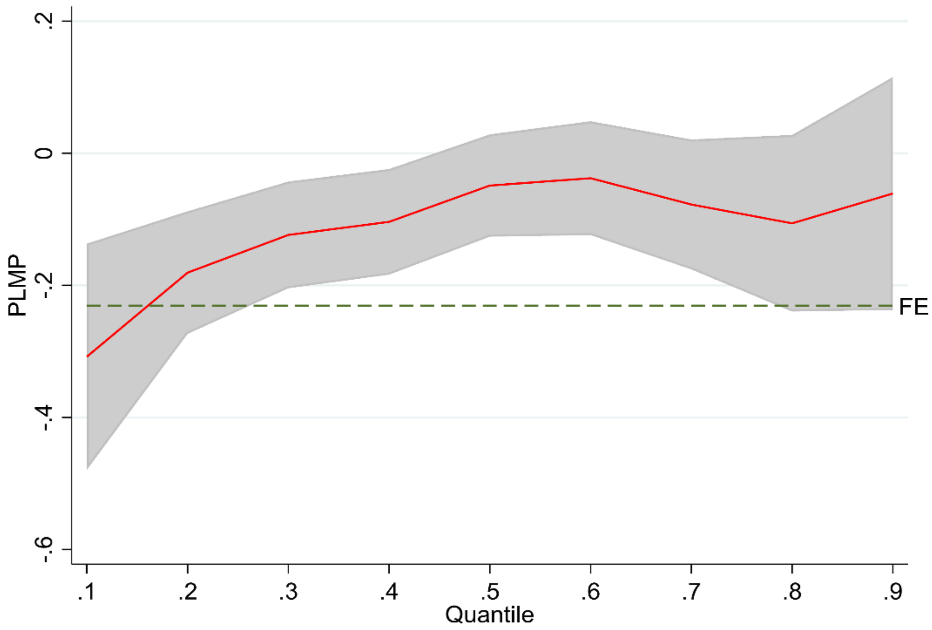

Figure 9. The effect of PLMPs on wages across deciles (SHARELIFE sample).

Table 1: Summary statistics

Variable	Obs.	Mean	Std. dev.	Min	Max
ALMP	4,565	0.724	0.513	0.065	2.318
PLMP	4,565	1.413	1.059	0.135	4.798
PES	4,565	0.123	0.070	0.000	0.359
Training	4,565	0.184	0.157	0.002	0.557
Employment incentives	4,565	0.115	0.114	0.000	0.490
Supported employment	4,565	0.102	0.108	0.000	0.479
Direct job creation	4,565	0.092	0.100	0.000	0.525
Start-up incentives	4,565	0.026	0.044	0.000	0.291
Out-of-work income	4,565	0.701	0.390	0.086	1.646
Early Retirement	4,565	0.183	0.228	0.000	0.827
Female	4,565	0.544	0.498	0	1
Age	4,565	46.365	8.858	19	64
Education	4,565	14.063	4.283	0	51
Tenure	4,565	15.092	10.963	1	50
Married	4,565	0.798	0.402	0	1
No. of children	4,565	1.855	1.213	0	11
Health (excellent, very good)	4,565	0.607	0.488	0	1
Re-employment after a year	4,565	0.598	0.49	0	1
Duration of Employment	3,373	8.025	6.612	1	33
Duration of Unemployment	4,321	2.922	4.305	1	33

Notes. *ALMP* and *PLMP* are expressed as a share of the GDP. *Education* refers to the number of years in education and job tenure refers to the job tenure of the last job until the time of displacement. *Children* refer to the number of children that the individual has and *Health* is an indicator of the individual's health based on their health in their childhood. It equals one when the respondent's health during her/his childhood was, in general, excellent or very good. *Re-employment* captures whether an individual found a job one year after displacement. *Duration of Employment* counts the number of years an individual stayed employed in the job following displacement (considering that re-employment after displacement occurred within one year). Given that not all respondents found a job after displacement, this variable includes fewer observations. *Duration of Unemployment* measures the number of years an individual remained unemployed following the job displacement. The cases where the respondent retired the same year the displacement took place are not dropped (that is, the cases where *Duration of Unemployment* equals zero).

Table 2: Baseline findings

	(1) *Re-employment probability*	(2) *Duration of employment*	(3) *Duration of unemployment*
ALMP	0.0887***	0.1339**	0.2692**
	(0.0323)	(0.0674)	(0.1058)
PLMP	-0.1506***	-0.2207***	-0.3905***
	(0.0238)	(0.0525)	(0.0751)
Female	-0.1488***	-0.1297***	-0.4239***
	(0.0133)	(0.0316)	(0.0451)
Age	0.0506***	0.0780***	0.1250***
	(0.0075)	(0.0188)	(0.0273)
Age-squared/100	-0.0714***	-0.1141***	-0.1823***
	(0.0079)	(0.0209)	(0.0298)
Education	0.0090***	0.0034	0.0250***
	(0.0019)	(0.0036)	(0.0052)
Tenure	-0.0021***	0.0070***	-0.0046*
	(0.0007)	(0.0021)	(0.0026)
Married	0.0117	0.0582	0.0698
	(0.0181)	(0.0371)	(0.0550)
Children	-0.0036	-0.0230*	-0.0217
	(0.0067)	(0.0119)	(0.0199)
Health (excellent, very good)	0.0157	0.0750**	0.0562
	(0.0142)	(0.0316)	(0.0420)
Constant		1.0399**	-1.0642*
		(0.4062)	(0.6067)
Observations	4,565	3,373	4,321
R-squared		0.163	

Notes. Column 1 reports the average marginal effects of the variables of interest after estimating a probit model with *Reemployment* as the dependent variable. Column 2 reports the results after estimating an OLS model with *Duration of Employment* as the dependent variable. Column 3 reports the findings from a survival analysis and a Weibull model where the outcome variable of interest is the time until re-employment occurs, *Duration of Unemployment*. Standard errors in parentheses are clustered at the country five-year time period. Time, country and industry dummies are included in all specifications. ***, **, * denote statistical significance at the 1%, 5% and 10% levels.

Table 3: Baseline findings - with interaction

	(1) *Re-employment probability*	(2) *Duration of employment*	(3) *Duration of unemployment*
ALMP	0.0701**	0.0641	0.1722
	(0.0357)	(0.0632)	(0.1179)
PLMP	-0.1931***	-0.3612***	-0.5978***
	(0.0292)	(0.0533)	(0.0985)
*ALMP*PLMP*	-0.0510**	-0.1669***	-0.2362***
	(0.0215)	(0.0386)	(0.0694)
Female	-0.1485***	-0.1300***	-0.4192***
	(0.0133)	(0.0314)	(0.0454)
Age	0.0515***	0.0804***	0.1285***
	(0.0075)	(0.0187)	(0.0275)
Age-squared	-0.0725***	-0.1169***	-0.1865***
	(0.0079)	(0.0208)	(0.0300)
Education	0.0090***	0.0033	0.0255***
	(0.0019)	(0.0036)	(0.0052)
Tenure	-0.0021***	0.0069***	-0.0045*
	(0.0007)	(0.0021)	(0.0026)
Married	0.0119	0.0579	0.0670
	(0.0180)	(0.0375)	(0.0549)
Children	-0.0038	-0.0237**	-0.0233
	(0.0067)	(0.0118)	(0.0199)
Health	0.0165	0.0778**	0.0593
	(0.0141)	(0.0316)	(0.0417)
Constant		0.9241**	-1.2082*
		(0.4028)	(0.6275)
Observations	4,565	3,373	4,321
R-squared		0.163	

Notes. Column 1 reports the average marginal effects of the variables of interest after estimating a probit model with *Reemployment* as the dependent variable. Column 2 reports the results after estimating an OLS model with *Duration of Employment* as the dependent variable. Column 3 reports the findings from a survival analysis and a Weibull model where the outcome variable of interest is the time until re-employment occurs, *Duration of Unemployment*. Standard errors in parentheses are clustered at the country five-year time period. Time, country and industry dummies are included in all specifications. ***, **, * denote statistical significance at the 1%, 5% and 10% levels.

Table 4: Baseline findings by LMP category

	(1) *Re-employment probability*	(2) *Duration of employment*	(3) *Duration of unemployment*
PES	-0.0261	1.0431**	0.1567
	(0.2738)	(0.5187)	(0.9000)
Training	-0.1671	0.3073	-0.5161
	(0.1218)	(0.3054)	(0.3842)
Employment incentives	-0.2647*	-0.3787	-1.0578**
	(0.1558)	(0.3898)	(0.5125)
Supported employment	0.5809**	-0.4185	1.4256**
	(0.2332)	(0.4160)	(0.6138)
Direct job creation	0.1541	-0.2499	0.2093
	(0.1270)	(0.3137)	(0.3990)
Start-up incentives	0.4723**	0.6072	1.4084*
	(0.2260)	(0.3932)	(0.7867)
Out-of-work income	-0.2392***	-0.4149***	-0.5633***
	(0.0400)	(0.1040)	(0.1441)
Early retirement	-0.1530	-0.0819	-0.4779
	(0.1161)	(0.1722)	(0.3492)
Female	-0.1480***	-0.1295***	-0.4205***
	(0.0131)	(0.0313)	(0.0451)
Age	0.0510***	0.0766***	0.1246***
	(0.0074)	(0.0190)	(0.0277)
Age-squared/100	-0.0719***	-0.1127***	-0.1821***
	(0.0078)	(0.0212)	(0.0305)
Education	0.0092***	0.0035	0.0270***
	(0.0019)	(0.0036)	(0.0053)
Tenure	-0.0020***	0.0073***	-0.0040
	(0.0007)	(0.0021)	(0.0026)
Married	0.0082	0.0550	0.0515
	(0.0182)	(0.0371)	(0.0556)
Children	-0.0034	-0.0219*	-0.0231
	(0.0068)	(0.0117)	(0.0199)
Health (excellent, very good)	0.0151	0.0729**	0.0527
	(0.0140)	(0.0312)	(0.0418)
Constant		1.0877***	-0.9079
		(0.4111)	(0.6199)
Observations	4,565	3,373	4,321
R-squared		0.166	

Notes. Column 1 reports the average marginal effects of the variables of interest after estimating a probit model with *Reemployment* as the dependent variable. Column 2 reports the results after estimating an OLS model with *DurationEmpl* as the dependent variable. Column 3 reports the findings from a survival analysis and a Weibull model where the outcome variable of interest is the time until re-employment occurs, *DurationUnempl*. Standard errors in parentheses are clustered at the country five-year time period. Time, country and industry dummies are included in all specifications. ***, **, * denote statistical significance at the 1%, 5% and 10% levels.

Table 5: Regional heterogeneity

Specification	Covariates	(1) Eastern	(2) Northern	(3) Southern	(4) Western
Panel A	*ALMP*	0.1487***	0.0334	-0.0741	0.0657
Re-employment		(0.0459)	(0.0529)	(0.1283)	(0.0640)
probability	*PLMP*	-0.1326***	-0.2468***	0.0297	-0.1164
		(0.0260)	(0.0664)	(0.0651)	(0.0743)
Observations		1,811	890	487	1,359
Panel B	*ALMP*	0.3135***	-0.1021	-0.0203	0.1684*
Employment		(0.1009)	(0.1417)	(0.1897)	(0.0998)
duration	*PLMP*	-0.1657**	-0.5591***	0.0952	-0.2468
		(0.0642)	(0.1240)	(0.1183)	(0.1535)
Observations		1,358	755	281	979
Panel C	*ALMP*	0.4251**	0.1222	-0.0963	0.0958
Unemployment		(0.2022)	(0.2992)	(0.3458)	(0.2047)
duration	*PLMP*	-0.2453***	-0.7375***	0.1528	-0.1380
		0.4251**	(0.2849)	(0.2139)	(0.2211)
Observations		1,695	848	478	1,300

Notes. Panel A reports the average marginal effects of the variables of interest after estimating a probit model with *Reemployment* as the dependent variable. Panel B reports the results after estimating an OLS model with *DurationEmpl* as the dependent variable. Panel C reports the findings from a survival analysis and a Weibull model where the outcome variable of interest is the time until re-employment occurs, *DurationUnempl*. Standard errors in parentheses are clustered at the country five-year time period. Time, country and industry dummies are included in all specifications. Only the coefficients of ALMP and PLMP are presented for brevity. *** and ** denote statistical significance at the 1% and 5% levels.

Table 6: Regional heterogeneity with interaction

Specification	Covariates	(1) Eastern	(2) Northern	(3) Southern	(4) Western
Panel A	*ALMP*	0.1403*	0.0238	0.0675	-0.3390***
Re-employment		(0.0787)	(0.0930)	(0.0638)	(0.1306)
probability	*PLMP*	-0.1415**	-0.2486***	-0.1252	-0.2978**
		(0.0607)	(0.0732)	(0.0779)	(0.1291)
	ALMP*PLMP	-0.0076	0.0235	-0.0228	-0.3822***
		(0.0515)	(0.1589)	(0.0435)	(0.1306)
Panel B	*ALMP*	0.2187	-0.3731**	0.4135	0.2068**
Employment		(0.1575)	(0.1687)	(0.4516)	(0.1000)
duration	*PLMP*	-0.2619**	-0.6044***	0.6514	-0.4162***
		(0.0966)	(0.0746)	(0.4345)	(0.1510)
	ALMP*PLMP	-0.0844	0.6933***	0.6419	-0.1580**
		(0.0847)	(0.2196)	(0.5018)	(0.0617)
Panel C	*ALMP*	0.5289**	-0.0763	0.1589	-0.8547**
Unemployment		(0.2514)	(0.4333)	(0.2201)	(0.3461)
duration	*PLMP*	-0.1386	-0.7833***	-0.3623	-0.9075*
		(0.1619)	(0.2771)	(0.2938)	(0.4851)
	ALMP*PLMP	0.0933	0.4925	-0.1855	-1.1879***
		(0.1477)	(0.6477)	(0.1133)	(0.4585)

Notes. Panel A reports the average marginal effects of the variables of interest after estimating a probit model with *Reemployment* as the dependent variable. Panel B reports the results after estimating an OLS model with *DurationEmpl* as the dependent variable. Panel C reports the findings from a survival analysis and a Weibull model where the outcome variable of interest is the time until re-employment occurs, *DurationUnempl*. Standard errors in parentheses are clustered at the country five-year time period. Time, country and industry dummies are included in all specifications. Only the coefficients of ALMP, PLMP, and of their interaction (ALMP*PLMP) are presented for brevity. *** and ** denote statistical significance at the 1% and 5% levels.

Table 7: Regional heterogeneity by LMP category

Specification	Covariates	(1) Eastern	(2) Northern	(3) Southern	(4) Western
Panel A	*PES*	0.2383	1.8146***	-3.7708	-0.1971
Re-employment		(0.5650)	(0.3220)	(2.5373)	(0.6342)
probability	*Training*	1.4048**	-0.0996	-1.2017	-0.0536
		(0.7019)	(0.1246)	(0.7592)	(0.3726)
	Employment incentives	0.5163	0.6251***	3.5512*	-0.5555**
		(0.7872)	(0.2233)	(1.9354)	(0.2644)
	Supported employment	1.2544**	-0.6575**	10.3086***	0.5850
		(0.6252)	(0.2943)	(3.1999)	(0.6544)
	Direct job creation	0.0162	-0.0607	-4.3867**	0.5343***
		(0.3404)	(0.1117)	(2.0685)	(0.1689)
	Start-up incentives	0.0489	2.9369***	0.5447	0.4474
		(0.2533)	(0.6285)	(1.0826)	(0.6483)
	Out-of-work income	-0.4068***	-0.5908***	0.8993**	-0.3643*
		(0.0805)	(0.0810)	(0.4355)	(0.1861)
	Early retirement	-0.3793*	-0.4484**	1.0936	-0.2735
		(0.2258)	(0.2013)	(0.9461)	(0.2266)
Observations		1,811	890	487	1,359
Panel B	*PES*	3.8267***	1.9084	-3.1551	-0.0644
Employment		(0.8699)	(1.1469)	(5.5285)	(2.0919)
duration	*Training*	0.6208	0.1991	0.3862	-0.7300
		(0.9602)	(0.4115)	(1.9290)	(1.2021)
	Employment incentives	-0.1899	1.8134***	4.9890	-2.3045**
		(1.2379)	(0.4395)	(3.9469)	(1.0406)
	Supported employment	-0.2741	-0.7318	-2.7941	3.4939
		(1.0585)	(1.0643)	(6.7807)	(2.1760)
	Direct job creation	1.8960***	-1.2716***	-3.5256	0.9423
		(0.4584)	(0.4151)	(6.2167)	(0.6086)
	Start-up incentives	0.6952*	1.6207	3.5549	0.7413
		(0.3938)	(1.6525)	(3.9188)	(2.5570)
	Out-of-work income	-0.3567**	-1.0903***	0.9709	-0.9758
		(0.1572)	(0.2562)	(0.8466)	(0.6002)
	Early retirement	0.0343	-0.6911	-4.3789	-0.3416
		(0.2608)	(0.5906)	(2.9369)	(0.7999)
Observations		1,358	755	281	979
Panel C	*PES*	0.1663	5.1903**	4.1715	-0.0644
Unemployment		(2.9207)	(2.0446)	(15.1728)	(2.0919)
duration	*Training*	3.6654	0.2000	-3.3670	-0.7300
		(3.0164)	(0.6659)	(4.3177)	(1.2021)
	Employment incentives	-2.0195	1.8214	0.4615	-2.3045**
		(2.8295)	(1.2550)	(6.5895)	(1.0406)
	Supported employment	6.2922**	-2.1976	42.5663**	3.4939
		(2.6206)	(2.0364)	(20.2510)	(2.1760)
	Direct job creation	0.4115	-0.5172	-6.6993	0.9423
		(1.6655)	(0.7615)	(10.4699)	(0.6086)
	Start-up incentives	-0.0769	8.7810**	-0.8908	0.7413
		(0.9037)	(3.9127)	(7.2209)	(2.5570)
	Out-of-work income	-0.8052***	-1.9118***	1.0887	-0.9758
		(0.2892)	(0.4854)	(0.9672)	(0.6002)
	Early retirement	-0.7728	-1.7687	8.6010	-0.3416
		(0.6888)	(1.1394)	(6.4536)	(0.7999)
Observations		1,695	848	478	1,300

Notes. Panel A reports the average marginal effects of the variables of interest after estimating a probit model with *Reemployment* as the dependent variable. Panel B reports the results after estimating an OLS model with *DurationEmpl* as the dependent variable. Panel C reports the findings from a survival analysis and a Weibull model where the outcome variable of interest is the time until re-employment occurs, *DurationUnempl*. Standard errors in parentheses are clustered at the country five-year time period. Time, country and industry dummies are included in all specifications. Only the coefficients of LMP components are presented for brevity. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels.

Table 8: Gender heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)
	Re-employment probability		*Duration of employment*		*Duration of unemployment*	
	Females	Males	Females	Males	Females	Males
ALMP	0.1165***	0.0395	0.1652*	0.1337	0.3060**	0.2016
	(0.0391)	(0.0421)	(0.0835)	(0.0995)	(0.1243)	(0.1583)
PLMP	-0.1571***	-0.1485***	-0.2296***	-0.2579***	-0.3722***	-0.4730***
	(0.0299)	(0.0293)	(0.0651)	(0.0692)	(0.0918)	(0.1003)
Age	0.0748***	0.0209**	0.0427	0.1043***	0.2217***	0.0133
	(0.0100)	(0.0092)	(0.0323)	(0.0272)	(0.0350)	(0.0324)
Age-squared/100	-0.1001***	-0.0389***	-0.0714*	-0.1439***	-0.3010***	-0.0575
	(0.0110)	(0.0099)	(0.0375)	(0.0285)	(0.0392)	(0.0367)
Education	0.0072**	0.0100***	0.0069	0.0041	0.0144*	0.0306***
	(0.0029)	(0.0022)	(0.0058)	(0.0049)	(0.0081)	(0.0063)
Tenure	-0.0025**	-0.0013	0.0081***	0.0061**	-0.0064	-0.0031
	(0.0012)	(0.0009)	(0.0028)	(0.0026)	(0.0042)	(0.0033)
Married	-0.0411*	0.0719***	0.1226**	-0.0229	-0.0913	0.2504***
	(0.0220)	(0.0241)	(0.0596)	(0.0508)	(0.0699)	(0.0750)
Children	-0.0133	0.0009	-0.0176	-0.0184	-0.0572*	-0.0004
	(0.0097)	(0.0087)	(0.0186)	(0.0186)	(0.0313)	(0.0263)
Health	0.0304	-0.0094	0.1277***	0.0089	0.1208**	-0.0403
	(0.0197)	(0.0185)	(0.0355)	(0.0514)	(0.0560)	(0.0663)
Constant			1.6476**	0.4399	-2.8716***	1.0416
			(0.6519)	(0.6048)	(0.7632)	(0.7265)
Observations	2,485	2,080	1,789	1,584	2,349	1,972
R-squared			0.158	0.208		
ln(p)					-1.798***	-1.740***

Notes. Columns 1 and 2 report the average marginal effects of the variables of interest after estimating a probit model with *Reemployment* as the dependent variable for females and males, respectively. Columns 3 and 4 report the results after estimating an OLS model with *Duration* as the dependent variable for females and males, respectively. Column 5 and 6 reports the findings from a survival analysis and a Weibull model where the outcome variable of interest is the time until re-employment occurs for females and males, respectively. Standard errors in parentheses are clustered at the country five-year time period. Time, country and industry dummies are included in all specifications. ***, **, * denote statistical significance at the 1%, 5% and 10% levels.

Table 9: Gender heterogeneity by LMP category

	(1) Females	(2) Males	(3) Females	(4) Males	(5) Females	(6) Males
PES	0.0815	-0.2802	0.3776	1.2968**	0.3196	-1.0352
	(0.3871)	(0.3092)	(0.7324)	(0.6323)	(1.1807)	(1.3083)
Training	-0.2073	-0.1509	0.4618	0.2398	-0.2941	-0.9583
	(0.1698)	(0.1788)	(0.3772)	(0.4400)	(0.5648)	(0.6586)
Employment incentives	0.0488	-0.5547**	-0.5430	-0.1959	-0.0631	-2.0797**
	(0.2348)	(0.2242)	(0.5966)	(0.4004)	(0.7432)	(0.8542)
Supported employment	0.8898***	0.2951	-0.4120	-0.4159	1.8605**	1.6362*
	(0.2897)	(0.3232)	(0.5924)	(0.5277)	(0.8811)	(0.9594)
Direct job creation	0.0811	0.2026	-0.3657	-0.0781	-0.1034	0.2628
	(0.2166)	(0.1590)	(0.4072)	(0.3183)	(0.6943)	(0.5587)
Start-up incentives	0.3402	0.4941*	1.5658**	-0.5432	0.8653	1.7770
	(0.2491)	(0.2895)	(0.7417)	(0.4084)	(0.8256)	(1.2463)
Out-of-work income	-0.2322***	-0.2575***	-0.4604***	-0.4446***	-0.5859***	-0.6267**
	(0.0514)	(0.0667)	(0.1394)	(0.1320)	(0.1752)	(0.2724)
Early retirement	-0.1410	-0.2043	-0.2605	0.1276	-0.4773	-0.5231
	(0.1547)	(0.1274)	(0.2711)	(0.2533)	(0.4670)	(0.4453)
Age	0.0741***	0.0228**	0.0432	0.1017***	0.2172***	0.0162
	(0.0098)	(0.0094)	(0.0329)	(0.0278)	(0.0349)	(0.0330)
Age-squared/100	-0.0994***	-0.0409***	-0.0724*	-0.1413***	-0.2960***	-0.0610
	(0.0107)	(0.0100)	(0.0382)	(0.0291)	(0.0391)	(0.0376)
Education	0.0072**	0.0106***	0.0060	0.0042	0.0150*	0.0344***
	(0.0029)	(0.0022)	(0.0057)	(0.0049)	(0.0082)	(0.0062)
Tenure	-0.0023*	-0.0012	0.0084***	0.0064**	-0.0060	-0.0024
	(0.0012)	(0.0009)	(0.0028)	(0.0027)	(0.0041)	(0.0034)
Married	-0.0462**	0.0687***	0.1216**	-0.0280	-0.1057	0.2249***
	(0.0219)	(0.0233)	(0.0595)	(0.0510)	(0.0712)	(0.0722)
Children	-0.0130	0.0012	-0.0153	-0.0175	-0.0608*	-0.0004
	(0.0098)	(0.0087)	(0.0188)	(0.0187)	(0.0314)	(0.0262)
Health	0.0294	-0.0098	0.1244***	0.0076	0.1145**	-0.0415
	(0.0196)	(0.0184)	(0.0352)	(0.0510)	(0.0568)	(0.0674)
Constant			1.7567**	0.4517	-2.6116***	1.3407*
			(0.6776)	(0.6229)	(0.7704)	(0.7695)
Observations	2,485	2,080	1,789	1,584	2,349	1,972
R-squared			0.162	0.213		
ln(p)					-1.794***	-1.737***

Notes. Columns 1 and 2 report the average marginal effects of the variables of interest after estimating a probit model with *Reemployment* as the dependent variable for females and males, respectively. Columns 3 and 4 report the results after estimating an OLS model with *Duration* as the dependent variable for females and males, respectively. Column 5 and 6 reports the findings from a survival analysis and a Weibull model where the outcome variable of interest is the time until re-employment occurs for females and males, respectively. Standard errors in parentheses are clustered at the country five-year time period. Time, country and industry dummies are included in all specifications. ***, **, * denote statistical significance at the 1%, 5% and 10% levels.

Table 10: Wages and LMPs across deciles

Quantile	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample		Females		Males	
	ALMP	*PLMP*	*ALMP*	*PLMP*	*ALMP*	*PLMP*
q_{10}	0.2888***	-0.3081***	0.3893**	-0.4865***	0.2155*	-0.2369**
	(0.1121)	(0.1041)	(0.1762)	(0.1568)	(0.1251)	(0.1159)
q_{20}	0.1306**	-0.1808***	-0.0025	-0.1409	0.1418	-0.1605*
	(0.0596)	(0.0564)	(0.1175)	(0.1100)	(0.0909)	(0.0857)
q_{30}	0.0334	-0.1237**	-0.0050	-0.1260	0.0735	-0.1182
	(0.0514)	(0.0491)	(0.1076)	(0.0927)	(0.0825)	(0.0854)
q_{40}	0.0047	-0.1039**	-0.1676	0.0002	0.0444	-0.1027
	(0.0544)	(0.0486)	(0.1058)	(0.0921)	(0.0804)	(0.0807)
q_{50}	-0.0928*	-0.0489	-0.1217	-0.0592	0.0752	-0.1469*
	(0.0541)	(0.0471)	(0.0978)	(0.0846)	(0.0824)	(0.0783)
q_{60}	-0.1278**	-0.0378	-0.1570	-0.0331	0.0343	-0.1347*
	(0.0597)	(0.0524)	(0.0968)	(0.0873)	(0.0911)	(0.0810)
q_{70}	-0.1119	-0.0776	-0.1553	-0.0811	-0.0455	-0.0688
	(0.0692)	(0.0598)	(0.1035)	(0.0959)	(0.0991)	(0.0850)
q_{80}	-0.1619*	-0.1061	-0.1917	-0.0428	-0.1355	-0.0670
	(0.0913)	(0.0813)	(0.1329)	(0.1232)	(0.1126)	(0.1026)
q_{90}	-0.2710**	-0.0610	-0.3074*	-0.0470	-0.1938*	-0.0596
	(0.1123)	(0.1072)	(0.1706)	(0.1579)	(0.1114)	(0.1127)
FE	0.0901	-0.2308	0.1347	-0.3161	0.0823	-0.1815
	(0.1465)	(0.1364)	(0.1782)	(0.1940)	(0.2546)	(0.2071)
Observations	1274		649		625	
R-squared (FE)	0.08		0.09		0.13	

Notes. L*ogwagepct* is the dependent variable. In all specifications, demographic controls, time and industry dummies as well as a constant term is included. Only the coefficients of the variables of interest are presented. Bootstrapped standard errors are presented in parentheses using 200 replications. The last row corresponds to a fixed effects regression model. ***, **, * denote statistical significance at the 1%, 5% and 10% levels.

Table A1: Reason left job

Reason left job	Frequency	Share (%)
I resigned	24,139	25.81
I was laid off	7,199	7.70
By mutual agreement	8,037	8.59
My plant or office closed	8,268	8.84
A temporary job had been completed	2,485	2.66
I retired	32,872	35.14
Other reason	10,540	11.27
Total	93,540	100%

Notes. JEP raw data for 24 countries.

Table A2: Observation window for each country

Country	**Observation window**
Austria	1985-2017
Belgium	1985-2017
Czech Republic	1991-2017
Denmark	1986-2017
Estonia	2003-2017
Finland	1985-2017
France	1985-2017
Germany	1985-2017
Greece	1985-1997
Hungary	1992-2017
Ireland	1985-2010
Israel	2004-2017
Italy	2004-2015
Latvia	2003-2017
Lithuania	2003-2017
Luxembourg	1985-2017
Netherlands	1985-2009
Poland	1993-2017
Portugal	1985-2017
Slovakia	1991-2017
Slovenia	2004-2017
Spain	1985-2017
Sweden	1985-2017
Switzerland	1985-2017

Notes. Observation window for each country. Time periods across countries differ due to different time period we observe each country in the OECD data and time of displacement.

Table A3: Correlation coefficient matrix

	ALMP	PLMP	PES	Training	Employment incentives	Supported employment	Direct job creation	Start-up	Out of work income	Early retirement
ALMP	1.000									
PLMP	0.660	1.000								
PES	0.734	0.351	1.000							
Training	0.906	0.586	0.622	1.000						
Employment incentives	0.753	0.539	0.328	0.613	1.000					
Supported employment	0.750	0.411	0.608	0.586	0.565	1.000				
Direct job creation	0.511	0.455	0.369	0.406	0.134	0.098	1.000			
Start-up	0.088	0.149	-0.028	0.007	0.091	-0.104	-0.020	1.000		
Out of work income	0.648	0.959	0.350	0.601	0.540	0.371	0.397	0.213	1.000	
Early retirement	0.376	0.634	0.185	0.264	0.279	0.325	0.394	-0.096	0.390	1.000

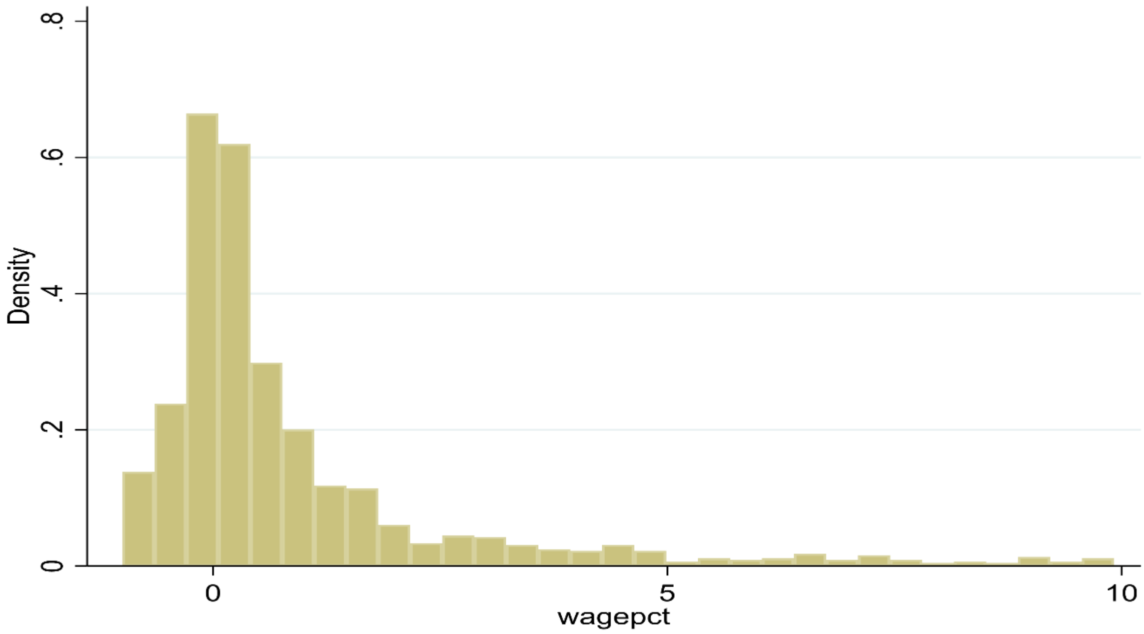

Figure A1. Distribution of percentage change between the initial wage (i.e., the wage of the last job before displacement) and the final wage (i.e., the wage of the first job after displacement).