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# Too Old to Work, Too Young to Retire?\*

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## Abstract

We study whether employment prospects of old and young workers differ after a plant closure. Using Austrian administrative data, we show that old and young workers face similar displacement costs in terms of employment in the long-run, but old workers lose considerably more initially and gain later. We interpret these findings using a search model with retirement as an absorbing state, that we calibrate to match the observed patterns. Our finding is that the dynamics of relative employment losses of old versus young workers after a displacement are mainly explained by different opportunities of transition into retirement. In contrast, differences in layoff rates and job offer arrival rates cannot explain these patterns. Our results support the idea that retirement incentives, more than weak labor demand, are responsible for the low employment rates of older workers.

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# 1 Introduction

The employment prospects of older workers who lose their job are the object of a hot debate in Europe. Grim anecdotal evidence is often brought to the attention of the public opinion with the goal of invoking special public assistance for an increasingly older working population, supposedly in need.<sup>1</sup> But precise evidence on the real dimension of the problem, based on representative data, is missing.

The first goal of this paper is to provide such evidence to inform the existing debate on a more solid base. Using Austrian Social Security data, we study the short- and long-term employment losses of “young” and “old” workers who got displaced because of a plant closure. Employment losses are calculated by comparing subsequent employment histories of displaced workers to otherwise similar workers (of the same age) who did not experience a displacement in the same period. We show that over the long-term (10-year period) employment losses of displaced old workers are equally large as the corresponding losses of the displaced young workers. However, the dynamic patterns of these employment losses differ strongly between the old and the young. Immediately after a plant closure, employment losses of displaced old workers are considerably higher, but later on those of the old fade away while those of the young persist. Hence, the substantially higher initial employment losses among the old contrast with substantially lower employment losses later on.

The second goal of our paper is to interpret our empirical findings – the differential dynamics of employment losses – in terms of a standard job search model. In this model, workers do not only move between employment and

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<sup>1</sup> See, for example, <http://www.independent.co.uk/voices/commentators/robert-chesshyre-too-old-to-work-but-too-young-to-retire-ndash-a-21stcentury-dilemma-2011031.html> or <http://www.telegraph.co.uk/comment/9226324/Too-young-to-retire-too-old-to-keep-the-job.html>. In Italy the recent pension reform of the Monti Government has re-ignited the public opinion debate because of the so called “Esodati” problem. These are workers who lost their pension rights because of the reform, while being very close to reaching the requirements that would have allowed them to retire. For some descriptive evidence on the employability of older workers across European countries see Leombruni and Villosio (2005).

unemployment but have also the option to withdraw from the labor force (retirement, disability, or other forms of non-employment). Withdrawing from the workforce (which we label as “early retirement”) is modeled as an absorbing state. The offer of early retirement options to displaced workers is a special feature of many European labor markets, used by governments to mitigate economic hardships for older workers in the course of industrial restructuring, adverse local labor market shocks or during recessions. We argue that considering the early retirement option is crucial to rationalize the differential employment losses of old and young displaced workers. Our model generates differential employment histories for displaced and non-displaced workers, based on the primitive parameters of our job search model: the exit rate from unemployment, the job offer arrival rate, the rate at which workers withdraw permanently from the labor market. We calibrate the parameters of this model by searching for those parameter configurations that minimize the differences between the employment patterns generated by the model and those observed in the data.

The parameters generated by this “minimum distance” procedure perform remarkably well in replicating the time series of employment patterns of displaced and non-displaced workers, both for young and for old workers. We use these parameters to understand the relative importance of labor supply and labor demand factors underlying the observed employment patterns.

Our analysis strongly suggests that higher inflows into early retirement of older but still potentially active workers (both from employment and from unemployment) explain the differential dynamics of employment losses after a plant closure. In contrast, the calibrated age-differences in unemployment entry and exit rates cannot explain these dynamic patterns. This suggests that retirement incentives (for both workers and firms) rather than high transitions into unemployment and low job-finding rates are the main driving force behind age-specific employment patterns. Old workers do neither face a higher probability of layoffs if employed, nor a lower arrival rate of job offers if unemployed. They instead face a higher probability of a transition to early retirement, in particular if they are unemployed. We also provide inde-

pendent evidence from the Austrian Micro Census that further suggests that search intensity for new working opportunities is significantly lower among older unemployed workers, probably because for them the exogenous arrival rate of new job offers is relatively higher and the opportunities of early retirement are more attractive.<sup>2</sup>

The paper is organized as follows. We describe the Austrian data and the matching strategy in Section 2, while the corresponding empirical evidence is presented in Section 3. In Section 4 we present the basic search framework, introduce the minimum distance procedure, and discuss the relative importance of labor demand and labor supply factors as the driving force behind the observed differences in employment experiences between young and old workers. Finally, Section 5 concludes.

## 2 Data and matching strategy

To assess the employment prospects of old and young workers after a displacement, we use administrative employment records from the Austrian Social Security Database (ASSD). The data set includes the universe of private sector workers in Austria covered by the social security system. All employment records can be linked to the establishment in which the worker is employed. The period of observation covers the years from 1978 to 1998. Daily employment and monthly earnings information is very reliable, because social security tax payments for firms as well as benefits for workers hinge on these data.<sup>3</sup> Monthly earnings are top-coded, which applies to approximately 10% of workers. We transformed monthly gross earnings in daily wages by dividing them by effective employment duration in each month of observation.

We concentrate on all workers employed in the period 1982 to 1988, who are therefore at risk of a firm<sup>4</sup> breakdown in this period; this allows us to

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<sup>2</sup>See Saint-Paul (2009) and Behaghel et al. (2008) for a more general discussion of the role of public policies in aggravating the employment problems of elderly workers.

<sup>3</sup>See Zweimüller et al. (2009) for a description of the data set.

<sup>4</sup>Although establishments, and not firms, are our units of observation for the identification of plant closures, we will use interchangeably these words for simplicity and

observe the workers in detail for 4 years prior to potential bankruptcy and for 10 years afterwards. We exclude firms from the construction and tourism industries, because in these sectors seasonal unemployment is very high and firms often close down out of season to reopen after several months with the same workforce. Moreover, we restrict ourselves to workers coming from firms with more than 5 employees at least once during the period 1982 to 1988 and having at least one year of tenure at their firm. To study the aging process we compare two cohorts: those of age 35 to 44 at the time of displacement – the “young” – and those between 45 and 55 – the “old”.<sup>5</sup>

Each establishment has an employer social security number. Hence, an exit of an establishment in the data occurs when the employer identifier ceases to exist. However, some of these cases are not true firm exits, and (most of the) employees continue under a new identifier, for example because of a takeover in a family business or other similar reasons. If more than 50% of the employees continue under a new employer identification number we do not consider this a failure of the establishment.<sup>6</sup>

This selection procedure identifies 12,102 workers involved in plant closures between 1982 and 1988, which we compare with workers from all firms not going bust between 1982 and 1988, with the same tenure, industry and age requirements as the displaced workers; this second group consists of 1,087,705 workers.<sup>7</sup> Our data set is ideal for matching. We have quarterly information for all workers over the four years before plant closure and have the universe of Austrian workers available as a potential control group. Detailed

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convenience.

<sup>5</sup>This distinction is somehow arbitrary and meant to simplify the analysis. It is reassuring that a specification with more but narrower age groups confirms the general pattern of our main result; See Table 4 in Ichino et al. (2007). More detailed evidence on this different specification is available from the authors.

<sup>6</sup>Workers from such firms are coded as “ambiguous” and are neither in the treatment nor the control group.

<sup>7</sup>In this analysis we limit the definition of displaced workers to workers employed in a closing plant at the period of closure. Schwerdt (2011) shows that neglecting early leavers can seriously bias estimates for costs of displacement. However, our estimate for the triple-difference parameter is qualitatively unaffected by the inclusion of early leavers. See Table 6 in Ichino et al. (2007).

past work histories, i.e. employment record and earnings, can be considered an almost sufficient statistic for the set of unobservable characteristics of workers (see for example Card and Sullivan, 1988).

Our matching procedure is therefore very simple: we perform exact matching between the displaced and non-displaced subjects on the following criteria: sex, age, broad occupation (blue- or white-collar), location of firm (9 provinces), industry (30 industries), employment history in each of the quarters 4, 5, 6 and 7 before plant closure.<sup>8</sup> We do almost exact matching on continuous variables such as: average daily wages in the quarters 8, 9, 10 and 11 before plant closure, that are matched by decile group<sup>9</sup>, and firm size in the two years before plant closure, that is matched by quartile groups. Thus, for each treated subject, our matching algorithm has to find a control subject with identical characteristics (according to the list mentioned above) at the date of plant closure. Applying this matching procedure we are able to identify at least one control subject for 6,630 treated subjects (out of a total of 12,102 subjects in the plant closure sample).<sup>10</sup> In total we end up with 36,677 matched controls. In the analysis, we compare results obtained for this matched sample with results obtained for a sample that contains all 12,102 treated workers and 3 randomly selected controls for each treated worker. We will refer to this sample as the “random control” sample.<sup>11</sup>

Table 1 provides descriptive statistics about the quality of the matching. While in the random control sample within-cohort differences in average characteristics between displaced and non-displaced workers are substantial, these differences (almost) disappear in the matched sample. This is true, by construction, for the exact-matching variables: i.e. gender, blue-collar status and age. Other variables such as tenure and work experience (only available since 1972) were not among the matching variables in our algorithm. It is

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<sup>8</sup>Note that we use only persons with tenure longer than one year in the current firm.

<sup>9</sup>We do not want to match earnings too close to firm failure, because there might be some anticipatory wage effects of firm breakdown.

<sup>10</sup>We experimented also with less restrictive matching algorithms that increase the number of matches without major quantitative changes in the results.

<sup>11</sup>Computational constraints prevent us from running our econometric analysis using *all* the potential controls in the “random control” sample.

therefore reassuring to see, that our matching strategy works perfectly in terms of tenure and work experience: mean differences between treated and controls are only marginal. Only in terms of plant size differences are slightly larger for young workers, but the gap is again very small for old workers.

As for (pre-displacement) daily wages, which have been matched by deciles in the quarters 8 to 11 prior to plant closure, the gap between the means of matched treated and control workers is very small. Figure 1 shows that this small gap in means does not hide large individual differences between each treated and his/her set of controls: the kernel density estimate of this “within match” difference in the quarters -8 to -11 shows that for both old and young workers, most of the density is in the region between plus and minus a quarter of a percent. The quality of the match in terms of wages is therefore very good for both young and old.

Finally, as far as pre-displacement wage *levels* are concerned, it is important for our analysis to emphasize that while in the random control sample there are differences between displaced and non-displaced workers within each cohort (which are eliminated by our matching strategy), there are essentially no differences between age cohorts. Before plant closure the old and the young earn approximately the same amount in both displacement groups and thus overall. This lack of cohort effects on earnings is not surprising if we think that the relationship between age and earnings in a crossection is typically hump-shaped with a maximum around age 45. This evidence justifies the assumptions about wages that we will make in the theoretical model described in Section 4.



### 3 Age and post-displacement labor market outcomes

#### 3.1 The overall long run effect

In order to obtain a preliminary image of the effect of aging on the employment rates<sup>12</sup> of young and old workers before and after potential displacement, we divide the sample in two groups defined by the binary variable:

$$OLD_i = \begin{cases} 1 & \text{if } a \in [45, 55], \\ 0 & \text{if } a \in [35, 44]. \end{cases} \quad (1)$$

In this way we concentrate our analysis on the comparison of the employment and earnings prospects of older relative to prime-age workers in the displacement and non-displacement groups.

We then estimate the following linear probability model:

$$\begin{aligned} Y_{i,t} = & \Theta(OLD_i * PC_i * POST_{i,t}) + \beta(OLD_i * POST_{i,t}) \\ & + \gamma(PC_i * POST_{i,t}) + \delta POST_{i,t} + \kappa_i + \tau_t + \epsilon_{i,t}. \end{aligned} \quad (2)$$

where  $Y_{i,t}$  is the binary employment status (employed or not employed) of worker  $i$  in calendar time  $t$  measured in quarters;  $PC_i$  is a dummy taking value 1 if  $i$  is displaced in a plant closure;  $POST_{i,t}$  is a dummy taking value 1 if quarter  $t$  is after plant closure;  $\kappa_i$  is an individual fixed effect,  $\tau_t$  captures calendar time effects and  $\epsilon_{i,t}$  captures unobservables of  $i$  at quarter  $t$  and  $\Theta, \beta, \gamma, \delta$  are the parameters that we would like to estimate.

Our results in Table 2 show that there is a large plant closure effect: on average over ten years after plant closure males lose 14 percentage points in employment rates and females lose almost 17 percentage points. These high non-employment rates over such a long time are large in comparison

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<sup>12</sup>While European studies on displacement effects are typically focused on employment, perhaps given the well known wage rigidities in the old continent, U.S. studies look typically at wage impacts of displacement or plant closure, e.g. Jacobson et al. (1993), Ruhm (1991) or Stevens (1997). Also in this paper the primary focus is on employment, but we will briefly discuss below some evidence on wages as well.

with those estimated for other OECD countries (see, for example, Kuhn (2002), Chan and Stevens (2001), Fallick (1996), Schmieder et al. (2009)). Moreover the old non-displaced of both genders experience on average lower employment rates than the young. But contrary to some expectations, there are no differential effects for elderly workers in case of displacement. The triple difference – giving us the additional plant closure effect for elderly workers – is exactly zero, both for men and women.<sup>13</sup>

These overall long run effects may hide more complex temporal patterns according to distance from displacement. We now explore these patterns in turn.

### 3.2 Outcomes at different distances from displacement

To explore the effects of the interaction between age and displacement at different distances from plant closure we expand the previous simple linear probability model (2) in the following way :

$$\begin{aligned}
Y_{i,t} = & \sum_{d=-16}^{40} \Theta_d(OLD_i * PC_i * Q_{i,t}^d) + \sum_{d=-16}^{40} \beta_d(OLD_i * Q_{i,t}^d) \quad (3) \\
& + \sum_{d=-16}^{40} \gamma_d(PC_i * Q_{i,t}^d) + \sum_{d=-16}^{40} \delta_d Q_{i,t}^d + \tau_t + \epsilon_{i,t}.
\end{aligned}$$

where  $d$  is the distance in quarters from potential or actual plant closure, which ranges in the data from  $-16$  to  $40$  with  $0$  denoting the last quarter before plant closure;  $Q_{i,t}^d$  is a dummy taking value  $1$  if  $i$  is observed in quarter  $t$  at a distance of  $d$  quarters from plant closure;  $\epsilon_{i,t}$  captures unobservables of  $i$  at quarter  $t$  and  $\Theta_d, \beta_d, \gamma_d, \delta_d$  and the calendar time effects  $\tau_t$  are the parameters that we would like to estimate. The other variables are defined as in equation (2).

This specification makes clear the nature of our identification assumption. The counterfactual of the displaced workers, at any age, are the non-displaced workers. The effect of being displaced at an older age as opposed to a younger

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<sup>13</sup>Kuhn (2002), for most of the countries compared in his study, finds a higher joblessness for elderly workers, but a lower incidence of displacement.

age is identified by how the difference of the employment profiles of displaced and non-displaced changes with age.

Figure 2 presents a graphical picture of these age differences. Panels A and B of the figure report, respectively, for the young and the old, the average employment rates of the displaced and non-displaced workers as a function of the distance from plant closure  $d$ , defined as follows using equation 3:

$$\begin{aligned}
E(Y_{i,t} \mid OLD_i = 0, PC_i = 0, Q_{i,t}^d = 1) &= \delta_d \\
E(Y_{i,t} \mid OLD_i = 0, PC_i = 1, Q_{i,t}^d = 1) &= \delta_d + \gamma_d \\
E(Y_{i,t} \mid OLD_i = 1, PC_i = 0, Q_{i,t}^d = 1) &= \delta_d + \beta_d \\
E(Y_{i,t} \mid OLD_i = 1, PC_i = 1, Q_{i,t}^d = 1) &= \delta_d + \beta_d + \gamma_d + \Theta_d.
\end{aligned}$$

By construction, the employment rates of both the matched displaced and non-displaced observations are equal to unity in the four quarters immediately prior to the plant closure date. The employment rates at earlier dates show that our matching procedure works perfectly as measured by the level of the outcome variable prior to plant closure. Indeed, both for the young and for the old, employment rates are identical also in the three years preceding the last before plant closure (actual or potential). After the plant closure date, instead, the employment rates of displaced and non-displaced workers diverge sharply for both the old and the young. Note that the rate of non-displaced workers decreases smoothly in both age groups, and particularly among the old. This reflects the dissolution of employment relationships that existed at the sampling date (i.e. the potential plant closure date) for non-displaced workers and that later dissolved because these workers got either unemployed or sick, retired, died, or dropped out of the labor force for other reasons.

Panel C of Figure 2 plots the within-age-group difference between the

employment rates of the displaced and the non-displaced

$$\begin{aligned}
& E(Y_{i,t} \mid OLD_i = 0, PC_i = 1, Q_{i,t}^d = 1) - E(Y_{i,t} \mid OLD_i = 0, PC_i = 0, Q_{i,t}^d = 1) \\
& \quad = \gamma_d \\
& E(Y_{i,t} \mid OLD_i = 1, PC_i = 1, Q_{i,t}^d = 1) - E(Y_{i,t} \mid OLD_i = 1, PC_i = 0, Q_{i,t}^d = 1) \\
& \quad = \gamma_d + \Theta_d.
\end{aligned}$$

The employment loss for the old displaced with respect to the non-displaced is initially larger (in absolute value) than the corresponding loss of the young, but approximately five years after displacement the ordering of two losses becomes the opposite: the old lose less with respect to their specific counterfactual. The empirical counterpart of this difference-in-differences,  $\Theta_d$ , is plotted in Panel D of Figure 2.

These estimates show that during the first five-year interval after plant closure the old suffer more severely than the young: the drop in employment rates of older displaced workers is significantly higher than the one of young displaced workers during the first 20 quarters. But, interestingly, the picture is turned on its head during the second five-year interval after the plant closure date. Here we observe a significantly smaller drop in employment rates for the old displaced workers than for the young displaced (relative to the never displaced in the corresponding cohorts).

Another way to state this fact is that while in the case of the young the employment rate decreases in an approximately parallel fashion for displaced and non-displaced workers, in the case of the old it decreases much faster for the non-displaced. The displacement, which occurred many years before, appears to be the only reason why the labor supply behavior of the old differs from that of the young, with respect to what would have happened in both age groups without displacement.

To complement the analysis of the employment consequences of a plant closure, we briefly look at earnings. Figure 3 reports results based on the same equation 3 in which  $Y_{i,t}$  now denotes the wage (nominal daily earnings for employed workers). A look at Panels A and B shows qualitatively very

similar effects across age groups. The first quarter after the plant closure indicates higher earnings due to selectivity. These workers are not only successful in searching for a new job, they are also the highly productive ones. From the third quarter after plant closure onwards also the less productive workers are back at work and daily earnings of displaced workers are lower than those of the non-displaced. This gap is increasing over time. Panel D of Figure 3 shows that earnings losses of prime-age workers are almost identical to those of older workers, except for the very last quarter 40. Note that also the pre-displacement wages of the young and the old are very similar, as shown in Table 1. So, both before and after displacement, we do not observe large earning differences between the young and old.

In sum, Figures 2 and 3 uncover temporal patterns for the employment rates of displaced and non-displaced workers in different age cohorts that need to be understood in the light of a theoretical model, in order to discriminate between possible explanations. However, since earning levels and losses appear to be essentially identical for young and old workers, the model that we will propose will take into account this evidence. We will come back to this issue in Section 4.

### 3.3 Controlling for pre-displacement heterogeneity

Figure 2 does not control for potential pre-displacement differences between displaced and non-displaced workers that remain after applying the exact matching algorithm. In order to do this we first modify equation 3 pooling over five consecutive two-years periods after plant closure denoted by a set of five dummies,  $YEAR(l, l + 1)$ , where  $l$  refers to the year relative to potential plant closure with  $l \in \{1, 3, 5, 7, 9\}$ .

Using these dummies we run a regression of the form

$$\begin{aligned}
Y_{i,t} = & \sum_l \Theta_l(OLD_i * PC_i * YEAR(l, l+1)_{i,t}) \\
& + \sum_l \beta_l(OLD_i * YEAR(l, l+1)_{i,t}) + \sum_l \gamma_l(PC_i * YEAR(l, l+1)_{i,t}) \\
& + \sum_l \delta_l YEAR(l, l+1)_{i,t} + \kappa_i + \tau_t + \epsilon_{i,t}
\end{aligned} \tag{4}$$

where  $\kappa_i$  is a worker fixed effects that controls for all pre-displacement and time invariant workers' characteristics.<sup>14</sup>

The interesting coefficients to be estimated in this regression are again the difference-in-difference parameters  $\Theta_l$ . These parameters describe the temporal evolution of the difference between the employment losses of young and old displaced workers relative to their specific non-displaced counterfactuals.

These estimates are reported in the first line of Table 3 and confirm that the evidence of Figure 2 is robust to the inclusion of workers' fixed effects in the specification. In the first two years after displacement the loss of the old, in absolute value, is 3.8 percentage points larger than that of the young. This gap then declines to become null five and six years after plant closure. Later on, the gap changes sign denoting that the young begin to lose more than the old relative to their counterfactual. In years nine and ten, the young lose 4.8 percentage points more than the old. We therefore conclude that this catch-up pattern of the old displaced relative to the young continues, even when we control for pre-displacement observable and unobservable characteristics.<sup>15</sup>

The estimates in Table 3 are based on the matched sample described in Table 1. As we explain in Section 2, this is our preferred sample because, thanks to the exact matching strategy that we can implement in our data, it

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<sup>14</sup>Ichino et al. (2007) in Table 3 show corresponding earnings regressions, which affirm the patterns from the graphical analysis.

<sup>15</sup>The other estimates in Table 3 reveal employment patterns comparable to the evidence presented in Figure 2. All displaced suffer from significant reductions in their employment probabilities with substantial losses in the first two years after displacement, which then start to decrease without completely disappearing even 10 years after displacement. Moreover, all workers experience decreasing employment probabilities independent of their displacement status with significantly larger reductions for older workers.

improves the comparability of displaced and non-displaced workers in terms of pre-displacement characteristics. However, using this sample, only 6,630 displaced workers (out of 12,102) can be matched with 36,777 controls out of more than one million observations in the random control sample. A legitimate worry is whether the advantage of a better comparability of displaced and non-displaced workers at the time of potential displacement comes at a large cost in terms of loss of observations. Such a loss not only decreases efficiency, but, perhaps more importantly, makes it harder to interpret the estimates given that it is not clear whether the matched sample is still representative of the full population of plant closure victims. We therefore explore how the estimates of Table 3 would change if we use all the observation in the full sample.

Table 4 provides a direct comparison of results based on the matched and on the full sample with and without fixed effects. The first column of this table reports, for the convenience of the reader, our preferred estimates displayed in the first row of Table 3. The second column shows the corresponding estimates in the full sample. The temporal pattern of the coefficients is qualitatively identical: the old lose more than the young in the first years after potential plant closure with respect to their specific counterfactual, but later on they lose less. For our claim, this is reassuring because it means that even using the full sample we find support for the hypothesis that the employment losses of the old displaced are higher at the beginning but lower later on as compared to the young displaced. Point estimates are, however, substantially larger, in absolute value, when the full sample is used.

The difference can be due to the fact that the full sample estimates are biased because of a worse comparability of displaced and non-displaced workers, or to the fact that the matched sample is not representative of the population. In principle, from the viewpoint of the paper, it is irrelevant to establish which of these two possibilities is correct, because we are primarily interested in the temporal profile implicit in the estimated parameters, which is the same in both specification. Nevertheless the comparison of columns 1 and 2 with columns 3 and 4 of Table 4 gives good reasons to conclude that

the most reliable specification should be the one based on both matching and workers' fixed effect. This is the specification presented in Table 3 and replicated in column 1 of Table 4.

The reason is the following: columns 3 and 4 of Table 4 report estimates of this equation

$$\begin{aligned}
Y_{i,t} = & \Theta_0(OLD_i * PC_i * YEAR(-4, 0)_{i,t}) + \sum_l \Theta_l(OLD_i * PC_i * YEAR(l, l+1)_{i,t}) \\
& + \beta_0(OLD_i * YEAR(-4, 0)_{i,t}) + \sum_l \beta_l(OLD_i * YEAR(l, l+1)_{i,t}) \\
& + \gamma_0(PC_i * YEAR(-4, 0)_{i,t}) + \sum_l \gamma_l(PC_i * YEAR(l, l+1)_{i,t}) \\
& + \sum_l \delta_l YEAR(l, l+1)_{i,t} + \tau_t + \epsilon_{i,t}
\end{aligned} \tag{5}$$

which does not include workers' fixed effect. Column 3 is for the matched sample while column 4 is for the full sample. Given the absence of fixed effects, now also the interactions with the dummy for the pre-displacement period are included in the specification. The coefficient  $\Theta_0$ , at the top of the table, provides an indication of how different the displaced and the non-displaced workers are in the period before potential displacement. While the coefficient is significantly different from zero in the full sample (column 4), no important difference emerges in the matched sample (column 3), which confirms the descriptive statistics presented in Table 1.

Interestingly, the point estimates of the other triple interaction terms  $\Theta_l$  are, respectively for each sample, very similar to the ones from the fixed effects model reported in columns 1 and 2 of the same table. This is expected in the case of the estimates based on the matched sample, because matching takes place on previous employment histories and characteristics, but might indicate a potential problem for the estimates that are based on the full sample. Clearly, one benefit of matching is that it immediately solves the problem of controlling for confounding factors when the outcome is binary (which is our case), whereas the inclusion of workers' fixed effects may not control sufficiently for (time invariant) confounding factors unless one has



many pre-treatment periods. In our case we have 16 quarters before plant closure, but due to our restriction that all workers should have at least one year of tenure before potential displacement, the binary outcome varies only in 12 pre-treatment quarters (years -3 and -2 before potential displacement). Hence, the variation in the outcome that we can exploit for the fixed effects estimation might not be sufficient to completely eliminate any bias due to time-invariant differences between displaced and non-displaced workers in the full sample. This is why we regard the combination of fixed effects and matching as our preferred specification, which is the one presented in Table 3 and replicated in column 1 of Table 4.

## 4 Modelling employment prospects of young and old workers after a job loss

In this section we present a job search model that allows us to interpret the evolution of employment histories after a displacement and that helps in understanding the different employment experiences of old and young workers after this kind of event.<sup>16</sup>

The basic job search model is typically used to make predictions about the steady-state (un)employment rate of a homogenous group of workers. The idea of our theoretical exercise is to use it, instead, to study the implications of a job loss at date  $t_0$  for the employment rates between  $t_1$  and some later date  $t_N$ . More precisely, on the basis of (i) the (constant) transition rates from employment to unemployment and (ii) the (constant) transition rate from employment (or unemployment) to early retirement, we calculate the probability that a worker who gets displaced at date  $t_0$  is found in employment at each date between  $t_1$  and  $t_N$ . To calculate employment losses

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<sup>16</sup>Our model implements a standard search framework that is extended by retirement as an absorbing state. We are implicitly assuming that new workers enter continuously the labor force and replace those who retire and study. Thus the labor market is in steady state. For a comprehensive treatment of the basic job search framework, see for example Mortensen (1986). See also Chemin and Wasmer (2012) for a similar exercise using ex-ante and ex-post evaluation of a policy reform.

within an age groups, we contrast the profile of employment probabilities for workers displaced at  $t_0$  with the corresponding profile for workers who are not displaced at the same date. The comparison between these two potentially different profiles is the theoretical counterpart of the object of interest of our empirical analysis in the previous sections: the difference between the employment losses (with respect to non-displaced workers in the same age cohort) of young and old displaced workers (i.e. the difference-in differences effect).

Thus, our theoretical exercise makes exactly the same counterfactual comparison that underlies our empirical analysis above: it aims at comparing the subsequent employment probabilities of two identical individuals who differ only with respect to displacement status at date  $t_0$ . One individual has lost her job at date  $t_0$  while the other individual has retained her job at the same date (although she may lose her job with positive probability in some later period).

To capture a crucial institutional feature of the (European) labor market we need to extend the simple structure of our standard search framework allowing for the option of early retirement. In the standard model (without a retirement option), any age differences in employment rates following a job loss can be captured by age-differences in transition rates between two states only: employment and unemployment. However, visual inspection of Figure 2 above shows that employment rates do not converge to a steady-state value (as predicted by the two-state job search framework), neither for old nor for young workers. Instead, the empirical employment rates fall monotonically with time since displacement. This is due to attrition: workers leave the labor force as they grow older.<sup>17</sup>

To capture this important empirical fact, we extend the basic job search model allowing for an absorbing state which we call “early retirement”. When the worker enters into this state, even if not old enough yet for regular retirement, she is assumed to abandon the regular labor market and to never

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<sup>17</sup>Huttunen et al. (2011) also show that a significant part of workers in Norway leave the labor force after displacement.

go back to a state of employment or unemployment. Therefore, the steady-state concept in our augmented search model implies that in each period some workers leave permanently the labor force while some workers enter into it, in a way such that inflows and outflows are balanced. Within this steady-state equilibrium, the simulation exercise described in the sequel looks at the evolution of employment rates for particular age cohorts.

#### 4.1 A search model with early retirement

We consider workers who, at some initial date, are either young or old and have just experienced a displacement. The notation that distinguishes these different initial conditions will be introduced later. For the moment, we focus on the period *that follows* this initial displacement date, in which we assume that these workers can be in one of three states: employment  $E$ , unemployment  $U$ , and (early) retirement  $R$  (i.e. permanent exit from the workforce). Denoting with  $r$  the discount rate, with  $w$  the wage rate and with  $p$  the pension-to-earnings replacement ratio, the value of retirement  $V_R$  is given by:

$$rV_R = pw. \quad (6)$$

Similarly, the values of employment  $V_E$  and unemployment  $V_U$  are given by:

$$rV_E = w - e - \lambda_U(V_E - V_U) + \lambda_R(V_R - V_E) \quad (7)$$

and

$$\max_s rV_U = bw - c(s) + s\mu_E(V_E - V_U) + \mu_R(V_R - V_U), \quad (8)$$

where  $e$  is the disutility of work,  $\lambda_U$  and  $\lambda_R$  are the transition rates from employment to unemployment and to retirement, respectively,  $b$  is the (unemployment) benefit-to-earnings replacement ratio,  $\mu_E$  is the job-offer arrival rate if the worker is unemployed, and  $\mu_R$  is the transition rate from unemployment to retirement.

It is worth noting from the outset that the wage  $w$  in the above equations will not be allowed to differ by age cohort. This assumption allows us to keep the model simple and tractable, without making our results less general, but

it is also grounded in the evidence described in Section 2 and 3, according to which there are no differences between the young and the old in terms of pre- and post-displacement wages. Moreover, to solve for the optimal search intensity, we only need to know the wage that a worker gets *after* a plant closure because it is the post-plant closure wage which determines the value of future employment  $V_E$ . This is the reason why the pre-displacement wage does not enter the equations described above. In our model, therefore, the restrictive assumption concerning wages is only that a worker experiences an earnings loss after the first displacement, but not after any potential future employment change. To put it differently, our assumptions imply that after the first (potential) displacement, which is the time origin in our setting, the wage  $w$  is (on average over time) similarly lower for the old and the young at each date and stays at this lower level in all future jobs.

The crucial endogenous variable is the intensity  $s$  at which unemployed workers search for a new job. We assume that searching is costly and that this cost is given by  $c(s) = \frac{As^2}{2}$ , where  $A > 0$  is a constant. From equation (8), optimal search intensity,  $s^*$ , is given by

$$As^* = \mu_E(V_E - V_U). \quad (9)$$

This equation says that the marginal cost of searching (i.e. the left hand side) has to equal the marginal benefit (i.e. the right hand side), which is the expected increase in income from a successful search. The system of four equations, (6), (7), (8) and (9), in the four unknowns  $s^*$ ,  $V_R$ ,  $V_E$ , and  $V_U$  defines the equilibrium. We can reduce the above system to a single (quadratic) equation which implicitly determines the optimal search intensity  $s^*$ :

$$As^* = \mu_E \left[ \frac{w - e - bw + \frac{As^{*2}}{2} + \frac{\lambda_R - \mu_R}{r + \mu_R} \left( w(p - b) + \frac{As^{*2}}{2} \right)}{r + \lambda_U + \lambda_R + \left( \frac{r + \lambda_R}{r + \mu_R} \right) s^* \mu_E} \right] \quad (10)$$

## 4.2 Age differences in employment prospect after displacement.

The model presented above allows us to characterize possible explanations of the employment patterns that we have described in Section 3 for displaced and non-displaced workers of different ages. We focus specifically on three possible sets of explanations, which we find most interesting.

*First*, young and old workers may face different labor demand conditions. For example, old unemployed workers may get fewer job offers, in which case  $\mu_E^{old} < \mu_E^{young}$ ; or face a higher risk of job loss if employed, in which case  $\lambda_U^{old} > \lambda_U^{young}$ ; or both. Note that our model predicts that these differential demand conditions will be partly accommodated by workers' responses in terms of search intensity  $s^*$ . Our goal is to show under which assumptions these endogenous workers' reactions in terms of search intensity can be disentangled from demand conditions as well as from other determinants of supply.

A *second* explanation of the observed age-differences in employment patterns after a job loss refers to workers' incentives. Old unemployed workers may have a lower incentive to (search hard for) work, either because working is more costly for them, in which case  $e^{old} > e^{young}$ , or because their search costs are higher, in which case  $A^{old} > A^{young}$ . In both cases we would expect that, because of these two reasons related to supply behavior, old workers, once displaced, will have lower employment rates than displaced young workers.

A *third* explanation looks at institutional determinants of labor supply. Old workers face better options to enter early retirement, both from employment and unemployment. In terms of the model parameters, this implies that  $\lambda_R^{old} > \lambda_R^{young}$ , and  $\mu_R^{old} > \mu_R^{young}$ , respectively. Note again that these age-differences in exogenous parameters will be accommodated (and possibly intensified) by the search behavior of young and old workers. Institutional differences may also arise because of more generous unemployment insurance for older workers and/or more generous early retirement benefits for workers

who have contributed to the system for a longer period of time.<sup>18</sup>

Our goal, now, is to compare the observed employment patterns, described in Section 3, with those that are simulated by the model under different parameter configurations in order to identify which one of these configurations is more likely to have generated the data.

### 4.3 A “minimum distance” calibration for the most likely configuration of parameters

The model presented above produces the following system of difference equations that describe the evolution of employment of young and old workers, respectively.

$$\begin{aligned} E_t^j &= (1 - \lambda_R^j - \lambda_U^j)E_{t-1}^j + \tilde{\mu}_E^j U_{t-1}^j \\ U_t^j &= \lambda_U^j E_{t-1}^j + (1 - \mu_R^j - \tilde{\mu}_E^j)U_{t-1}^j \end{aligned} \quad (11)$$

where  $j \in \{young, old\}$  and the effective arrival rate of job offers is  $\tilde{\mu}_E^j = s^j \mu_E^j$ ; therefore note that the model cannot disentangle directly the arrival rate of job offers that are created for the unemployed ( $\mu_E^j$ ) from their search intensity ( $s^j$ ), a problem we will deal with later. Moreover within each age group, displaced and non-displaced workers follow the same dynamics. This reproduces the maintained hypothesis, which is at the basis of the matching estimation strategy implemented in Section 3, according to which displaced workers are randomly selected from the overall population (conditioning on observables) and any difference between the two groups is caused by the event of displacement only. In other words, displaced and non-displaced workers differ only because of their initial conditions of employment or non-employment at the time of plant closure. Therefore, at date  $t = 0$ , when the event of plant closure takes place, we set  $E_0^j = 0$  and  $U_0^j = 1$  for the displaced and  $E_0^j = 1$  and  $U_0^j = 0$  for the non-displaced.<sup>19</sup>

<sup>18</sup>See the Appendix for institutional details on retirement and early retirement schemes in Austria.

<sup>19</sup>Note that the parameters of the dynamic system (11) do not differ by displacement status. This restriction make sense for  $\mu_R^j$  and  $\tilde{\mu}_E^j$ , because, in a stationary environment, it is reasonable that the exit rates from unemployment are the same for those who were recently displaced and for those who will experience displacement in the future. It is

In matrix notation, the above system (11) of difference equations can be written as  $\mathbf{Y}_t^j = \Phi \mathbf{Y}_{t-1}^j$ , where  $\mathbf{Y}_t^j = (E_t^j, U_t^j)'$  and  $\Phi$  is the 2x2 matrix of the system parameters, that are in turn functions of the primitive model parameters  $\lambda_R^j, \lambda_U^j, \mu_R^j$ , and  $\tilde{\mu}_E^j$ . The solution to this system is straightforward and given by

$$\mathbf{Y}_t^j = \Phi^j \mathbf{Y}_0^j.$$

To calibrate the parameters of the model ( $\lambda_R^j, \lambda_U^j, \mu_R^j$ , and  $\tilde{\mu}_E^j$ ) we proceed as follows. We choose the parameter values that (i) obey the above system of difference equations and (ii) minimize the distance between the observed and the calibrated employment patterns. The goal of this calibration strategy is to generate predicted time paths that match the evolution of employment rates (and of the differences between these rates) that we have described in Figure 2 for the four groups defined by age cohort and displacement status. In particular, we want to explore which parameter values are able to replicate the remarkable catch-up behavior of old workers: i.e. that in the first five years they suffer more from a plant closure as compared to the young, while after five years this pattern turns around.

Formally, given these goals, we look for the parameter values  $\lambda_R^j, \lambda_U^j, \mu_R^j$ ,

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instead restrictive to assume that the exit rates from employment  $\lambda_R^j$  and  $\lambda_U^j$  are the same independently of a recent displacement event. This because it is plausible that recently displaced workers who found a new job face a higher risk of being dismissed. We plan to relax this restrictive assumption in future work, but it is remarkable, as we will see, that even with this restriction the employment histories predicted by the model match very closely those observed in the data.

and  $\tilde{\mu}_E^j$  that minimize the following objective function:

$$\begin{aligned}
\Omega = & \sum_{t=1}^{32} (E_t^{y,npc} - \hat{E}_t^{y,npc})^2 + \sum_{t=1}^{32} (E_t^{y,pc} - \hat{E}_t^{y,pc})^2 \\
& + \sum_{t=1}^{32} (E_t^{o,npc} - \hat{E}_t^{o,npc})^2 + \sum_{t=1}^{32} (E_t^{o,pc} - \hat{E}_t^{o,pc})^2 \\
& + \sum_{t=1}^{32} (U_t^{y,npc} - \hat{U}_t^{y,npc})^2 + \sum_{t=1}^{32} (U_t^{y,pc} - \hat{U}_t^{y,pc})^2 \\
& + \sum_{t=1}^{32} (U_t^{o,npc} - \hat{U}_t^{o,npc})^2 + \sum_{t=1}^{32} (U_t^{o,pc} - \hat{U}_t^{o,pc})^2. \tag{12}
\end{aligned}$$

Note that this objective function is the sum of two parts: The first part is the sum of the squared distances between the observed ( $E_t$ ) and the simulated ( $\hat{E}_t$ ) employment rates in the four groups of workers (by age cohort and plant closure status) for which we have data: old displaced (o,pc), old non-displaced (o,npc), young displaced (y,pc), young non-displaced (y,npc). The second part is the sum of the squared distances between the simulated and the observed unemployment rates across the four groups. This reproduces the dynamic paths of all three states: employment, unemployment and – as a residual – the retirement state.

In order to properly distinguish unemployment from retirement (which in our context is defined as a permanent exit from the labour force), we proceed as follows: we count a worker as a permanent dropout (a “retiree”) if she/he exits from employment in a given quarter and remains not employed for all the remaining quarters of our observation period. Since the exits observed towards the end of the period could be temporary even if lasting until quarter 40, we run the simulation until quarter 32, so that at least 8 quarters of non-employment are necessary to classify a worker as permanently dropout.

The minimization of the objective function (12) yields the calibrated parameters reported in Table 5. Before commenting on these parameter values, however, it is important to show, in Figure 4, that they generate simulated patterns that fit the observed ones very well. This close correspondence emerges not only for the levels of the employment rates, by displacement



status of the young and the old (in the top Panels of the figure), but also for the differences (in the bottom left Panel) and for the differences-in-differences (in the bottom right Panel).

Looking specifically at this last panel, the calibrated values indicate that the old displaced lose up to 3 percent more than the young displaced (relative to their respective counterfactuals), in the first five years after displacement. The corresponding maximum loss observed in the actual data is just slightly higher, at 5 percent. Moreover, the model and the data coincide quite closely in showing that, after the fifth year from plant closure, the old displaced begin to gain with respect to the young displaced (relative to their respective counterfactuals). In other words, the minimum distance calibration of the parameters is capable to capture fairly well the finding that, after the fifth year, the old catch up with the young regain what they have lost in the first five years.

As far as the employment *levels* are concerned, the model's predictions for the young workers, both displaced and non-displaced, match quite well what we see in the data (left upper panel of Figure 4). The employment rates of older workers are also predicted quite well, though somewhat less precisely than those for younger workers (right upper panel of Figure 4). One feature that the model does not capture well enough for old workers is the concavity of the employment profile over time as observed in the data, that suggests increasing rather than constant transition rates to retirement with increasing age; a fact which cannot be dealt with in our simple time-invariant specification.

All in all, the minimum distance calibration of the search model's parameters, displayed in Table 5, does surprisingly well in predicting the employment prospects of the old and the young workers who are displaced in a plant closure as well as the analogous prospects of their non-displaced counterfactuals. Hence, we can now turn with confidence to the interpretation of the calibrated parameters displayed in Table 5, in order to understand whether supply or demand factors are more likely to have driven the observed patterns.

#### 4.4 What drives the employment prospect of young and old workers

The first column of Table 5 reports the calibration of  $\lambda_u$ , which is the transition rate from employment to unemployment or, in other words, the instantaneous probability of layoff. For the old this parameter is calibrated to be fairly low, at a rate of 1.7% per quarter, while for the young it is almost twice as high at a level of 2.6% per quarter. This is in line with the international evidence offered by Kuhn (2002), who finds a lower displacement risk for elderly workers in many countries. It is actually not surprising if we consider that “First - in - last - out” seniority rules govern layoffs in many Austrian (and continental European) companies.

The second column of the Table reports the calibrated transition rates from employment to (early) retirement, which are measured by the parameter  $\lambda_r$ . In this case, the ranking of the parameters for the young and the old is inverted. As expected, this instantaneous probability is zero for the young who have very limited opportunities to access early retirement. It is instead quite large (1.9%) for the old who, in Austria like in other European countries, can typically use many channels to leave work and receive an early pension income.<sup>20</sup>

This differential pattern of early retirement opportunities for the young and the old is confirmed as well by the calibration of the parameter  $\mu_r$ , which measures the transition rate from unemployment into the absorbing state that we have labelled “early retirement”, in which the worker remains out of the labor force, possibly receiving an early pension income (Column 3 of Table 5). For both young and old workers, the probability of a transition to retirement is higher from unemployment ( $\mu_r > \lambda_r$ ). While for the young  $\mu_r = 0.08$  (8.0% per quarter), for the old it reaches the high level of 13.7% per quarter, which indicates that for an unemployed worker in Austria, particularly if old but also if young, feasible opportunities to exit the work force

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<sup>20</sup>Note that the total exit rate from employment ( $\lambda_u + \lambda_r$ ) is much higher for old than for young workers (3.6% vs. 2.6%).

permanently are easier to grab than for an employed worker.<sup>21</sup> This is not surprising given the strong reactions that unemployment typically generates in the public opinion, particularly in the case of old citizens<sup>22</sup>, inducing governments to put in place schemes that offer to unemployed, but still active, workers easier and more generous possibilities of transition into early retirement, sometimes through intermediate periods of “protected joblessness.”<sup>23</sup>

Looking together at the three parameters analyzed so far, demand factors do not seem to be the most important ones for an explanation of the more adverse employment prospects observed for older workers in the first five years after displacement. If anything, they push in the opposite direction. On the one hand, the rate  $\lambda_u$  at which old workers lose their job, provided they have one, is fairly low, while it is almost twice as big for the young. On the other hand, the old have much larger opportunities to retire ( $\mu_r$  and  $\lambda_r$ ) than the young, particularly if they are unemployed. Thus, more accessible retirement opportunities for the old, seem, if anything, to be more relevant for an explanation of the observed patterns, although it is not clear to what extent they are driven by supply factors only – e.g. generous retirement incentives – or whether demand factors might play a role as well. This could happen, for example, if these retirement schemes make it easier for firms to get rid of their most expensive unwanted workers, as suggested by Hakola and Uusitalo (2005) and Frimmel et al. (2013). But also in this case the responsibility would fall on public policies aimed at creating incentives to early retirement which would display their effects through demand as well as through supply.

The remaining parameter  $\tilde{\mu}_e$  in Table 5 is, however, the one on which most attention in the public opinion is typically focused. This is the effective arrival rate of job offers to unemployed workers, which results from the interaction between their search intensity and the job creation activity of firms.

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<sup>21</sup>See also Tatsiramos (2010) who finds that displaced older workers in Spain and Germany frequently enter early retirement, but less so in Italy or the U.K.

<sup>22</sup>See again footnote 1

<sup>23</sup>The Appendix gives some institutional evidence on these schemes for Austria.

Interestingly, the calibration of this parameter (Column 4) delivers figures that are remarkably similar for the young and the old. The instantaneous probability of a transition from unemployment to employment is equal to 0.419 for a young unemployed worker and is only slightly smaller (0.416) for an old unemployed worker.

It should be remembered, though, that  $\tilde{\mu}_e = s\mu_e$ . In other words, what our calibration procedure can pin down is just the product of the search intensity  $s$  and the arrival rate of new offers from companies  $\mu_e$ . Therefore, on the basis of this product  $\tilde{\mu}_e$ , one cannot immediately jump to the conclusion that the young and the old unemployed have the same working opportunities simply because  $\tilde{\mu}_e$  is equal. In order to answer this question we need an estimate for job search intensity by age.

Well accepted and clear-cut empirical indicators of search intensity are difficult to define and find, since search effort is a multi-faceted and hard-to-measure concept. Therefore, we use a combination of questions from the 2002, 2004 and 2006 waves of the Austrian Microcensus; all these surveys have exactly the same questions on job search behavior. Taking the three surveys together we come up with 812 unemployed individuals in the age group 35-55; 391 of them young and 423 old.

The survey asks detailed questions about job search methods, including whether the intermediation by the employment office was requested or not. In total, respondents can chose one or more of the following eight job search methods. Three involve the intermediation of the employment office: to visit personally the employment office, to study job offers there, to visit a firm with the help of the employment office. Five more methods do not involve the employment office intermediation: to read newspaper advertisements, to inquire with friends and acquaintances, to call firms, to send application letters, to visit a firm. On the basis of the respondents' choices concerning these methods, we constructed two indicators of job search intensity: a) the average number of search methods that a person has been using (search depth) and b) the percentage of persons who have used at least one search method (search width).

Results suggest unambiguously that both search intensity measures decrease with age. As far as search depth is concerned, the young unemployed, use on average 2.72 of the available search methods relative to an average of 2.19 for the unemployed old ones. The difference is statistically significant with a t-value of 3.38. As far as search width is concerned, 72.4% of young unemployed workers are active searchers, i.e. they use at least one method, as compared to 61.9% of the old. Also this difference is statistically significant with a t-value of 3.18. These differential search patterns by age cohort are also confirmed by the answers to another question of the survey. When respondents have to say whether they are “currently looking for a job” the answer is affirmative for 81.5% of the young unemployed while the same is true for only 68.4% of the old unemployed (the difference is statistically significant with a t-value of 4.14).<sup>24</sup>

This evidence suggests unambiguously that  $s^{old} < s^{young}$ , i.e. the old search less intensively than the young. Since the minimum distance calibration indicates that

$$\tilde{\mu}_e^{old} \equiv s^{old} \mu_e^{old} \approx s^{young} \mu_e^{young} \equiv \tilde{\mu}_e^{young} \quad (13)$$

the inequality of search intensity by age cohort must imply that

$$\mu_e^{old} \geq \mu_e^{young} \quad (14)$$

i.e. that the arrival rate of job offers to the old unemployed is unlikely to be smaller, and most probably larger, than the respective arrival rate for the young.

Figure 5 shows from another angle how relevant retirement incentives are likely to be in explaining the observed employment patterns after a displacement. The figure reports the “real data” and the “calibrated” relative employment losses of old versus young workers – i.e. the difference-in-difference

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<sup>24</sup>Likewise, Eriksson et al. (2002) show that job search intensity – whether measured in the number of search methods used or the hours per week spent – is lower for workers above 50 relative to younger ones in Finland, Denmark and Norway. Krueger and Mueller (2012) show – using time use data for six countries - that the time spent in job search is decreasing after age 30, while in the US the maximum is reached for the age group 46-50 (Aguiar et al. (2013))

patterns plotted in panels D of Figures 2 and 4 respectively – side by side with two “counterfactual” simulations of these relative employment losses.

Counterfactual 1 sets transition rates of the old between the states of employment and unemployment equal to the corresponding calibrated rates for the young. This counterfactual shuts down the possibility that differences in layoff rates and in the arrival of job offers for young and old workers might explain the observed patterns of relative employment losses, but leaves open the other channels of explanation. In this case, the counterfactual pattern is qualitatively very similar to the calibrated and the real data patterns, suggesting that differences between young and old workers in layoff rates and job offer arrival rates cannot explain why the relative employment losses of old workers after a displacement are initially larger and later smaller than those of young workers.

Counterfactual 2, instead, sets the transition rates into retirement of the old equal to the corresponding rates for the young. This counterfactual shuts down the possibility that differences in retirement opportunities of young and old workers explain the patterns of relative employment losses, but leaves open the other channels of explanation. In this case, it is evident that the counterfactual pattern is completely different from the observed and the calibrated ones, being flat and close to zero. This suggests that, in the absence of differences in retiring opportunities between young and old workers, we would not see the evolution of relative employment losses that are instead observed in the real data as well as those that can be calibrated within our theoretical model

To conclude, the analysis of the minimum distance calibration of the model parameters, joined with independent evidence on search behaviour, suggests that retirement incentives rather than factors affecting transitions between unemployment and employment (in both directions) are responsible for the observed patterns of relative employment losses of old versus young workers after a displacement. The old seem to face a smaller firing probability if employed and a higher job arrival rate if unemployed. They also enjoy significantly higher opportunities to take up early retirement schemes, partic-

ularly when unemployed. As a result of this configuration of parameters, the old search less intensively for new working opportunities, when unemployed, both in terms of search depth (number of search methods used) and search width (probability of being an active searcher).

## 5 Conclusions

In this paper we provided fresh evidence on two questions that are the object of a hot debate in the aging European society: are there significant differences in the employment prospects of old and young workers, particularly when they lose their job? And, if these differences exist, what are their driving forces?

To answer the first question we have used representative data from the Austrian administrative records that allow us to study the employment histories of old (45-55 years of age) and young (35-45 years of age) workers who have lost their job due to an exogenous event – a plant closure –, comparing them to a control sample of non-displaced workers who were matched according to a host of pre-plant closure characteristics. This comparison suggests that, over the long term time horizon of ten years after plant closure, the old displaced do not have, overall, worse employment opportunities than the young displaced, relative to their respective non-displaced counterfactuals. However, this long term absence of differences hides more diversified and puzzling short term patterns. In the first five years after plant closure the old displaced experience significantly higher losses than the young, with respect to the counterfactuals, but regain completely the lost terrain in the subsequent five years.

To interpret these findings and thus answer the second question, we set up a standard job search model and extend it by allowing for an absorbing state that captures the option of “early retirement”, defined as a situation of permanent exit from the workforce. Using a simple minimum distance algorithm to calibrate the transition parameters, we find that the model does remarkably well in replicating the observed employment patterns not only in

terms of *levels* for each group but also in terms of *differences* and *differences between differences* across the four groups. We conclude that our framework provides a helpful tool to explore the reasons of the observed differential consequences of job displacement between older and younger workers.

The analysis strongly suggests that retirement incentives are mainly responsible for the observed employment patterns. Old workers do not face a higher probability of layoff if employed, nor a lower arrival rate of job offers if unemployed. They instead face a higher probability of a transition to early retirement in particular when they are unemployed. Independent evidence from the Austrian Micro Census further suggests that search intensity for new working opportunities is significantly lower among older unemployed workers, probably because for them the exogenous arrival rate of new job offers is not lower and the opportunities of early retirement are more attractive.

From a policy perspective, our paper suggests that measures aimed at bringing older unemployed workers back to work after a displacement, such as specifically targeted training programs and/or incentives for firms to hire older unemployed workers, should substitute early retirement schemes with possible savings for public finances.



## Appendix: The pension and unemployment insurance system in Austria

Austria has a fairly generous pay-as-you-go pension system which allows fairly early retirement options. The regular pension can be claimed at age 65 for men and 60 for women provided they paid contributions for at least 180 months. If the individual has worked for more than 420 months, early retirement due to “sufficient insurance contributions” is possible.<sup>25</sup> Apart from these general rules, long-term unemployment allowed retirement at age 60 (55) for men (women) if the person was unemployed for at least 52 weeks in the last 15 months.

Although the regular retirement age is similar to that in other European countries, the actual retirement age of men decreased steadily from nearly 62 in the 1970s to about 58 in 1995. Since then, it has increased slightly to around 59 years since 2005. Despite the different statutory retirement age for men and women, the actual retirement age for women is less than half a year lower than the one for males (Hofer and Koman, 2006).

Early retirement due to reduced working capacity was possible in the 1990s for men and women after age 55. This option requires that the claimant – due to health reasons – could not continue the work predominantly pursued in the last 15 years. A similar case is an invalidity pension, which could be claimed, in principle, at any age, but offers only a considerably lower pension. For both alternatives, a doctor has to check whether or not the applicant has reduced working capacity.

The formula for calculating old-age pension levels is based on the retirement age, the number of insurance years and the level of income prior to the time of retirement. In the case of the normal old-age pension at the statutory retirement age, the best 5-15 years of earnings (below a certain upper contribution cap) are used to calculate the basis of assessment (Hofer and Koman, 2006). In the eighties the five best years of earnings were used only, which was later on extended.

Until 1989, an unemployed person could draw regular unemployment benefits for a maximum period of 30 weeks provided that he or she had paid unemployment insurance contributions for at least 156 weeks within the last 5 years. In August 1989 the potential duration of these payments became dependent on age. Benefit duration for the age group 40-49 was increased to 39 weeks if the unemployed has been employed 312 weeks within the last 10 years prior to the current spell. For the age group 50 and older, benefit duration was increased to 52 weeks if the unemployed has been employed for at least 468 weeks within the last 15 years. After 1988 – after a severe steel crises – in certain regions of the country, benefit duration for workers 50 years of age and older was extended to 209 weeks provided they had long contribution periods.<sup>26</sup>

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<sup>25</sup>These rules are shown for the 1980s. In 1992 the unequal retirement age for men and women was abolished, which will take effect only for women born after 1963.

<sup>26</sup>See Winter-Ebmer (1998) or Lalive and Zweimüller (2004) for an analysis of these benefit extensions. In Table 6 Ichino et al. (2007) show that these benefit extensions do

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not dominate the main pattern of our empirical analysis.

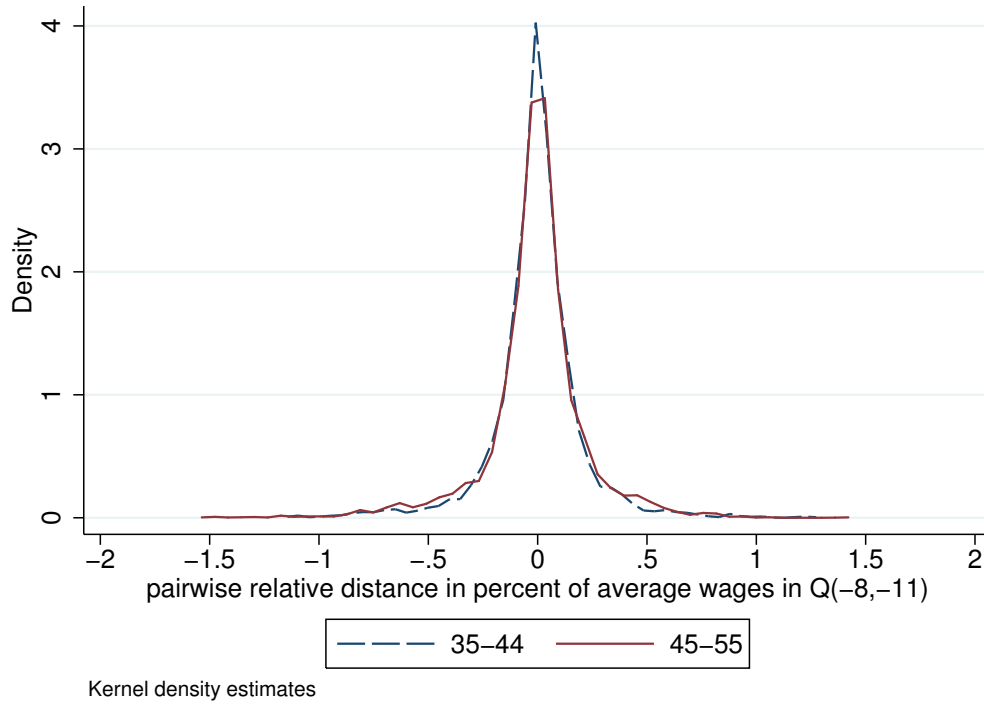
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Table 1: Descriptive Statistics by Displacement Status and Cohort

|                            | Random Control Sample |                  |                  |                  | Matched Sample   |                  |                  |                  |
|----------------------------|-----------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|
|                            | <i>“Young”</i>        |                  | <i>“Old”</i>     |                  | <i>“Young”</i>   |                  | <i>“Old”</i>     |                  |
|                            | displ                 | non-displ        | displ            | non-displ        | displ            | non-displ        | displ            | non-displ        |
| Female                     | .5                    | .41              | .52              | .4               | .49              | .49              | .48              | .48              |
| Blue collar                | .38                   | .43              | .43              | .51              | .33              | .33              | .42              | .42              |
| Age (years)                | 40<br>(2.9)           | 40<br>(2.9)      | 50<br>(3.2)      | 50<br>(3.2)      | 40<br>(2.8)      | 40<br>(2.8)      | 49<br>(3.2)      | 49<br>(3.2)      |
| Tenure (days)              | 2,546<br>(1,631)      | 3,000<br>(1,600) | 3,164<br>(1,732) | 3,620<br>(1,595) | 2,797<br>(1,558) | 2,794<br>(1,550) | 3,330<br>(1,651) | 3,328<br>(1,618) |
| Experience (days)          | 4,105<br>(1,217)      | 4,270<br>(1,147) | 4,441<br>(1,097) | 4,557<br>(1,044) | 4,205<br>(1,100) | 4,192<br>(1,130) | 4,502<br>(1,021) | 4,485<br>(1,053) |
| Average daily wage (euros) | 29.30<br>(13.43)      | 33.89<br>(13.08) | 29.64<br>(13.71) | 34.27<br>(13.52) | 29.91<br>(13.79) | 30.09<br>(13.57) | 30.57<br>(13.91) | 30.74<br>(13.99) |
| Plant size                 | 79<br>(283)           | 1,791<br>(4,763) | 107<br>(171)     | 2,131<br>(5,245) | 85<br>(263)      | 67<br>(198)      | 97<br>(256)      | 100<br>(256)     |
| Number of workers          | 6,523                 | 19,776           | 5,579            | 16,530           | 3,807            | 20,342           | 2,823            | 16,335           |

Note: Sample averages with standard deviations in parentheses. All variables, except wage and plant size, are measured at the quarter immediately before (potential or actual) plant closure. The average daily wage is in nominal terms and measured 2 years before plant closure. Plant size is measured 3 quarters before plant closure.

Figure 1: Relative Difference in average pre-displacement wages between treated and matched controls



*Note:* Kernel density estimates of the “within match” relative difference in average pre-closure wages between displaced workers and their matched controls, performed separately for old and young workers. The “within match” relative difference in average pre-closure wages is measured in percent of average wages in the quarters 8 to 11 prior to potential plant closure.

Table 2: The Effect of Plant Closure on Future Employment

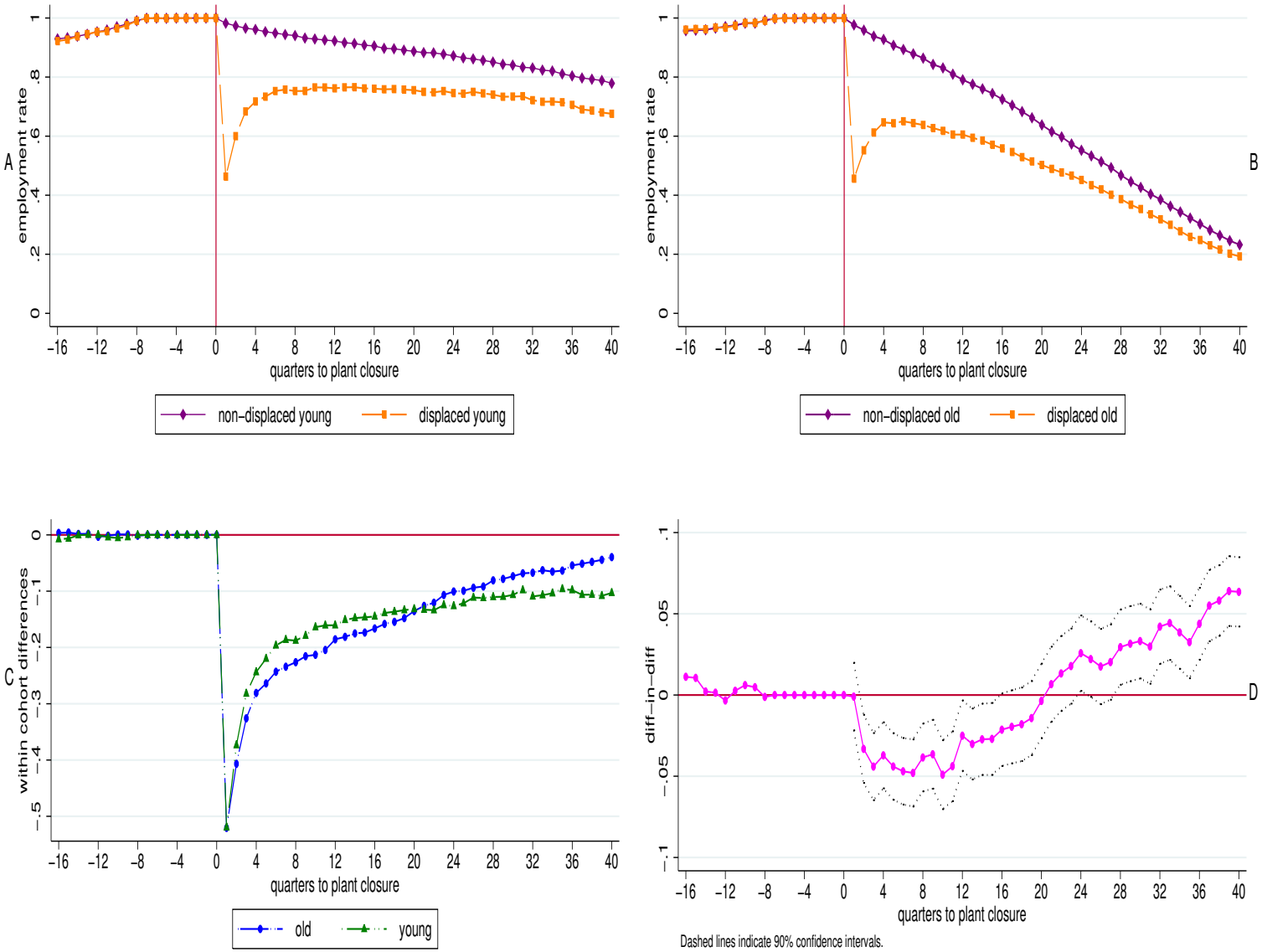
|              | All                  | Male                 | Female               |
|--------------|----------------------|----------------------|----------------------|
| OLD*PC*POST  | 0.000<br>(0.010)     | 0.006<br>(0.014)     | -0.007<br>(0.015)    |
| OLD*POST     | -0.274***<br>(0.005) | -0.203***<br>(0.006) | -0.350***<br>(0.008) |
| PC*POST      | -0.154***<br>(0.006) | -0.140***<br>(0.008) | -0.169***<br>(0.009) |
| POST         | -0.094***<br>(0.003) | -0.096***<br>(0.004) | -0.092***<br>(0.004) |
| Constant     | 0.980***<br>(0.002)  | 0.985***<br>(0.002)  | 0.974***<br>(0.003)  |
| Observations | 2,465,250            | 1,420,497            | 1,044,753            |
| $R^2$        | 0.479                | 0.456                | 0.499                |

\* p<0.10, \*\* p<0.05, \*\*\* p<0.01

*Note:* Estimates based on equation 2. The dependent variable is a dummy for the employment status of the worker. All specifications include individual fixed effects and calendar time effects. Estimation results are based on the matched sample. Clustered standard errors at the individual level in parentheses.

Figure 2: Descriptive Statistics on Employment

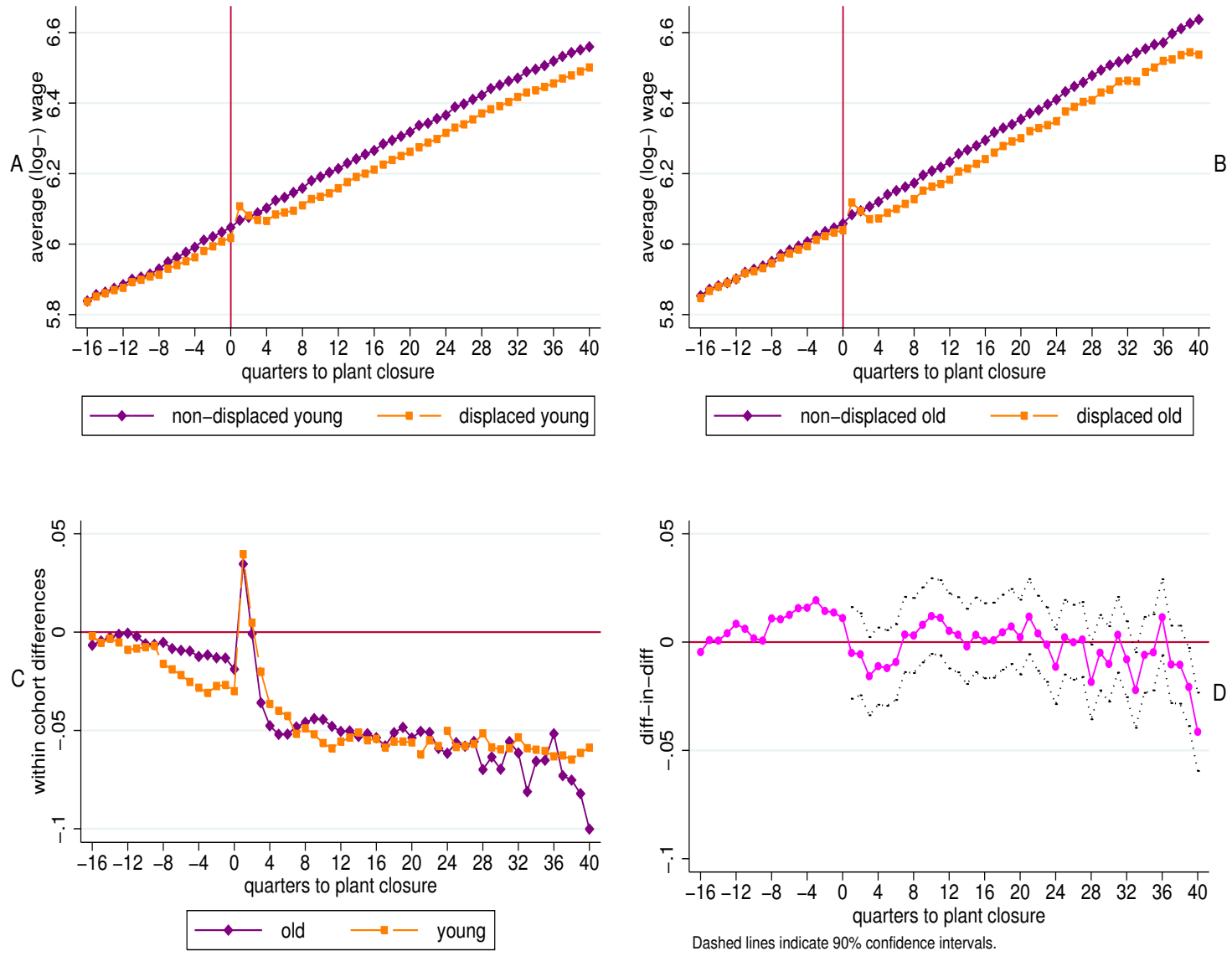
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Note: Predicted values based on the estimation of equation (3), using employment status as the dependent variable.

Figure 3: Descriptive Statistics on Wages

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Note: Predicted values based on the estimation of equation (3), using the log of daily earnings for employed persons as the dependent variable.



Table 3: Fixed effects estimates

|             | Years after Potential Displacement |                   |                   |                   |                   |
|-------------|------------------------------------|-------------------|-------------------|-------------------|-------------------|
|             | 1 - 2                              | 3 - 4             | 5 - 6             | 7 - 8             | 9 - 10            |
| OLD*PC*YEAR | -.038<br>(.010)**                  | -.034<br>(.012)** | .000<br>(.013)    | .026<br>(.013)*   | .048<br>(.013)**  |
| PC*YEAR     | -.273<br>(.006)**                  | -.154<br>(.007)** | -.130<br>(.007)** | -.107<br>(.008)** | -.101<br>(.008)** |
| OLD*YEAR    | -.047<br>(.004)**                  | -.141<br>(.006)** | -.265<br>(.007)** | -.396<br>(.007)** | -.514<br>(.007)** |
| YEAR        | -.026<br>(.002)**                  | -.069<br>(.003)** | -.106<br>(.005)** | -.149<br>(.006)** | -.195<br>(.007)** |

*Note:* Estimates based on equation 4. The dependent variable is a dummy for the employment status of the worker. The specification includes individual fixed effects, calendar time effects and a constant term (.939\*\*). Estimation results are based on the matched sample with 2,465,250 worker-quarter observations. The  $R^2$  equals .543 and the  $F$  statistic equals 317.4. Clustered standard errors at the individual level in parentheses.

Table 4: Matched versus random control sample  
with FE                      without FE

|                   | Matched           | Full              | Matched           | Full              |
|-------------------|-------------------|-------------------|-------------------|-------------------|
| OLD*PC*YEAR(-4-0) |                   |                   | .002<br>(.002)    | .009<br>(.002)**  |
| OLD*PC*YEAR(1-2)  | -.038<br>(.01)**  | -.067<br>(.007)** | -.036<br>(.010)** | -.063<br>(.007)** |
| OLD*PC*YEAR(3-4)  | -.034<br>(.012)** | -.070<br>(.009)** | -.032<br>(.012)** | -.065<br>(.008)** |
| OLD*PC*YEAR(5-6)  | .000<br>(.013)    | -.012<br>(.009)   | .001<br>(.013)    | -.007<br>(.009)   |
| OLD*PC*YEAR(7-8)  | .026<br>(.013)*   | .036<br>(.009)**  | .028<br>(.013)*   | .040<br>(.009)**  |
| OLD*PC*YEAR(9-10) | .048<br>(.013)**  | .072<br>(.009)**  | .05<br>(.012)**   | .067<br>(.008)**  |
| Fixed effects     | yes               | yes               | no                | no                |
| Observations      | 2,465,250         | 2,759,256         | 2,465,250         | 2,759,256         |
| $R^2$             | .543              | .551              | .259              | .286              |
| $F$ statistic     | 317.403           | 730.448           | 290.368           | 735.716           |

*Note:* Estimation results in columns 1 and 2 are based on equation 4, columns 3 and 4 report results based on equation 5. The dependent variable is a dummy for the employment status of the worker. Only the triple interaction terms are reported. All specifications include calendar time effects. Columns 1 and 3 report estimation results based on the matched sample, column 2 and 4 report results based on the full sample. Clustered standard errors at the individual level in parentheses.

Table 5: Minimum distance calibration of the model's parameters

|                 | $\lambda_u$ | $\lambda_r$ | $\mu_r$ | $\tilde{\mu}_e$ |
|-----------------|-------------|-------------|---------|-----------------|
| Young workers   | 0.026       | 0.0         | 0.080   | 0.419           |
| Old workers     | 0.017       | 0.019       | 0.137   | 0.416           |
| Sum of squares: | 0.1707      |             |         |                 |

*Note:* The table reports the configuration of parameters in model (11)

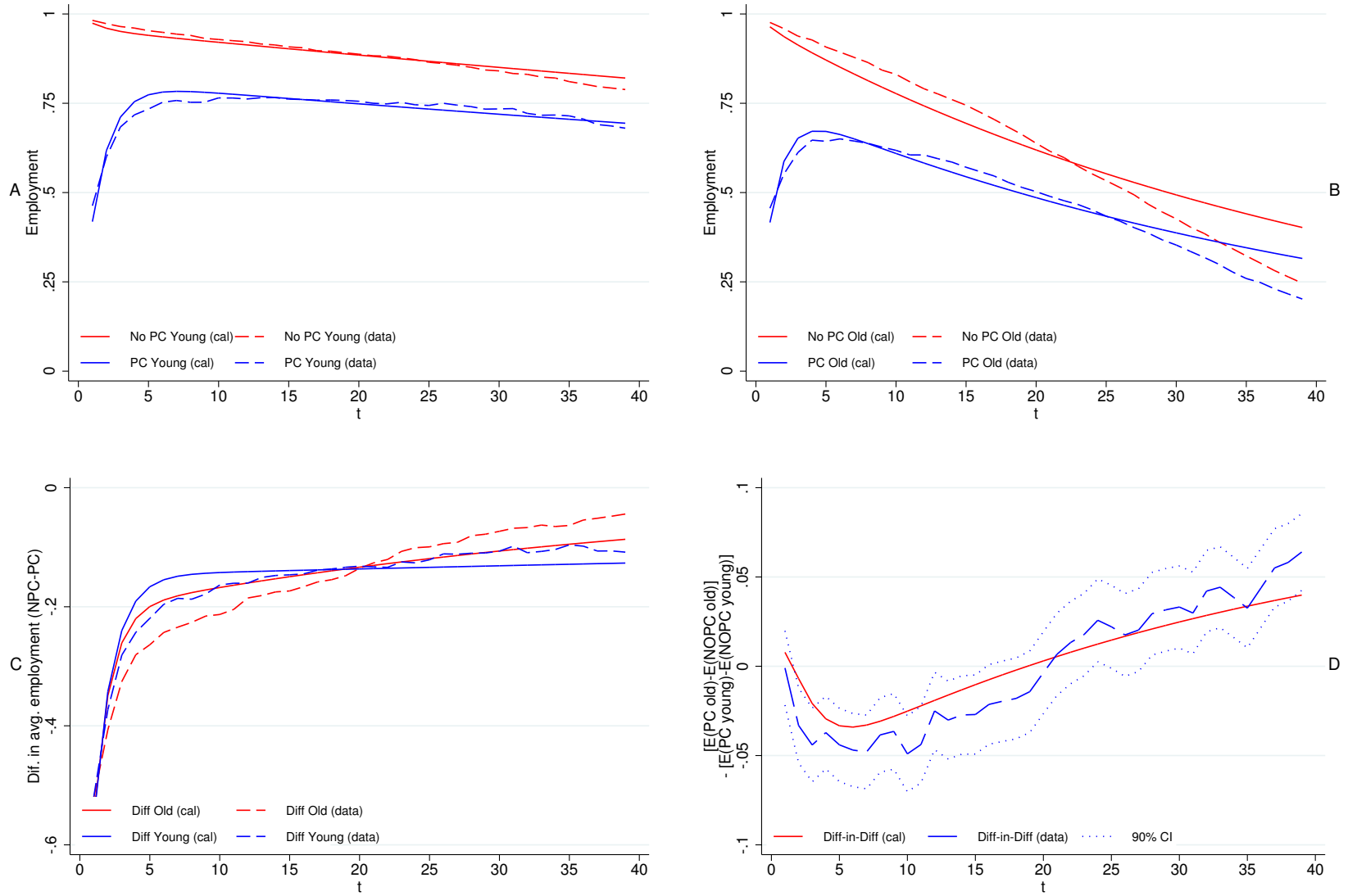
$$\begin{aligned} E_t^j &= (1 - \lambda_R^j - \lambda_U^j)E_{t-1}^j + \tilde{\mu}_E^j U_{t-1}^j, \\ U_t^j &= \lambda_U^j E_{t-1}^j + (1 - \mu_R^j - \tilde{\mu}_E^j)U_{t-1}^j, \end{aligned}$$

which minimizes the objective function

$$\begin{aligned} \Omega = & \sum_{t=1}^{32} (E_t^{y, npc} - \hat{E}_t^{y, npc})^2 + \sum_{t=1}^{32} (E_t^{y, pc} - \hat{E}_t^{y, pc})^2 + \sum_{t=1}^{32} (E_t^{o, npc} - \hat{E}_t^{o, npc})^2 + \sum_{t=1}^{32} (E_t^{o, pc} - \hat{E}_t^{o, pc})^2 \\ & + \sum_{t=1}^{32} (U_t^{y, npc} - \hat{U}_t^{y, npc})^2 + \sum_{t=1}^{32} (U_t^{y, pc} - \hat{U}_t^{y, pc})^2 + \sum_{t=1}^{32} (U_t^{o, npc} - \hat{U}_t^{o, npc})^2 + \sum_{t=1}^{32} (U_t^{o, pc} - \hat{U}_t^{o, pc})^2. \end{aligned}$$

Figure 4: Calibrated and real data employment patterns for young and old workers according to displacement status

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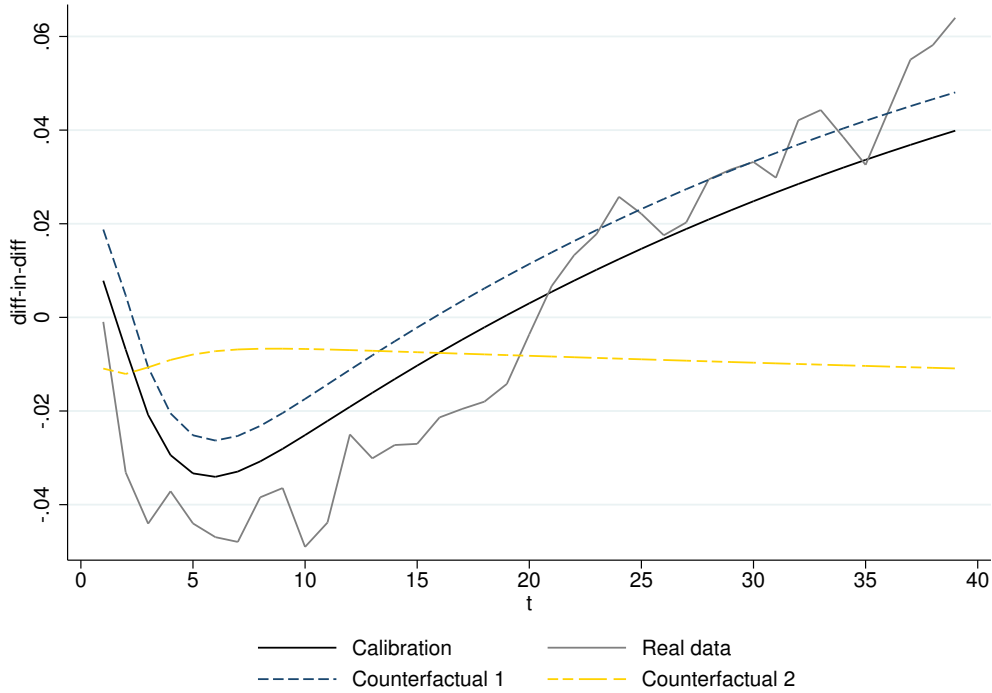


*Note:* The dashed lines in this figure reproduce the actual data patterns displayed in Figure 2. The continuous lines are instead the pattern simulated by the model

$$\begin{aligned} E_t^j &= (1 - \lambda_R^j - \lambda_U^j)E_{t-1}^j + \tilde{\mu}_E^j U_{t-1}^j \\ U_t^j &= \lambda_U^j E_{t-1}^j + (1 - \mu_R^j - \tilde{\mu}_E^j)U_{t-1}^j \end{aligned} ,$$

for the four relevant groups of workers defined by age cohort and displacement status, under the optimal minimum distance configuration of the parameters.

Figure 5: Comparison between, real data, calibrated and counterfactual relative employment losses of old versus young workers after a displacement



*Note:* The figure reports the “real data” and the “calibrated” relative employment losses of old versus young workers – i.e. the difference-in-difference patterns plotted in panels D of Figures 2 and 4 respectively – together with two “counterfactual” simulations of these relative employment losses.

Counterfactual 1 sets transition rates of the old between the states of employment and unemployment equal to the corresponding calibrated rates for the young. This counterfactual shuts down the possibility that differences in layoff rates and in the arrival of job offers for young and old workers might explain the patterns of relative employment losses, but leaves open the other channels of explanation.

Counterfactual 2 sets the transition rates into retirements of the old equal to the corresponding rates for the young. This counterfactual shuts down the possibility that differences in retirement opportunities of young and old workers explain the patterns of relative employment losses, but leaves open the other channels of explanation.