# The Sources of the Wage Losses of Displaced Workers

## The Role of the Reallocation of Workers into Firms, Matches, and Job Titles

**Pedro Raposo**
**Pedro Portugal**
**Anabela Carneiro**

ABSTRACT

*We evaluate the sources of wage losses of workers displaced due to firm closure by comparison of workers' wages before and after displacement. We decompose the sources of the wage losses into the contribution of firm, match quality, and job title fixed effects. Sorting into lower paying job titles represents the largest component of the monthly wage loss of displaced workers, accounting for 37 percent of the total average monthly wage loss compared to 31 percent for the firm and 32 percent for the match effects. With respect to the hourly wage losses, job title effects account for 46 percent of the total loss, while firm and match effects contribute in equal shares representing each 27 percent of the loss.*

*Pedro Raposo is at Católica Lisbon School of Business and Economics. Pedro Portugal is at Banco de Portugal, NOVA School of Business and Economics (pportugal@bportugal.pt). Anabela Carneiro is at the Universidade do Porto and CEF.UP–Center for Economics and Finance at the University of Porto.* *The authors are grateful to António Antunes, Paulo Guimarães, Daniel S. Hamermesh, Joop Hartog, Tobias Klein, Matteo Picchio, Jan van Ours, Arthur van Soest, and José Varejão for helpful comments and suggestions, as well as Lucena Vieira for outstanding data and computational assistance. The authors gratefully acknowledge financial support from Fundação para a Ciência e a Tecnologia, FCT (PTDC/EGE-ECO/29121/2017; UID/ECO/00124/2013; UID/ECO/00124/2019; UIDB/04105/2020) and Social Sciences DataLab, LISBOA-01-0145-FEDER-022209, POR Lisboa (LISBOA-01-0145-FEDER-007722, LISBOA-01-0145-FEDER-022209) and POR Norte (LISBOA-01-0145-FEDER-022209). The data used in this paper (Quadros de Pessoal - QP) builds on anonymized micro data sets that can be obtained by filling an accreditation form according to the protocol established by Statistics Portugal (INE). Requests for access can be emailed to info@ine.pt. The authors are willing to assist in this process (Pedro Raposo; pedro.raposo@ucp.pt). The data request forms are available in the Online Appendix.*
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## I. Introduction

Worker displacement is the subject of an extensive and growing literature. The costs of job loss in terms of unemployment, future employment prospects, and earnings change have been the most studied aspects of job displacement.[1] Focusing on the last of these, this study provides a detailed decomposition of the wage losses of displaced workers into its most important dimensions—firm, job title, and match quality characteristics. Understanding the causes of the wage reductions might also shed some light on potential policy options to ease the burden of adjustment on these workers (for example, retraining and job search support programs).

Earlier literature on the earnings impact of job displacement has now convincingly established that American displaced workers experience large and long-lasting reductions in earnings, driven mainly by lower wages in postdisplacement jobs.[2] Studies in Europe have been showing that earnings losses are not caused primarily by wage losses upon reemployment, but are mostly due to spells of nonemployment.[3] Less explored in the literature are the mechanisms that generate the wage losses. This study offers a novel evaluation of the sources of wage losses incurred by workers displaced due to firm closure, bearing in mind that wages in the previous job are a function of a set of worker characteristics (for instance, gender, education, and experience) that are expected to yield, in general, the same return on the previous job and on the subsequent job, and a set of firm, job title, and match characteristics that do not necessarily yield the same return in subsequent jobs (Hamermesh 1987). Hence, if wages primarily reflect workers' characteristics, then individual wages will be highly persistent and largely invariant to where individuals work, and potential losses due to displacement will be negligible. If, on the other hand, firm, job title, and match-specific heterogeneity are important, then the costs of displacement incurred by workers could be considerable.

It is well documented in the empirical literature on wage differentials drawn from linked employer–employee data that observed and unobserved characteristics of workers, firms, and worker–firm match quality are important determinants of wages.[4] Since our focus is also on those determinants of wages, we will not consider in this study the earnings losses generated by nonemployment spells. An additional contribution is to account for occupational heterogeneity in the pre- and postdisplacement jobs by considering a fourth dimension of wage formation—job title heterogeneity. A major strength of our data set is the inclusion of worker job titles, which reflect a worker's position in the hierarchy of an occupation, with occupations varying somewhat by industry. The identification of job titles is thorough and reliable because it comes directly from the definition of wage floors settled by collective bargaining for each occupational category. In a typical year around 30,000 wage floors are agreed upon (Martins 2014; Carneiro, Portugal, and Varejão 2014). The detailed classification of the job titles

1. For enlightening reviews of the literature see Hamermesh (1989), Kletzer (1998), and Carrington and Fallick (2014).
2. See, Addison and Portugal (1989); Jacobson, LaLonde, and Sullivan (1993); Couch and Placzek (2010); and Davis and von Wachter (2011).
3. See, Burda and Mertens (2001); Bender et al. (2002); Lehmann, Philips, and Wadsworth (2005); Eliason and Storrie (2006); Hijzen, Upward, and Wright (2010).
4. See, Abowd, Kramarz, and Margolis (1999); Goux and Maurin (1999); Woodcock (2008); and Torres et al. (2018).

accounts for the complexity of the tasks, the hierarchical standing of the worker, and the stress of the working conditions. We believe that our results for job titles are likely to generalize to most countries of continental Europe, as they have similar bargaining systems to that in Portugal. See Burda and Mertens (2001) for Germany and Garda (2012) for Spain.

A displacement event could lead to the loss of occupation-specific human capital due to the difficulty of finding a job that uses existing skills optimally or due to the depreciation of specific human capital during nonemployment spells.[5] Human capital has a decisive role during the early phase of the joblessness spell because larger human capital endowments are initially associated with greater job opportunities and higher opportunity costs of unemployment that necessarily erode with the progression of the unemployment spell.[6]

Earlier literature has sought to evaluate this effect by measuring specific human capital based on tenure at the occupation, firm, and industry level. However, a long job tenure may signal the high unobserved quality of the match and/or a high-ability worker, because more able workers and workers in good jobs are less likely to separate. To account for endogeneity bias due to correlation of tenure with the unobserved effects, earlier studies used an instrumental variables approach.[7] We contribute to the literature by addressing this source of wage loss looking directly at changes of job titles in the aftermath of a displacement event using a fixed-effects approach that allows us to net out worker, firm, and match quality effects.

We also take into consideration the worker, firm, and match components documented in the previous literature. Firms seem to be quite heterogenous in terms of their market power and wage compensation policies (Cardoso 2000; Webber 2015). The existence of labor market frictions, such as imperfect information and mobility costs, can explain the persistence of interfirm and interindustry compensation differentials (for example, Burdett and Mortensen 1998). These search frictions give firms monopsony power and the possibility to offer a wage that deviates from the competitive market wage (Manning 2003, 2011; Félix and Portugal 2016).

In this framework it is important to distinguish a good worker in a good firm from a good worker–firm match (that is, a match with higher quality). In the event of a displacement, a loss occurs if a high-quality job match between the worker and the firm is dissolved.[8,9] Furthermore, match-specific human capital accumulated over the course of the employment relationship is permanently destroyed when a job separation occurs.



5. See Poletaev and Robinson (2008) and Kambourov and Manovskii (2009) for discussions on the role of occupational specific human capital as a major determinant of earnings. See also Cortes (2016) for an in-depth discussion of the effects of technological routine-change on the evolution of the occupation wage premium in the past three decades for U.S. workers, highlighting the role of occupational mobility in explaining individual wage changes over the lifetime.

6. Addison and Portugal (1989); Hijzen, Upward, and Wright (2010); and Farber (2017), among others, highlight the role of nonemployment spells in explaining the income losses of displaced workers in the U.K. and the U.S. contexts.

7. See, among others, Carrington (1993), Neal (1995), Parent (2000), Poletaev and Robinson (2008), and Kambourov and Manovskii (2009).

8. However, displacement might increase earnings, for instance, if displacement dissolves a bad job match that was not perceived as such by the employee.

9. See, among others, the studies of Abraham and Farber (1987, 1988), Altonji and Shakotko (1987), Topel (1991), and Dustmann and Meghir (2005).

Its value is lost to both match participants and to the society as a whole (Woodcock 2015). Recent studies by Jung and Kuhn (2019) and Krolikowski (2017) provide a useful theoretical background regarding the importance of match quality effects in explaining the large and persistent earnings losses observed in the empirical data following displacement.

Moreover, accounting for match quality has important consequences in terms of the econometric model specification. It is insufficient to account solely for worker and firm unobserved effects, as the omission of match quality effects biases the estimated returns to observed characteristics and the estimated worker and firm fixed effects.[10] In the current study we separate the role of the quality of the match from the role of worker and firm permanent heterogeneity, providing direct evidence of the importance of match quality effects in driving the wage loss of the displaced.

To sensibly incorporate these many wage determinants, our methodology relies heavily on the estimation of a wage equation with two high-dimensional fixed effects—worker–firm fixed effect and job title fixed effect—using a unified procedure that appeals to the omitted variables bias formula (Gelbach 2016) to compute the independent contribution of each fixed effect to the monthly wage losses of displaced workers. For this purpose, we use a nationally representative matched employer–employee data set, Quadros de Pessoal (QP). The universal coverage of the employed population in the private sector in Portugal combined with these econometric tools creates the favorable conditions for this exercise.

We acknowledge that we do not offer a methodological contribution to either the estimation of high-dimensional fixed-effects regression models or to the application of the Gelbach decomposition in the context of high-dimensional fixed effects. Our methodological contribution is best seen as an extension of the Gelbach decomposition applied to the components of the worker–firm fixed effect (worker, firm, and match quality) to investigate the sources of the displacement wage losses.

The wage loss estimates reported here represent, on average, a penalty of 7.2 log points on predisplacement wages. Furthermore, we conclude that, in general, sorting into lower paying job titles (below called "job title downgrading") represents the largest component of the wage losses of the displaced worker. The unfavorable allocation to employers that remunerate less generously and the loss of worker–firm match skills also play a nonnegligible role as a source of the wage losses of those who are displaced. Overall, job title downgrading accounts for 37 (46) percent of the average monthly (hourly) wage loss, while sorting among firms accounts for 31 (27) percent of the monthly (hourly) wage loss. Allocation of workers into poorer quality matches accounts for the remaining 32 (27) percent of the average monthly (hourly) wage loss.

## II. Wage Setting in the Portuguese Labor Market

The Portuguese constitution provides the legal principles of collective bargaining and grants unions the right to negotiate. The effects of the agreements are formally recognized and considered valid sources of labor law.

10. For a detailed discussion on the consequences of omitting match effects see Woodcock (2015).

Conventional bargaining results from direct negotiation between employers' and workers' representatives. Collective negotiations are conducted at the industry or, occasionally, at the occupation level. Firm-level negotiation, which for a time was a common practice in large public enterprises, has lost importance.

Since most collective agreements are industry-wide, covering companies of very different size and economic condition, their contents tend to be general, setting minimum working conditions, in particular the base monthly wage for each category of worker, overtime pay, and the normal duration of work.[11]

The Ministry of Employment can extend an existing collective agreement to other workers initially not covered by it, and frequently it does via the use of Portarias de Extensão. This mandatory regime is applied when workers are not covered by unions, when one of the parties involved refuses to negotiate, or bargaining is obstructed in any other way. Overall, coverage of collective agreements in the Portuguese private sector is above 90 percent.[12]

Whatever the wage floor agreed upon for each category of worker at the collective bargaining table, firms are free to pay higher wages, and they often deviate from that benchmark, adjusting to firm-specific conditions. Cardoso and Portugal (2005) call this the "wage cushion," the difference between the actual wage and the contractual part of the wage. They estimate that in 1999 actual wages exceeded the level of bargained wages by 20–50 percent.

In addition to the collective bargaining system, wage floors are also set under the national legal minimum wage system. Every year after discussing with the social partners, the government sets a mandatory national minimum wage that binds all the workers. Thus, the compensation floors defined at the collective bargaining table apply only if they are set above the national minimum wage. In 2016 the national minimum monthly wage was set at 530 euros.

## III. The Data

### A. *The Quadros de Pessoal Data Set*

In this study we use a longitudinal matched employer–employee–job title data set called Quadros de Pessoal (QP, Lists of Personnel) for the 1986–2016 period. The data are gathered annually by the Portuguese Ministry of Employment through a survey that every establishment with at least a single wage-earner is obliged by law to complete. Reported data cover the firm, the establishment, and each of its workers. Currently, QP gathers information on more than 300,000 firms and about three million workers. Given the mandatory nature of the survey plus the fact that these data cover all wage-earners in the private sector in Portugal, problems commonly associated with panel data sets, such as panel attrition, are considerably reduced. The reporting of worker information reduces measurement error, especially for earnings.

Each firm entering the database is assigned a unique identifying number, and the Ministry implements several checks to ensure that a firm that has already reported to the

11. For a study on the role of bargained wages on job flows see Guimarães, Martins, and Portugal (2017).
12. For a detailed discussion of the Portuguese wage bargaining system see Addison, Portugal, and Vilares (2017).

QP data set is not assigned a different identification number. Using this identifier it is possible to pinpoint all firms that have entered and exited economic activity. An exit from the database should signal a firm that has ceased its activity. The firm data include detailed information on industry, region, ownership type, and size. The worker's identification number is based on their social security number. Finally, this data source enables the matching of firms with their workers, which allows us to identify the worker–firm pair.

Data on workers include gender, age, schooling, and detailed information on monthly earnings, including base wages, regular benefits (for instance, seniority), irregular benefits (profit distributions and premiums), overtime payments, and hours of work (normal and overtime). Our main results are based on the monthly wage defined as the sum of total regular (base wage and regular benefits) and irregular payroll (irregular benefits and overtime payments) in the reference month. As an alternative measure, we use the hourly wage computed as the ratio between the monthly wage and the total number of normal and extra hours worked.[13]

### *B. Sample Construction: Displaced Workers*

Our treatment group includes 25 cohorts of workers who lost their jobs between 1988 and 2014 due to firm closure.[14] A firm is classified as an exiting firm in year $t+1$ if it is present in the QP files in year $t$, but absent in $t+1$, $t+2$, and all of the subsequent years. To ensure that we are observing true firm closures and not mergers or acquisitions, we excluded from the sample those firms where workers appeared in the database in the period following displacement with a year of admission in the new job less than the year of displacement minus one.[15] These exclusions reduced the sample size by around 3 percent.

Within the reference period, some individuals experience successive firm closures of firms that are necessarily different. To adequately date the time to displacement, we used only information from the first firm closure within the reference period. Excluding repeated firm closures reduced the displacement sample size by 10 percent.

For comparison purposes the samples used in this study are selected in the spirit of Jacobson, LaLonde, and Sullivan (1993) and Couch and Placzek (2010). To be included in the sample a worker must report positive earnings and have at least two years of tenure in the year that immediately precedes the displacement event. Furthermore, a worker must report positive earnings at least once thereafter. The sample was restricted to full-time wage-earners in the private nonfarm sector, aged 16–64 years, who were employed in a firm with at least 20 employees, and whose base wages were above 80 percent of the mandatory minimum wage.[16] Other restrictions were placed: (i) observations with missing values in the covariates were excised, (ii) the sample was restricted to the largest connected set (the largest group of connected worker–firm pairs and job titles), and (iii) singleton observations (groups that are reduced to just one observation, and which by

13. All wage variables were deflated using the Consumer Price Index (with base-year 2016).

14. Worker files are not available for the years of 1990 and 2001.

15. For example, if a worker was displaced in 1997 and appears in the database in the postdisplacement period with a year of admission in the new job earlier than 1997, they are excluded from the sample.

16. In the Portuguese labor market, apprenticeships may collect 80 percent of the minimum wage.

**Table 1**
*Sample Composition: Displaced Workers*

| Year | Displaced |
|---|---|
| $D_{-10}$ | 18,279 |
| $D_{-9}$ | 24,986 |
| $D_{-8}$ | 28,828 |
| $D_{-7}$ | 38,463 |
| $D_{-6}$ | 47,253 |
| $D_{-5}$ | 56,456 |
| $D_{-4}$ | 65,070 |
| $D_{-3}$ | 79,297 |
| $D_{-2}$ | 94,667 |
| $D_{-1}$ | 98,274 |
| $D_0$ | 119,895 |
| $D_1$ | 22,934 |
| $D_2$ | 37,136 |
| $D_3$ | 43,634 |
| $D_4$ | 48,125 |
| $D_5$ | 47,747 |
| $D_6$ | 44,904 |
| $D_7$ | 40,527 |
| $D_8$ | 33,233 |
| $D_9$ | 31,048 |
| $D_{10}$ | 27,274 |
| Total | 1,048,030 |

Notes: The sample includes all displaced individuals who are employed in the year of the displacement $D_0$ and have at least two years of tenure and who are in reemployment in at least one year before the end of the sample period.

construction do not affect the coefficient estimates in the fixed-effects model, in particular, the displacement dummies coefficients) were also excluded.[17]

For estimation purposes, we define time with reference to the last year the individual is observed in the QP files before displacement ($D_0$). For example, $D_0$ equals 1997 for individuals who were working in 1997 and whose firm closed between November 1997 and September 1998. The data set combines 25 cohorts (1988–2014) of displaced workers observed during a 21-year window ranging from $D_{-10}$ to $D_{10}$.

Table 1 reports the number of worker–year observations for the sample of workers displaced due to firm closure. According to Table 1, 119,895 workers employed in firms with at least 20 employees were displaced due to firm closure in the 1988–2014 period (1,048,030 worker–year observations). Temporary exits from the data set may occur if

17. Appendix Table A1 reports the impact of the sample restrictions on the original sample.

the survey form was not received in the Ministry of Employment before the date when the recording operations were closed. This explains why in $D_{-2}$ and $D_{-1}$ there are fewer observations than in $D_0$.

### *C. Sample Construction: Nondisplaced Workers*

The group of nondisplaced workers (the control group) includes all individuals who were employed in firms that did not close in the 1986–2016 period. As before, the group of nondisplaced workers was restricted to full-time wage-earners in the private nonfarm sector, aged 16–64, with at least two years of tenure, who were employed in a firm with at least 20 employees, and whose base wages were above 80 percent of the mandatory minimum wage. We obtained a control group composed of 15,683,082 nondisplaced worker–year observations. Table 2 reports the number of observations per year in the sample of nondisplaced workers over the 1986–2016 period. The same information is reported for the sample of displaced workers.

### *D. Sample Descriptive Statistics*

Table A2 in Appendix 1 presents the descriptive statistics in the analyzed period for both groups of workers, displaced and nondisplaced. Displaced workers are slightly younger and have fewer years of education and tenure in comparison with their nondisplaced counterparts. Moreover, the proportion of women is higher in the group of displaced workers when compared with the nondisplaced group. As expected, firms that shut down are smaller and are mainly operating in the sectors of manufacturing and wholesale and retail trade.

Displaced workers earn significantly lower wages than their nondisplaced counterparts. The average real monthly wage (the sum of the base wage, regular payments, irregular benefits, and overtime payments) amounts to 1,035 euros for the displaced, while for the nondisplaced it equals 1,337 euros.

### *E. The Notion of Job Title*

In our framework the notion of job title comes simply from distinct categories (Categoria Profissional) within each collective wage agreement (Instrumento de Regulamentação Colectiva). The job title can be seen as a collection of tasks that is sufficiently relevant to justify a negotiation regarding its corresponding wage floor.[18] In this vein, job titles summarize the skill requirements of the worker, in particular those that are industry and occupation specific. They also reflect the hierarchical standing of the worker. Given the way the job titles were identified, they may also reflect the bargaining power of the workers' organizations.[19] In each year, there are around 300 collective agreements that define wage floors for, on average, 100 occupational categories. Overall, in a given year there are around 30,000 collective agreement–occupational category

18. It is worth noting that the Ministry of Employment collects the QP data in order to check if employers are complying with the wage floors agreed upon for each occupational category.

19. Addison, Portugal, and Vilares (2018) show that the power of unions (union wage gap) is partially manifested through better paying job titles.

**Table 2**
*Sample Composition: Nondisplaced and Displaced Workers*

| Year | Nondisplaced | Displaced |
|---|---|---|
| 1986 | 451,578 | 12,519 |
| 1987 | 481,633 | 15,871 |
| 1988 | 480,262 | 17,847 |
| 1989 | 469,080 | 21,013 |
| 1991 | 484,867 | 26,721 |
| 1992 | 499,639 | 28,325 |
| 1993 | 480,024 | 31,164 |
| 1994 | 496,539 | 31,844 |
| 1995 | 547,391 | 38,520 |
| 1996 | 535,738 | 41,146 |
| 1997 | 523,839 | 42,946 |
| 1998 | 531,134 | 48,036 |
| 1999 | 540,294 | 52,214 |
| 2000 | 511,017 | 48,834 |
| 2002 | 477,744 | 39,211 |
| 2003 | 517,165 | 45,262 |
| 2004 | 547,764 | 48,623 |
| 2005 | 578,419 | 52,031 |
| 2006 | 560,374 | 49,621 |
| 2007 | 571,065 | 50,101 |
| 2008 | 578,779 | 49,746 |
| 2009 | 565,862 | 45,957 |
| 2010 | 621,955 | 41,963 |
| 2011 | 630,049 | 33,422 |
| 2012 | 614,107 | 29,691 |
| 2013 | 616,207 | 28,254 |
| 2014 | 610,349 | 28,298 |
| 2015 | 606,483 | 27,039 |
| 2016 | 553,725 | 21,811 |
| Total | 15,683,082 | 1,048,030 |

Notes: Composition of the sample by year and displacement status.



combinations to which workers are assigned. The consistent classification of job titles over time allows us to mitigate measurement error in the estimates of its corresponding fixed effect.

After the displacement event the contributions of a change in the job title to the wage loss can be rooted in a number of factors:

(i) a switch in the occupational category code within the same collective agreement. Holding other factors constant, severe losses in the returns to the job title may be explained by the difficulty of finding a job that uses existing skills optimally, or due to the depreciation/obsolescence of specific human capital during nonemployment spells, or due to a loss of job shopping rents.[20]

(ii) a switch in the collective agreement. This change may reflect the loss/gains of rents associated with the bargaining power of unions at the bargaining table and industry-specific skills (Neal 1995);

(iii) a switch in the hierarchical standing within the same collective agreement/occupational category. This type of change is quite often related to the loss of tenure in the previous job/firm and should reflect the loss of returns on specific human capital. The nature of this change may also be related with the loss of rents associated with promotion practices inside the firm (Hamermesh 1987).



## IV. Econometric Framework

### *A. The High-Dimensional Fixed-Effects Regression Model*

To evaluate the effect of displacement on wages we start by using a methodological framework that closely follows Jacobson, LaLonde, and Sullivan (1993). In our benchmark regression model, it is assumed that workers' wages, at a given time period, depend on the event of displacement and on some controls for fixed and time-varying characteristics of the worker and the economy:

$$(1) \quad w_{it} = \alpha_i + \gamma_t + \beta \mathbf{X}_{it} + \sum_{k \geq -m} D_{it}^k \delta_k + u_{it}$$

where $w_{it}$ represents the monthly wages (in logs) for each individual $i$ in year $t$. $D_{it}^k$ are dummy variables where $k$ is equal to $-m$, $-(m-1)$, …, 0, 1, 2, …, which represent time to the event of displacement. $\delta_k$ represents the effect of displacement on worker's wages $k$ years prior to, and following, its occurrence. The worker fixed effect, $\alpha_i$, captures the impact of permanent differences among worker's permanent observed and unobserved characteristics, and $\gamma_t$ are calendar year fixed effects included to capture the macroeconomic environment (business cycle). Finally, the vector $\mathbf{X}_{it}$ represents age and age squared, and $\beta$ are their corresponding coefficients. The composite error term, $u_{it}$, is assumed to be uncorrelated with the covariates. We provide a thorough discussion of the stochastic structure of the error term ($u_{it}$) below.

In essence, we compare the wage changes of displaced workers over a long-term period with the wage changes that would have occurred if the displaced had not lost their jobs. Since this latter outcome variable is not observable, a comparison group of nondisplaced workers is used. The presence of the control group allows us to account for aggregate yearly real wage growth properly, and it helps the estimation of the age earnings profile. Permanent differences between displaced and nondisplaced workers are, of course, subsumed in the worker fixed effect, $\alpha_i$.

20. See Johnson (1978), Addison and Portugal (1989), Topel and Ward (1992), Mroz and Savage (2006), and Huckfeldt (2018). The relevance of job shopping in wage determination is corroborated by recent studies that attempt to model earnings dynamics over the life cycle. See, for instance, Postel-Vinay and Robin (2002) for France; Jarosch (2014) for Germany; and Altonji, Smith, and Vidangos (2013) and Jung and Kuhn (2019) for the United States.

Ideally, we would like to estimate the four-way, high-dimensional fixed-effects regression model:

$$(2)\quad w_{it} = \alpha_i + \lambda_{J(i,t)} + \theta_{F(i,t)} + \psi_{iF(i,t)} + \gamma_t + \beta \mathbf{X}_{it} + \sum_{k \geq -m} D_{it}^k \delta_k + u_{it}$$

where $\lambda_{J(i,t)}$ is a job title fixed effect that accounts for the time-invariant (observed and unobserved) characteristics of the job title, $\theta_{F(i,t)}$ is a firm fixed effect that controls for permanent characteristics of the firm, and $\psi_{iF(i,t)}$ is a match quality effect that measures the returns to time-invariant characteristics of the worker–firm match.[21] The composite error term, $u_{it}$, is assumed to be uncorrelated with the covariates and can be decomposed into five components:

$$(3)\quad u_{it} = \zeta_{it} + \nu_{J(i,t)t} + \eta_{F(i,t)t} + \mu_{iF(i,t)t} + \varepsilon_{it}$$

where $\zeta_{\mathrm{it}}$ is the unit root component that captures individual random trends, $\nu_{J(i,t)t}$ accounts for the time-varying component of the job title stochastic term, $\eta_{F(i,t)t}$ accounts for the time-varying component of the firm stochastic term, and $\mu_{iF(i,t)t}$ corresponds to the time-varying component of the match quality stochastic term. Finally, $\varepsilon_{it}$ represents the idiosyncratic error term (zero mean and constant variance).

Consistency of the ordinary least squares (OLS) estimator of this regression model requires that we can rule out endogenous mobility. This means that the job changes have to be unrelated with $\zeta_{\mathrm{it}}$, $\nu_{J(i,t)t}$, $\eta_{F(i,t)t}$, or $\mu_{iF(i,t)t}$. For example, workers may systematically move away from firms or job titles with negative wage trends. For its part, human capital accumulation (as measured by $\zeta_{\mathrm{it}}$) may translate into job promotions or firm mobility. This can simply be interpreted as a worker, firm, or job title manifestation of the Ashenfelter dip. In practice, in our data there is no indication that this source of endogeneity is materially relevant. The evidence in Figures A1 and A2 in Appendix A based on the approach provided by Card, Cardoso, and Kline (2016) does not suggest the presence of predictable trends prior to firm (or job) changes, for either displaced or nondisplaced workers. Therefore, we rule out these situations.

Looking at Figures A1 and A2 there is some evidence that the wage gains of individuals who move up the distribution seem to exceed the losses of those who move down the distribution, especially for the nondisplaced. This asymmetry in the wage gains and losses may be driven by sorting into better matches, firms, or jobs. This evidence against the additive separability assumption is less of a concern in our analysis because our full model accounts for firm, job title, and match quality effects, allowing us to mitigate the possible endogeneity of mobility decisions.

### *B. Identification and Estimation*

For identification, we build on Woodcock (2008, 2015), who extended the worker and firm fixed-effects model of Abowd, Kramarz, and Margolis (1999) to account for match quality heterogeneity. We restrict our sample to the largest connected set.[22] This is done

21. The index $J(i,t)$ indicates the job title $j$ at which worker $i$ was employed in period $t$. $F(i,t)$ indicates the firm at which worker $i$ was employed in period $t$. $iF(i, t)$ the worker–firm pair at which worker $i$ was employed in period $t$.
22. The largest connected group represents more than 96 percent of the original data.

in order to warrant that the fixed effects are identified. A connected set is defined when at least one element of a worker–firm pair and job title links the rest of the group (Abowd, Creecy, and Kramarz 2002).

The identification of the job title fixed effect ($\lambda_{J(i,t)}$) poses no particular challenge as it can be achieved by transitions into or out of a job title that may occur during the sample period. The identification of the firm fixed effect ($\theta_{F(i,t)}$) is slightly more involved for firms that shut down than for those that do not and must rely on workers who join or separate from those firms before the displacement event.

Without additional assumptions, the identification of match quality effects poses the greatest challenges given that Model 2 is overparameterized, making it impossible to disentangle the worker, the firm, and the match quality effects. In this model, the quality of the worker–firm match is indistinguishable from a good employee working in a good firm.

A feasible procedure that allows us to estimate job title effects and the combination of the other three sets of effects (worker, firm, and match quality fixed effects, which call the worker–firm fixed effect) is to replace these three fixed effects with a single set of fixed effects for each worker–firm pair, $\varphi_{iF(i,t)}$. The full model is now written as:

$$(4) \quad w_{it} = \phi_{iF(i,t)} + \lambda_{J(i,t)} + \gamma_t + \beta \mathbf{X}_{it} + \sum_{k \geq -m} D_{it}^k \delta_k + u_{it}$$

This regression model incorporates two high-dimensional fixed effects and will be estimated employing the algorithm developed by Guimarães and Portugal (2010).[23]

### *C. The Decomposition of the Wage Losses*

It is possible to calculate the independent contribution of each fixed effect to the wage losses of displaced workers. For this purpose we adapt the methodology developed in Gelbach (2016), which appeals to the omitted variables bias formula to compute a detailed decomposition. Beginning with a baseline specification to which covariates are added, Gelbach's procedure allows us to compute the contribution of each new covariate to the change in the estimate of the coefficient of the variable under scrutiny. In our case, it allows us to unambiguously disentangle the contribution of each excluded variable (each fixed effect) to the variation of the coefficient estimates of the displacement dummies.

The benchmark regression wage loss equation, corresponding to Equation 1, can be presented in a matrix formulation as:

$$(5) \quad \mathbf{Y} = \mathbf{X}\boldsymbol{\beta}_0 + \mathbf{W}\boldsymbol{\alpha}_0 + \mathbf{D}\boldsymbol{\delta}_0 + \mathbf{u}_0,$$

where $\mathbf{Y}$ represents wages, $\mathbf{X}$ denotes the matrix of control variables (in our case, time dummies and a quadratic in age), $\boldsymbol{\beta}_0$ is a vector of regression coefficients, $\mathbf{W}$ is a matrix collecting worker dummies, the vector $\boldsymbol{\alpha}_0$ represents their coefficients, $\mathbf{D}$ contains the displacement dummies of interest, $\boldsymbol{\delta}_0$ represent the (conditional) wage losses, and $\mathbf{u}_0$ stands for the error term. The subscript 0 denotes the benchmark specification.

23. In Appendix 2 we describe the procedure that allows the estimation of a wage equation that incorporates two high-dimensional fixed effects.

It will be useful to collapse $\mathbf{X\beta}_0+\mathbf{W\alpha}_0$ into $\mathbf{Z\eta}_0$, where $\mathbf{Z}=[\mathbf{XW}]$, emphasizing the displacement effects, leading to

$$(6)\quad \mathbf{Y}=\mathbf{Z\eta}_0+\mathbf{D\delta}_0+\mathbf{u}_0$$

Our first step is to estimate $\boldsymbol{\delta}_0$. At this point, with just one high-dimensional fixed effect—the worker fixed effect—the estimation of $\boldsymbol{\delta}_0$ can be achieved straightforwardly employing the within estimator. More generally, we can use the Frisch–Waugh–Lovell theorem to express the least squares estimate of $\boldsymbol{\delta}_0$ as the result of running a regression of $\mathbf{Y}$ on $\mathbf{D}$, after partialing out the effect of $\mathbf{Z}$ (that is, after purging $\mathbf{D}$ and $\mathbf{Y}$ from the linear influence of the covariates and the worker dummies). That is,

$$(7)\quad \hat{\boldsymbol{\delta}}_0=(\mathbf{D}'\mathbf{P_Z D})^{-1}\mathbf{D}'\mathbf{P}_Z\boldsymbol{Y},$$

where $\mathbf{P_Z}=[\mathbf{I}-\mathbf{Z}(\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{Z}']$ is the residual-maker (or "annihilator" matrix). The purpose of $\mathbf{P_Z}$ is, of course, to partial out the effect of $\mathbf{Z}$ on $\mathbf{D}$ and of $\mathbf{Z}$ on $\mathbf{Y}$, providing the residuals from regressing $\mathbf{D}$ on $\mathbf{Z}$ and the residuals from regressing $\mathbf{Y}$ on $\mathbf{Z}$.

More compactly, we can write

$$(8)\quad \hat{\boldsymbol{\delta}}_0=\mathbf{A}_Z\mathbf{Y},$$

and introduce the definition of the matrix $\mathbf{A_Z}=(\mathbf{D'P_Z D})^{-1}\mathbf{D'P_Z}$, which will be instrumental in the application of the omitted variable bias formula. In general, if we premultiply any variable by $\mathbf{A_Z}$, we will always obtain the corresponding regression coefficient estimates of the displacement dummies, after controlling for the variables included in $\mathbf{Z}$.

In our second step we expand our model to include worker-firm dummies (in the matrix $\mathbf{M}$) and job title dummies (in the matrix $\mathbf{J}$) in the wage regression. Including the complete set of worker–firm dummies of course subsumes the worker dummies. The estimating full regression model, corresponding to Equation 4, can be expressed as

$$(9)\quad \mathbf{Y}=\mathbf{X\beta}_1+\mathbf{M\phi}_1+\mathbf{J\lambda}_1+\mathbf{D\delta}_1+\boldsymbol{u}_1,$$

where $\boldsymbol{\phi}_1$ and $\boldsymbol{\lambda}_1$ denote the worker–firm and job title coefficients, respectively. The subscript 1 denotes the full model specification. This is now a linear regression with two high-dimensional fixed effects that no longer can be estimated using conventional methods. We obtain $\hat{\boldsymbol{\delta}}_1$ (and $\hat{\boldsymbol{\beta}}_1$, $\hat{\boldsymbol{\phi}}_1$, and $\hat{\boldsymbol{\lambda}}_1$) from the least squares solution, using the Guimarães and Portugal (2010) iterative procedure. After estimation, observed $\mathbf{Y}$ can be written as:

$$(10)\quad \mathbf{Y}=\mathbf{X}\hat{\boldsymbol{\beta}}_1+\mathbf{M}\hat{\boldsymbol{\phi}}_1+\mathbf{J}\hat{\boldsymbol{\lambda}}_1+\mathbf{D}\hat{\boldsymbol{\delta}}_1+\hat{\boldsymbol{u}}_1,$$

The difference between $\hat{\boldsymbol{\delta}}_0$ and $\hat{\boldsymbol{\delta}}_1$ is that $\hat{\boldsymbol{\delta}}_0$ is biased due to the omission of firm and match quality fixed effects (which are included in $\mathbf{M}\hat{\boldsymbol{\phi}}_1$, along with the worker fixed effects) and the job title fixed effects ($\mathbf{J}\hat{\boldsymbol{\lambda}}_1$).

Our third step is to build on Gelbach (2016), who uses the OLS omitted variable bias formula to decompose the contributions of added covariates to changes in the estimates of the regression coefficient of interest. In our case we are interested in the role of worker–firm dummies and job title dummies in explaining the raw wage losses of displacement. This can be achieved by multiplying both sides of Equation 10 by $\mathbf{A_Z}$, and moving $\hat{\boldsymbol{\delta}}_1$ to the left-hand side of the equation:

(11) $\hat{\boldsymbol{\delta}}_0 - \hat{\boldsymbol{\delta}}_1 = \mathbf{A_Z M}\hat{\boldsymbol{\phi}}_1 + \mathbf{A_Z J}\hat{\boldsymbol{\lambda}}_1 = \hat{\boldsymbol{\tau}}_\phi + \hat{\boldsymbol{\tau}}_\lambda,$

where $\hat{\boldsymbol{\tau}}_\phi$ is the bias that arrives from omitting the worker–firm component, and $\hat{\boldsymbol{\tau}}_\lambda$ is the bias that arrives from omitting the job title component. The derivation makes use of the following identities: $\mathbf{A_Z}\boldsymbol{Y} = \hat{\boldsymbol{\delta}}_0$, $\mathbf{A_Z}\boldsymbol{X} = 0$, $\boldsymbol{A_Z D} = \mathbf{I}$, and $\mathbf{A_Z}\hat{\boldsymbol{u}}_1 = 0$. Notice that since the worker dummies are in the base specification, that is, $\mathbf{W}$ is included in $\mathbf{Z}$, the components of the bias ($\hat{\boldsymbol{\tau}}_\phi$ and $\hat{\boldsymbol{\tau}}_\lambda$) are cleaned from the influence of worker heterogeneity.

In practice, what we need to do is first compute $\mathbf{A_Z M}\hat{\boldsymbol{\phi}}_1$, which is no more than a regression of the worker–firm fixed effects on the covariates of the base model, $\mathbf{Z}$ and $\mathbf{D}$, allowing us to obtain $\hat{\boldsymbol{\tau}}_\phi$ from the regression coefficient estimates of the displacement dummies. Second, we calculate $\mathbf{A_Z J}\hat{\boldsymbol{\lambda}}_1$, which is simply a regression of the job title fixed effects on the covariates of the base model, enabling us to estimate $\hat{\boldsymbol{\tau}}_\lambda$.

Our final goal is to decompose the worker–firm component in a way that will enable us to distinguish between the worker, the firm, and the match quality components of the wage loss. To do this, in our fourth step, we begin by writing the worker–firm fixed effect as the sum of a worker fixed effect, a firm fixed effect, and an error term:

(12) $\mathbf{M}\hat{\boldsymbol{\phi}}_1 = \mathbf{W\Omega} + \mathbf{F\Theta} + \boldsymbol{\nu},$

where $\mathbf{F}$ is a matrix collecting the firm dummies, $\boldsymbol{\Omega}$ and $\boldsymbol{\Theta}$ represent, respectively, the worker and the firm regression coefficients, and $\boldsymbol{\nu}$ is a residual term that can be interpreted as a measure of match quality. As discussed above, in general, without additional assumptions, we cannot separately identify the worker, firm, and match quality fixed effects. A workable assumption, and in this framework a natural assumption, is to consider that the match quality fixed effect is orthogonal to the worker and firm fixed effects. This approach was first suggested by Woodcook (2008). By considering that the match quality fixed effects are uncorrelated with the worker and firm fixed effects, the match quality component of the wage loss is best seen as a lower bound. Assuming orthogonality, we can proceed by obtaining the least squares solution to the estimation of the parsimonious two-way, high-dimensional fixed-effects model in Equation 12 to obtain:

(13) $\mathbf{M}\hat{\boldsymbol{\phi}}_1 = \mathbf{W}\hat{\boldsymbol{\Omega}} + \mathbf{F}\hat{\boldsymbol{\Theta}} + \hat{\boldsymbol{\nu}}.$

where the residuals $\hat{\boldsymbol{\nu}}$ are taken as estimates of the match quality fixed effects. Once we have decomposed the worker–firm fixed effect into its three estimated fixed effects, the firm component ($\boldsymbol{\tau}_\theta$) of the wage loss can be distinguished from the match quality component ($\boldsymbol{\tau}_\psi$) by multiplying, as before, both sides of Equation 13 by $\mathbf{A_Z}$: $\boldsymbol{A_Z}\mathbf{M}\hat{\boldsymbol{\phi}}_1 = \boldsymbol{A_Z}\mathbf{F}\hat{\boldsymbol{\Theta}} + \boldsymbol{A_Z}\hat{\boldsymbol{\nu}}$ since $\mathbf{A_Z W} = 0$, or more succinctly, $\hat{\boldsymbol{\tau}}_\phi = \hat{\boldsymbol{\tau}}_\theta + \hat{\boldsymbol{\tau}}_\psi$.

In practice, we obtain $\hat{\boldsymbol{\tau}}_\theta$ from $\boldsymbol{A_Z}\mathbf{F}\hat{\boldsymbol{\Theta}}$, which is no more than a regression of the estimated firm fixed effects on $\mathbf{Z}$ and $\mathbf{D}$. Similarly, we compute $\hat{\boldsymbol{\tau}}_\psi$ from $\mathbf{A_Z}\hat{\boldsymbol{\nu}}$ , which is simply a regression of the OLS residuals on $\mathbf{Z}$ and $\mathbf{D}$.[24]

24. $\hat{\boldsymbol{\tau}}_\psi$ can also be obtained by simply comparing the displacement effects in the full regression model (Equation 10) with the displacement effects of a regression model that, instead of the worker–firm fixed effects, includes the worker and firm fixed effects separately. The equivalence was first noted by Figueiredo, Guimarães, and Woodward (2014).
Alternatively and equivalently, $\hat{\boldsymbol{\tau}}_\psi$ can be directly obtained from a regression of the worker-firm fixed effects ($\mathbf{M}\hat{\boldsymbol{\phi}}_1$, ) on $\mathbf{X}$, $\mathbf{W}$, $\mathbf{F}$, and $\mathbf{D}$.

# V. Empirical Results

## *A. Regression Results*

The results of the base and full models described in Equations 1 and 4 are reported in Columns 2 and 3 of Table 3, respectively, while the OLS estimates without worker, firm, job title, or match quality fixed effects are reported in Column 1. In particular, the results in Columns 1–3 correspond, respectively, to the estimates of the coefficients of the displacement dummies ($\delta$) for the OLS model, the base model defined in Equation 1, and for the full model defined in Equation 4. For the same models, in the bottom part of the table we report the wage loss estimates for two different specifications. Specification 2 aggregates the pre- and postdisplacement years into two periods—before (years $D_{-10}$ to $D_0$) and after (years $D_1$ to $D_{10}$) displacement—rows labeled "Predisplacement" and "Postdisplacement," respectively. Finally, Specification 3 is a simple reparametrization of Specification 2 providing the net effect—row labeled "Net." Thus, Specification 2 was estimated with a normalization that allows us to extract the coefficients for before and after displacement, while in Specification 3 we employ a normalization that allows us to directly estimate the net effect.[25]

The three models were estimated for the sample of 16,731,112 worker–year observations for the treated and control groups, after guaranteeing that we are working with the largest connected set and that we are not including singletons.

Disregarding different types of selectivity, the OLS estimates provided in Specification 1 (Column 1) can be interpreted as showing that, on average, displaced workers earn lower wages than their nondisplaced counterparts, most notably after displacement. In fact, these estimates show that the time pattern of the wage differential between the displaced and the nondisplaced is fairly constant in the predisplacement period but seems to increase after displacement. According to Specification 3 (Column 1), the monthly wage gap between displaced and their similar nondisplaced counterparts increased, on average, by 10.6 log points in the postdisplacement period relative to the predisplacement period.

According to the estimates of Specification 1 of the base regression model in Column 2 (which includes a worker fixed effect), the within time pattern reveals a decreasing wage trend.[26] The results also highlight the persistence of the effects of displacement on wages. Ten years after the displacement event the monthly wages of displaced workers remain around 7.6 log points below their wage levels in the reference year, ($\hat{\delta}_{10}^{base} - \hat{\delta}_{0}^{base} = -0.067 - 0.009$). Turning our attention to average differences in the periods before and after displacement (Specification 3), we conclude that postdisplacement monthly wages of the displaced are, on average, 7.2 log points lower than their predisplacement monthly wages.

25. This procedure is identical to estimating a regression model that accounts for gender effects, where we use male and female dummy variables (implicitly imposing that the constant is equal to zero) or, alternatively, a more conventional approach where we use only one dummy variable for one of the categories.

26. Recall that in the fixed-effects model, the estimates of the coefficients of the displacement dummies do not have a straightforward interpretation in terms of wage losses of displaced workers relative to nondisplaced workers, since the coefficients represent within-individual wage changes over time.

**Table 3**
*Wage Loss Estimates*

| | $\hat{\delta}_k^{ols}$ | SE | $\hat{\delta}_k^{base}$ | SE | $\hat{\delta}_k^{full}$ | SE |
|---|---|---|---|---|---|---|
| | (1) | | (2) | | (3) | |
| Specification 1 | | | | | | |
| $D_{-10}$ | –0.218 | (0.003) | 0.061 | (0.002) | 0.003 | (0.001) |
| $D_{-9}$ | –0.178 | (0.003) | 0.061 | (0.001) | 0.008 | (0.001) |
| $D_{-8}$ | –0.183 | (0.003) | 0.044 | (0.001) | 0.000 | (0.001) |
| $D_{-7}$ | –0.135 | (0.003) | 0.042 | (0.001) | 0.005 | (0.001) |
| $D_{-6}$ | –0.122 | (0.003) | 0.067 | (0.001) | 0.032 | (0.001) |
| $D_{-5}$ | –0.159 | (0.002) | 0.032 | (0.001) | –0.002 | (0.001) |
| $D_{-4}$ | –0.171 | (0.002) | 0.024 | (0.001) | –0.004 | (0.001) |
| $D_{-3}$ | –0.176 | (0.002) | 0.021 | (0.001) | –0.003 | (0.001) |
| $D_{-2}$ | –0.181 | (0.002) | 0.018 | (0.001) | –0.002 | (0.001) |
| $D_{-1}$ | –0.185 | (0.002) | 0.015 | (0.001) | –0.003 | (0.001) |
| $D_0$ | –0.213 | (0.002) | 0.009 | (0.001) | –0.008 | (0.001) |
| $D_1$ | –0.156 | (0.004) | –0.013 | (0.001) | –0.024 | (0.001) |
| $D_2$ | –0.219 | (0.003) | –0.018 | (0.001) | –0.011 | (0.001) |
| $D_3$ | –0.241 | (0.003) | –0.029 | (0.001) | –0.005 | (0.001) |
| $D_4$ | –0.240 | (0.002) | –0.039 | (0.001) | –0.002 | (0.001) |
| $D_5$ | –0.268 | (0.003) | –0.048 | (0.001) | 0.001 | (0.001) |
| $D_6$ | –0.294 | (0.003) | –0.056 | (0.001) | 0.002 | (0.001) |
| $D_7$ | –0.334 | (0.003) | –0.062 | (0.001) | 0.005 | (0.001) |
| $D_8$ | –0.377 | (0.003) | –0.072 | (0.001) | 0.006 | (0.001) |
| $D_9$ | –0.373 | (0.003) | –0.072 | (0.001) | 0.011 | (0.001) |
| $D_{10}$ | –0.349 | (0.003) | –0.067 | (0.001) | 0.013 | (0.001) |
| $R^2$ | 0.11 | | 0.89 | | 0.92 | |
| Specification 2 | | | | | | |
| Predisplacement | –0.218 | (0.003) | 0.026 | (0.000) | 0.000 | |
| Postdisplacement | –0.178 | (0.003) | –0.046 | (0.000) | 0.000 | |
| $R^2$ | 0.11 | | 0.89 | | 0.92 | |
| Specification 3 | | | | | | |
| Net | –0.106 | (0.002) | –0.072 | (0.000) | 0.000 | |
| $R^2$ | 0.11 | | 0.89 | | 0.92 | |

Notes: The dependent variable in all regression models is the natural log of the real monthly wages. Columns 1, 2, and 3 report, respectively, the OLS, the base, and full model regression coefficient estimates. Age (and its square) and time dummies included in the OLS model; age squared, time dummies, and worker fixed effects included in the base model; age squared, time dummies, worker–firm, and job title fixed effects included in the full model. Specification 1 presents the estimates of the coefficients of the displacement dummies for each year before and after displacement. Specification 2 aggregates the years into two periods before (years $D_{-10}$–$D_0$) and after (years $D_1$–$D_{10}$) displacement; Specification 3 is a simple reparametrization of Specification 2 providing the net effect. Standard errors in Column 1 are clustered by worker and firm and in Columns 2 and 3 are bootstrapped at the worker level using 500 resamplings. The total number of observations equals 16,731,112.

Even though Portugal and the United States have different institutional labor market frameworks (Blanchard and Portugal 2001), our base model results are in accordance with earlier studies for the United States based on the Jacobson, LaLonde, and Sullivan (1993) methodology.

By construction, the estimates of the full model (Column 3) have zero mean in both the pre- and postdisplacement period. This occurs because we are now including match quality fixed effects. The estimates of the coefficients of the displacement dummies in Specification 1 provide only the time pattern of the wage losses. There is no visible trend in either the pre- or the postdisplacement periods, meaning that there is no indication of early leaving effects and that the recovery pattern is fairly smooth.

### B. The Empirical Distributions of Wages and Its Components

In Figure 1 we start by graphing the empirical wage distributions (and their components) of workers displaced due to firm closures and their nondisplaced counterparts in the predisplacement period, while in Figure 2 we compare the distribution of wages (and their components) of displaced workers based on values before and after displacement.[27]

It is clear in Panel A of Figure 1 that the wages of displaced workers are lower (22 percent, on average) and less dispersed when compared with those of the nondisplaced.

Panel B in Figure 1 depicts the empirical distribution of worker permanent heterogeneity. The graph is based on the 2,114,316 estimates of worker fixed effects. Not surprisingly, the shape of the distributions closely resembles the distributional shape of log wages. The linear correlation between log wages and worker fixed effects is 0.55. From the comparison between displaced and nondisplaced workers it is clear that those workers who exited their firms have permanent (observed and unobserved) characteristics that are associated with substantially lower wages.

Less well studied is the heterogeneity of wage policies across firms. In Panel C of Figure 1 we present the empirical distribution of the 51,976 firm fixed effects. A high firm fixed effect (high-wage policy from the firm) is a firm with total compensation higher than expected on the basis of observable time-varying regressors, once we take into account the (permanent) heterogeneity of workers, job titles, and match quality effects. The role of firm heterogeneity on wage formation is quite important. The linear correlation coefficient between log wages and firm fixed effects is no less than 0.51. Not surprisingly, the comparison between the two distributions shows that displaced workers earned much lower wages in part because the firms from which they separated exhibited a less generous wage policy.

The heterogeneity of job title fixed effects is likely to be generated by variations across occupations and skills and by differences across collective wage agreements. As discussed above, the notion of job title comes simply from the identification of distinct occupational categories within each collective wage agreement. Throughout the years of the survey we could estimate 99,307 job title fixed effects. A high job title fixed effect (job title premium) is a job title with total compensation higher than expected on the basis of observable time-varying regressors after controlling for the heterogeneity of workers, firms, and match quality effects. Job title heterogeneity has a nontrivial impact

27. Figure 1, Panels B–E, and Figure 2, Panels B–E, are based on the results from the estimation of the full model (Specification 1).

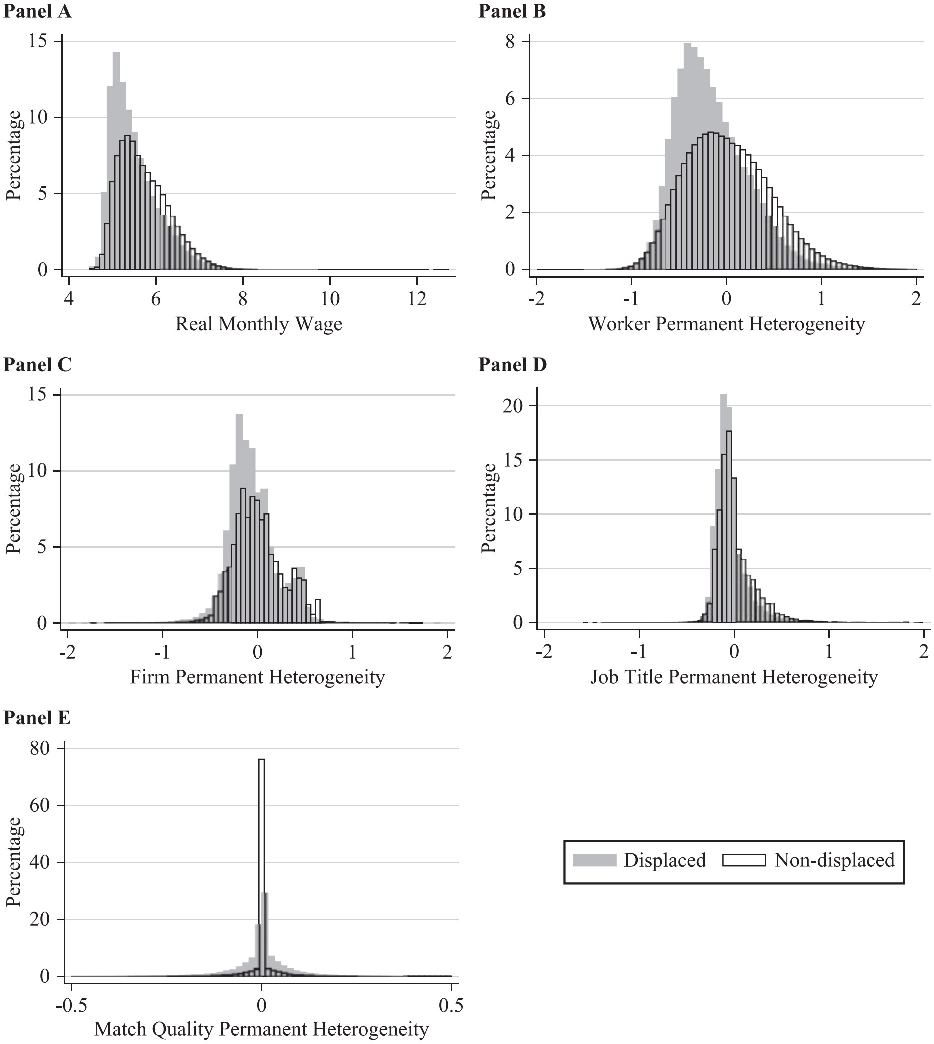


**Figure 1**

*Empirical Distribution of Wages and Wage Components for Displaced and Nondisplaced Workers*

Notes: This figure plots the empirical distributions of wages and wage components before displacement of workers displaced due to firm closures and their nondisplaced counterparts. Plots for displaced workers correspond to the year of displacement ($D_0$).

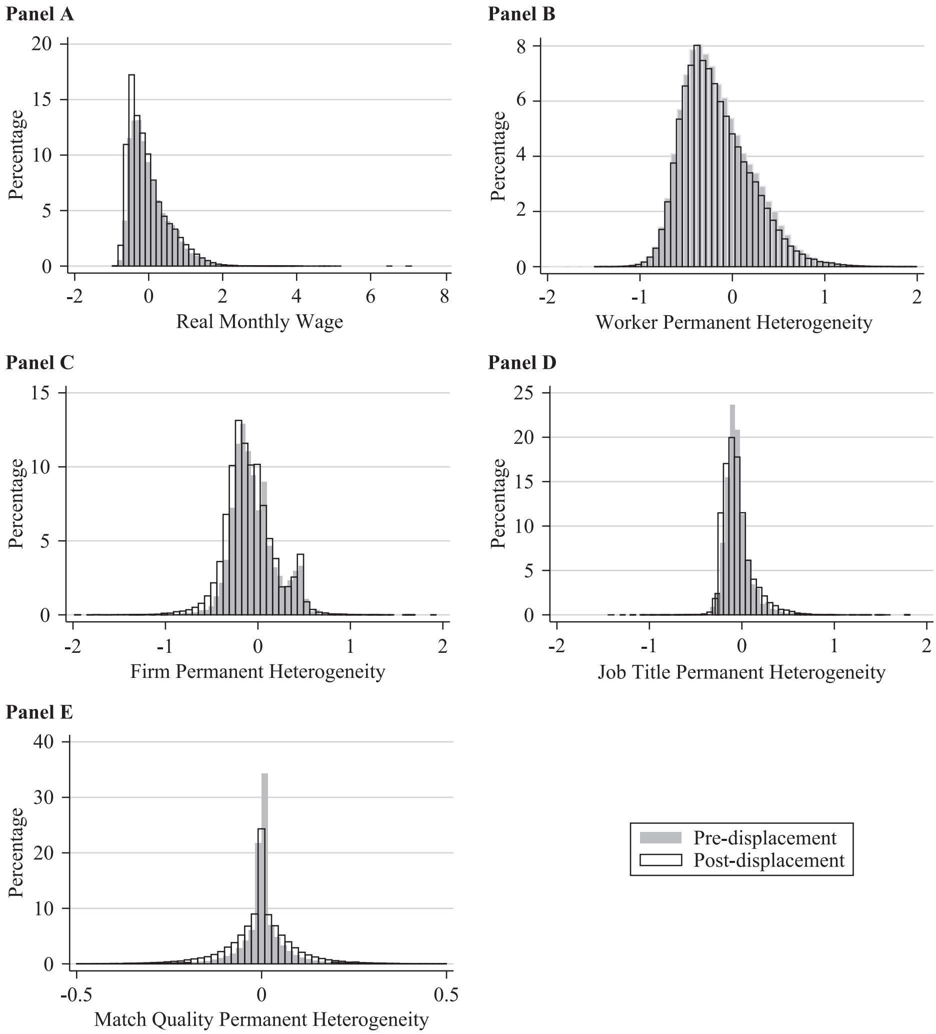


**Figure 2**

*Empirical Distribution of Wages and Wage Components of Displaced Workers: Pre- and Postdisplacement*

Notes: Displaced workers' empirical distributions in the last year before displacement and in the first year after displacement.

on the determination of wages. The linear correlation between job title fixed effects and wages is a respectable 0.39. From Panel D in Figure 1 it is clear that prior to firm closure displaced workers filled positions that were paid below those of the nondisplaced.

Figure 1, Panel E displays the empirical distribution of the 2,606,452 match quality fixed effects.[28] A high match quality fixed effect is a worker–firm match with total compensation higher than expected, conditional on observable time-varying regressors, workers, firms, and job titles time-invariant observed and unobserved characteristics. The linear correlation between log wages and match quality fixed effects is non-negligible (0.09). The figure shows that the empirical distribution of the match quality fixed effects is more compressed around zero for the nondisplaced.

The pre- and postdisplacement comparisons for the displaced also corroborate our previous findings. Panel A of Figure 2 shows that the distribution of wages was shifted to the left, evincing some wage losses associated with firm closures. Panel B has the worker fixed effect distribution. Except for the self-selection generated by different timing of reemployment, the two distributions should coincide exactly, which for the most part they do, suggesting that the time profile of reemployment is not a serious concern, at least in the worker heterogeneity dimension.[29] Panels C–E reveal that workers moved, on average, to lower paying firms, job titles, and matches. As a matter of fact, 56 percent of displaced workers moved to more poorly paying firms, 56 percent moved to job titles that are more poorly paid than their predisplacement job title, and 57 percent moved to less remunerated matches.[30]

### *C. The Sources of the Wage Loss*

The results of the wage loss decomposition detailed in Section IV.C are reported in Table 4. Column 1 displays the observed change in the wage loss estimates from the base to the full model. The values in Columns 2–4 were computed according to the procedure described in Section IV.C. They are interpreted as the contribution of the corresponding fixed effect for the observed change in the estimates of $\delta$ from the base model specification to the full model specification. Focusing on Specification 3, which provides the net effect on the monthly wage loss, we conclude that the firm fixed effect accounts for 2.2 log points of the difference of 7.2 log points between the wages before and after displacement, the match quality fixed effect accounts for 2.3 log points of the difference, and the job title fixed effect for 2.7 log points. Thus, in relative terms, we find that the allocation into unfavorable job titles accounts for 37 percent of the total wage loss

28. As discussed above, we obtained the match quality fixed effects assuming orthogonality between them and the worker and the firm fixed effects.

29. Conditional on being displaced and returning, 27 percent of the individuals return in the first year, 21 percent return after two years, 16 percent return after three years. Thus, 64 percent of the displaced return to work after three years. This rate compares with the figures for the United States reported by Farber (2017), who found that fewer than 50 percent of the job losers in the 2007–2009 Great Recession reported being employed in the 2010 Displaced Workers Survey.

30. We took a close look at the more frequent job title moves among displaced workers. However, given the unusually high level of disaggregation, it is very hard to establish clear patterns of job title movements. Some illustrative changes can nevertheless reveal the job title dynamics. For example, we observe a considerable number of truck drivers becoming lower paying car drivers, earlier dress makers working as lower paying janitors, and shoemakers converting to lower paying cloth-workers.

**Table 4**
*Decomposition of the Wage Loss into the Contribution of Firm, Match Quality, and Job Title Fixed Effects*

| | Wage Loss | Decomposition of the Wage Loss into | | | | | |
|---|---|---|---|---|---|---|---|
| | | Firm FE | | Match Quality FE | | Job Title FE | |
| | $\hat{\delta}_k^{base} - \hat{\delta}_k^{full}$ | $\hat{\tau}_k^{\theta}$ | SE | $\hat{\tau}_k^{\psi}$ | SE | $\hat{\tau}_k^{\lambda}$ | SE |
| | (1) | (2) | | (3) | | (4) | |
| Specification 1 | | | | | | | |
| $D_{-10}$ | 0.058 | 0.016 | (0.000) | 0.014 | (0.000) | 0.028 | (0.001) |
| $D_{-9}$ | 0.053 | 0.016 | (0.000) | 0.013 | (0.000) | 0.023 | (0.000) |
| $D_{-8}$ | 0.044 | 0.015 | (0.000) | 0.011 | (0.000) | 0.018 | (0.000) |
| $D_{-7}$ | 0.037 | 0.013 | (0.000) | 0.011 | (0.000) | 0.013 | (0.000) |
| $D_{-6}$ | 0.035 | 0.011 | (0.000) | 0.010 | (0.000) | 0.014 | (0.000) |
| $D_{-5}$ | 0.034 | 0.012 | (0.000) | 0.009 | (0.000) | 0.012 | (0.000) |
| $D_{-4}$ | 0.028 | 0.010 | (0.000) | 0.008 | (0.000) | 0.010 | (0.000) |
| $D_{-3}$ | 0.024 | 0.008 | (0.000) | 0.007 | (0.000) | 0.008 | (0.000) |
| $D_{-2}$ | 0.020 | 0.006 | (0.000) | 0.007 | (0.000) | 0.007 | (0.000) |
| $D_{-1}$ | 0.018 | 0.005 | (0.000) | 0.007 | (0.000) | 0.006 | (0.000) |
| $D_{0}$ | 0.017 | 0.005 | (0.000) | 0.006 | (0.000) | 0.005 | (0.000) |
| $D_{1}$ | 0.011 | 0.014 | (0.000) | –0.006 | (0.001) | 0.003 | (0.000) |
| $D_{2}$ | –0.007 | 0.006 | (0.001) | –0.008 | (0.001) | –0.004 | (0.000) |
| $D_{3}$ | –0.024 | –0.003 | (0.001) | –0.011 | (0.000) | –0.010 | (0.000) |
| $D_{4}$ | –0.037 | –0.011 | (0.001) | –0.012 | (0.000) | –0.014 | (0.000) |
| $D_{5}$ | –0.049 | –0.017 | (0.001) | –0.015 | (0.000) | –0.017 | (0.000) |
| $D_{6}$ | –0.058 | –0.023 | (0.001) | –0.015 | (0.000) | –0.020 | (0.000) |
| $D_{7}$ | –0.067 | –0.026 | (0.001) | –0.018 | (0.000) | –0.023 | (0.000) |
| $D_{8}$ | –0.078 | –0.031 | (0.001) | –0.020 | (0.001) | –0.028 | (0.000) |
| $D_{9}$ | –0.083 | –0.031 | (0.001) | –0.021 | (0.001) | –0.031 | (0.000) |
| $D_{10}$ | –0.080 | –0.027 | (0.001) | –0.020 | (0.001) | –0.033 | (0.000) |
| $R^2$ | | 0.96 | | 0.99 | | 0.99 | |
| Specification 2 | | | | | | | |
| Predisplacement | 0.026 | 0.008 | (0.001) | 0.008 | (0.001) | 0.010 | (0.001) |
| Postdisplacement | –0.046 | –0.014 | (0.002) | –0.015 | (0.001) | –0.017 | (0.001) |
| $R^2$ | | 0.96 | | 0.99 | | 0.99 | |
| Specification 3 | | | | | | | |
| Net | –0.072 | –0.022 | (0.001) | –0.023 | (0.001) | –0.027 | (0.001) |
| $R^2$ | | 0.96 | | 0.99 | | 0.99 | |

Notes: This table reports the decomposition of the wage loss variation of displaced workers from the base (Column 2) to the full models (Column 3) of Table 3. Columns 2–4 report the contribution of the corresponding fixed effect for the observed change in the estimates of the wage loss from the base to the full model computed according to the procedure described in Section IV.C. Bootstrapped standard errors in parentheses, where resampling was done at the worker level using 500 replications. The total number of observations equals 16,731,112.

(–0.027/–0.072), sorting into matches with lower quality accounts for 32 percent (–0.023/–0.072), while allocation into low-paying firms accounts for the remaining 31 percent (–0.022/–0.072) of the loss.

The empirical evidence on the importance of the job title in explaining about one-third of the total monthly wage loss clearly indicates that the worker's placement at the compensation tables of the collective agreement plays a nontrivial role in driving those losses. This result is in line with recent studies on the Portuguese labor market that emphasize the role of job title heterogeneity on wage formation (Carneiro, Guimarães, and Portugal 2012; Addison, Portugal, and Vilares 2018; Torres et al. 2018).

Our empirical exercise also highlights the importance of match quality effects in driving the wage loss estimates of the displaced, corroborating recent studies that provide a useful theoretical background regarding the importance of match effects in explaining the high and persistent earnings cost of job loss observed in the empirical data (Jarosch 2015; Huckfeldt 2018; Jung and Kuhn 2019; Krolikowski 2017). According to these search and matching models, the existence of significant job ladder and stable jobs at the top of the ladder helps us to understand why earnings losses are largely driven by the loss of match-specific effects.

Finally, sorting into firms also plays an important role in driving the wage losses, corroborating previous findings that even in more centralized wage setting systems like the one prevailing in Portugal, firms often deviate from the wage floor agreed upon at the collective bargaining table for each occupational category, adjusting to firm-specific conditions (Cardoso and Portugal 2005).

To shed further light on the role of firm, job title, and match quality fixed effects in explaining the wage losses following displacement, in the next section we present the decomposition of the wage losses in terms of the bargained wage and the wage cushion.

### *D. Assessing the Role of the Bargained Wage and the Wage Cushion*

In this section we split the wage rate into two components, the bargained wage and the wage cushion, and proceed, as before, with the decomposition exercise.

The bargained wage corresponds to the wage floor negotiated (typically at the industry level) between the trade unions and employers' associations for each job title. Firms often pay wages above this floor (as discussed above), leading to a gap between the actual wage paid and the bargained wage, which we call the wage cushion.[31] Because we cannot directly observe the bargained wage, we compute the modal base wage for each job title (in any given year) and use it as a proxy for the collectively agreed wage, a methodology identical to the one pursued by Cardoso and Portugal (2005).

Table 5 shows the results of the exercise for the bargained wage.[32] A useful way to look at the decompositions is to think of an artificial situation in which all workers simply collect the bargained wage corresponding to their job titles. In this case, the wage loss of the displaced workers would be generated by changes in the (imputed)

31. As discussed by Cardoso and Portugal (2005), the expression "wage cushion" was preferred to the expression "wage drift," as the latter most often refers to the difference between the total wage growth in actual wages and the growth in contractual wages. According to the authors' definition, the wage cushion corresponds to the difference between the log current wage and the log current bargained wage.

32. To save space, we present the estimates only for Specifications 2 and 3. Results for Specification 1 are available upon request.

**Table 5**
*Decomposition of the Wage Loss into the Contribution of Firm, Match Quality, and Job Title Fixed Effects—Bargained Wage*

| | Wage Loss | | | Decomposition of the Wage Loss into: Firm FE | Match Quality FE | Job Title FE |
|---|---|---|---|---|---|---|
| Period | $\hat{\delta}_k^{base}$ | $\hat{\delta}_k^{full}$ | $\hat{\delta}_k^{base} - \hat{\delta}_k^{full}$ | $\hat{\tau}_k^{\theta}$ | $\hat{\tau}_k^{\psi}$ | $\hat{\tau}_k^{\lambda}$ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Specification 2 | | | | | | |
| Predisplacement | 0.023 | 0.000 | 0.023 | 0.001 | –0.001 | 0.022 |
| | (0.000) | | | (0.000) | (0.000) | (0.000) |
| Postdisplacement | –0.040 | 0.000 | –0.040 | –0.002 | 0.002 | –0.039 |
| | (0.000) | | | (0.000) | (0.000) | (0.000) |
| $R^2$ | 0.85 | 0.93 | | 0.91 | 0.89 | 0.90 |
| Specification 3 | | | | | | |
| Net | –0.063 | 0.000 | –0.063 | –0.004 | 0.003 | –0.062 |
| | (0.000) | | | (0.000) | (0.000) | (0.000) |
| $R^2$ | 0.85 | 0.93 | | 0.91 | 0.89 | 0.90 |

Notes: See the notes to Table 4.



remuneration of job titles, before and after displacement. The results of Specification 3 indicate that job downgrading plays a very important role, implying a loss of 6.2 log points. In other words, if workers receive exactly the bargained wage, the wage loss of displaced workers would have been, on average, 6.3 log points. By construction, in this decomposition there is no role for the allocation of displaced workers among firms and sorting into lower quality matches, and, in fact, the estimated impact of these factors is negligible.

The wage policy of the firms and the quality of the match are much more important in the determination of the wage cushion. Table 6 (Specification 3) shows that displaced workers are allocated to relatively less generous firms in terms of the wage cushion, implying a wage loss of around 1.9 log points associated with the firm fixed effects. Loss of match quality explains 2.5 log points of the wage cushion loss. Displaced workers are allocated to relatively better paying job titles in terms of the wage cushion, partially offsetting (by 3.5 log points) the loss in terms of the bargained wage. This result is consistent with the fact that industries that pay a lower bargained wage (say, with weak union power) have more room to maneuver to pay wages above the bargained wage (that is, a higher wage cushion) (Cardoso and Portugal 2005; Dolado, Felgueroso, and Jimeno 1997).

Overall, the decompositions for the bargained wage and the wage cushion are consistent with the decomposition of the total wage provided in Table 4. The unexplained

**Table 6**
*Decomposition of the Wage Loss Variation into the Contribution of Firm, Match Quality, and Job Title Fixed Effects—Wage Cushion*

| | Wage Loss | | | Decomposition of the Wage Loss into | | |
|---|---|---|---|---|---|---|
| | | | | Firm FE | Match Quality FE | Job Title FE |
| Period | $\hat{\delta}_k^{base}$ | $\hat{\delta}_k^{full}$ | $\hat{\delta}_k^{base} - \hat{\delta}_k^{full}$ | $\hat{\tau}_k^{\theta}$ | $\hat{\tau}_k^{\psi}$ | $\hat{\tau}_k^{\lambda}$ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Specification 2 | | | | | | |
| Predisplacement | 0.003 | 0.000 | 0.003 | 0.007 | 0.009 | –0.013 |
| | (0.000) | | | (0.000) | (0.000) | (0.000) |
| Postdisplacement | –0.006 | 0.000 | –0.006 | –0.012 | –0.016 | 0.022 |
| | (0.000) | | | (0.000) | (0.000) | (0.000) |
| $R^2$ | 0.85 | 0.93 | | 0.96 | 0.99 | 0.95 |
| Specification 3 | | | | | | |
| Net | –0.009 | 0.000 | –0.009 | –0.019 | –0.025 | 0.035 |
| | (0.000) | | | (0.000) | (0.000) | (0.000) |
| $R^2$ | 0.85 | 0.93 | | 0.96 | 0.99 | 0.95 |

Notes: See the notes to Table 4.



sources of wage losses and those related with firm and match allocation are rooted solely in the determination of the wage cushion. The wage losses associated with the allocation among job titles, however, are negatively affected by the bargained wage and positively affected by the wage cushion.

## VI. Robustness Checks

### *A. Alternative Samples*

In this section the results of the wage loss decomposition are provided for alternative samples. Table 7 reports the decomposition of the wage loss relaxing the tenure restrictions on both groups of workers—displaced and nondisplaced—in the sense that the sample may also include individuals with less than two years of tenure. The results reveal that including short-tenured individuals in the sample (and by comparison with the estimates reported in Table 4) tends to reduce, as expected, the contribution of match quality effects to the total loss and to increase the role of firm effects in explaining the total wage loss.

Table 8 reports the results of the Gelbach decomposition based on a sample that included small firms, that is, those between 10 and 20 employees. Comparing with the estimates from Table 4, the results indicate that the inclusion of smaller firms decreases

**Table 7**
*Decomposition of the Wage Loss Variation into the Contribution of Firm, Match Quality, and Job Title Fixed Effects: Alternative Sample—Relaxing the Tenure Restrictions on Both Groups by Including Individuals with Less Than Two Years of Tenure*

| | Wage Loss | | | Decomposition of the Wage Loss into: Firm FE | Match Quality FE | Job Title FE |
|---|---|---|---|---|---|---|
| Period | $\hat{\delta}_k^{base}$ (1) | $\hat{\delta}_k^{full}$ (2) | $\hat{\delta}_k^{base} - \hat{\delta}_k^{full}$ (3) | $\hat{\tau}_k^{\theta}$ (4) | $\hat{\tau}_k^{\psi}$ (5) | $\hat{\tau}_k^{\lambda}$ (6) |
| Specification 3 | | | | | | |
| Net | –0.071 | 0.000 | –0.071 | –0.030 | –0.016 | –0.025 |
| | (0.000) | | | (0.000) | (0.000) | (0.000) |
| $R^2$ | 0.87 | 0.91 | | 0.94 | 0.99 | 0.99 |

Notes: See the notes to Table 4. We report the wage loss estimates following a simple reparametrization providing the net effect—row labeled "Net." The total number of observations equals 20,484,030.

**Table 8**
*Decomposition of the Wage Loss Variation into the Contribution of Firm, Match Quality, and Job Title Fixed Effects: Alternative Sample—Relaxing Firm Size Restrictions by Including Individuals Employed in Small Firms (10–20 Employees)*

| | Wage Loss | | | Decomposition of the Wage Loss into: Firm FE | Match Quality FE | Job Title FE |
|---|---|---|---|---|---|---|
| Period | $\hat{\delta}_k^{base}$ (1) | $\hat{\delta}_k^{full}$ (2) | $\hat{\delta}_k^{base} - \hat{\delta}_k^{full}$ (3) | $\hat{\tau}_k^{\theta}$ (4) | $\hat{\tau}_k^{\psi}$ (5) | $\hat{\tau}_k^{\lambda}$ (6) |
| Specification 3 | | | | | | |
| Net | –0.060 | 0.000 | –0.060 | –0.014 | –0.024 | –0.022 |
| | (0.000) | | | (0.000) | (0.000) | (0.000) |
| $R^2$ | 0.88 | 0.91 | | 0.95 | 0.99 | 0.96 |

Notes: See the notes to Table 4. We report the wage loss estimates following a simple reparametrization providing the net effect—row labeled "Net." The total number of observations equals 19,228,339.

**Table 9**
*Decomposition of the Wage Loss Variation into the Contribution of Firm, Match Quality, and Job Title Fixed Effects: Alternative Sample—Relaxing the Definition of Displacement by Including Individuals Displaced Due to Mass Layoffs*

| | | | | Decomposition of the Wage Loss into | | |
|---|---|---|---|---|---|---|
| | Wage Loss | | | Firm FE | Match Quality FE | Job Title FE |
| Period | $\hat{\delta}_k^{base}$ (1) | $\hat{\delta}_k^{full}$ (2) | $\hat{\delta}_k^{base} - \hat{\delta}_k^{full}$ (3) | $\hat{\tau}_k^{\theta}$ (4) | $\hat{\tau}_k^{\psi}$ (5) | $\hat{\tau}_k^{\lambda}$ (6) |
| Specification 3 | | | | | | |
| Net | –0.092 | 0.000 | –0.092 | –0.042 | –0.016 | –0.034 |
| | (0.000) | | | (0.000) | (0.000) | (0.000) |
| $R^2$ | 0.88 | 0.91 | | 0.96 | 0.99 | 0.99 |

Notes: See the notes to Table 4. We report the wage loss estimates following a simple reparametrization providing the net effect—row labeled "Net." A mass layoff occurs when a firm reduces its workforce by more than 30 percent in two consecutive periods with a minimum of six separations. The total number of observations equals 15,982,889.

the proportion of the wage loss explained by firm fixed effects and increases the proportion attributed to match quality effects.

Finally, Table 9 provides the decomposition exercise for a sample of workers displaced due to mass layoffs. In our definition, a mass layoff occurs when a firm reduces its workforce by more than 30 percent in two consecutive periods with a minimum of six separations. For the same identification reasons applied to firm closures, we used information from only the first mass layoff within the reference period. For workers displaced due to mass layoffs, the net loss is slightly higher, reaching 9.2 log points. Regarding the sources of that loss, negative sorting across firms becomes relatively more important in this context, while sorting into poorer quality matches becomes less important. The relative role of job title downgrading remains unchanged.

### *B. Alternative Specifications*

In order to check whether our results are sensitive to different wage measures, we replicated our decomposition procedure using hourly wages as an alternative definition. Hourly wages are computed as the ratio between monthly wages and the total number of normal and extra hours worked. The results reported in Table 10 are qualitatively similar to those based on monthly wages. In Specification 3, it can be seen that the allocation into low-paying job titles is again the largest component of the wage loss, accounting for 46 percent of the total loss (–0.032/–0.072). The allocation of workers into poorer matches and low-paying firms each account for 27 percent (–0.019/–0.072) of the total wage loss.

Finally, in order to account for different individual time trends, we added an individual-specific time trend to our baseline and full models (Heckman and Hotz 1989). The results of the random trend model are reported in Table 11. As expected,

**Table 10**

*Decomposition of the Wage Loss Variation into the Contribution of Firm, Match Quality, and Job Title Fixed Effects: Alternative Model Specification—Using Hourly Wages as the Dependent Variable in the Base and Full Models*

| | Wage Loss | | | Decomposition of the Wage Loss into | | |
|---|---|---|---|---|---|---|
| | | | | Firm FE | Match Quality FE | Job Title FE |
| Period | $\hat{\delta}_k^{base}$ (1) | $\hat{\delta}_k^{full}$ (2) | $\hat{\delta}_k^{base} - \hat{\delta}_k^{full}$ (3) | $\hat{\tau}_k^{\theta}$ (4) | $\hat{\tau}_k^{\psi}$ (5) | $\hat{\tau}_k^{\lambda}$. (6) |
| Specification 3 | | | | | | |
| Net | –0.072 | 0.000 | –0.072 | –0.019 | –0.019 | –0.032 |
| | (0.000) | | | (0.000) | (0.000) | (0.000) |
| $R^2$ | 0.90 | 0.93 | | 0.96 | 0.99 | 0.99 |

Notes: See the notes to Table 4. We report the wage loss estimates following a simple reparametrization providing the net effect—row labeled “Net.” The total number of observations equals 16,731,112.



**Table 11**

*Decomposition of the Wage Loss Variation into the Contribution of Firm, Match Quality, and Job Title Fixed Effects: Alternative Model Specification—Using a Random Trend Model*

| | Wage Loss | | | Decomposition of the Wage Loss into | | |
|---|---|---|---|---|---|---|
| | | | | Firm FE | Match Quality FE | Job Title FE |
| Period | $\hat{\delta}_k^{base}$ (1) | $\hat{\delta}_k^{full}$ (2) | $\hat{\delta}_k^{base} - \hat{\delta}_k^{full}$ (3) | $\hat{\tau}_k^{\theta}$ (4) | $\hat{\tau}_k^{\psi}$ (5) | $\hat{\tau}_k^{\lambda}$ (6) |
| Specification 3 | | | | | | |
| Net | –0.037 | 0.000 | –0.037 | –0.016 | –0.012 | –0.009 |
| | (0.000) | | | (0.000) | (0.000) | (0.000) |
| $R^2$ | 0.93 | 0.94 | | 0.99 | 0.99 | 0.97 |

Notes: See the notes to Table 4. We report the wage loss estimates following a simple reparametrization providing the net effect—row labeled “Net.” The total number of observations equals 16,731,112. The random trend model adds an individual-specific time trend to the base and full models.

accounting for individual time trends reduces considerably the total average wage loss estimate (from 7.2 log points to 3.7 log points). Furthermore, and comparing to the results reported in Table 4, the relative contribution of firm fixed effects as a source of wage loss increases, while the relative contribution of job title fixed effects decreases by almost the same amount. In relative terms, the contribution of match quality effects remains unchanged.

## VII. Concluding Remarks

Wage losses of displaced workers can be related to the firm, job title, and match quality that existed before and after displacement. In this work we first explored the sources of those losses, estimating a multiway high-dimensional fixed-effects regression model, which enabled us to decompose the wage losses into the contribution of each fixed effect. Our approach provides a unified framework that allows us to identify the components of the sources of the wage losses associated with the worker–firm pair separately into the contribution of worker, firm, and match quality.

Based on the Jacobson, LaLonde, and Sullivan (1993) methodology we found that postdisplacement monthly wages are, on average, 7.2 log points lower than predisplacement wages. Using the conditional decomposition method suggested by Gelbach (2016), the results showed that sorting into job titles plays a very sizable role in explaining the losses experienced by workers displaced through firm closures, accounting for 37 percent of the total average monthly wage loss and for 46 percent of the hourly wage loss. The loss of match quality effects also plays a significant role, accounting for 32 percent of the total average monthly wage loss and for 27 percent of the total hourly wage loss. The remaining 31 and 27 percent of the total average monthly and hourly wage loss, respectively, are attributed to the negative sorting of workers across firms with different pay standards.

Overall, our robustness checks showed that the wage loss due to the allocation into lower paying firms becomes relatively less important as the sample is augmented to include smaller firms, while match quality effects become less important when tenure restrictions on both groups of workers are relaxed.

There are some potentially important policy prescriptions that may be derived from the results reported in this study. Severe losses in the returns to the job title may be due to depreciation of specific human capital or to the difficulty of finding a new job requiring skills similar to those acquired in the predisplacement job. Here, retraining programs may be of some help.

Losses related to the firm or match quality fixed effects may mean that a worker is moving from a high-paying firm or high-quality match to a low-paying firm or low-quality match. Indeed, with the occurrence of a displacement event, successful job searchers may lose their "job shopping" investment (Johnson 1978). To the extent that the returns from job shopping investment are significant, job search assistance programs and mandatory prenotification of mandatory layoff may be justified.

# Appendix 1

**Table A1**
*Sample Restrictions on Original Data*

| | Observations |
|---|---|
| Original data | 47,520,802 |
| Firm size ≥20 | 29,717,803 |
| Tenure restrictions (24 months) | 22,124,787 |
| Nonmissing values of the covariates | 19,783,524 |
| Age of the worker 16–64 | 19,625,875 |
| Base wage >80% of the legal minimum wage | 19,578,581 |
| Excluding observations for displaced workers before or after the 20-year window around the displacement | 18,901,738 |
| Restricting to the largest connected set | 18,157,787 |
| Excluding singletons | 16,731,112 |

Notes: The largest connected set is the largest group of connected worker–firm pairs and job titles. Singletons are groups with only one observation.

**Table A2**
*Sample Descriptive Statistics by Displacement Status, 1986–2016*

| | Nondisplaced | Displaced |
|---|---|---|
| Total monthly wages (2016 euros) | 1,337 | 1,035 |
| Minimum monthly wage (2016 euros) | 530 | 530 |
| Age (in years) | 40 | 37 |
| Tenure (in years) | 16 | 8 |
| Female (%) | 41 | 47 |
| Education (%): | | |
| Less than basic school | 3 | 2 |
| Basic school | 31 | 32 |
| Preparatory | 18 | 26 |
| Lower secondary | 19 | 19 |
| Upper secondary | 18 | 15 |
| College | 11 | 6 |
| Firm size (no. coworkers) | 1,784 | 520 |
| Industry (%): | | |
| Manufacturing | 42 | 53 |
| Construction | 6 | 9 |
| Wholesale and retail trade | 19 | 19 |
| Transports | 10 | 4 |
| Financial services | 13 | 11 |
| Education/health | 10 | 4 |
| Observations | 15,683,082 | 1,048,030 |

Notes: This table reports summary statistics (mean) for the sample. The units are in parentheses.

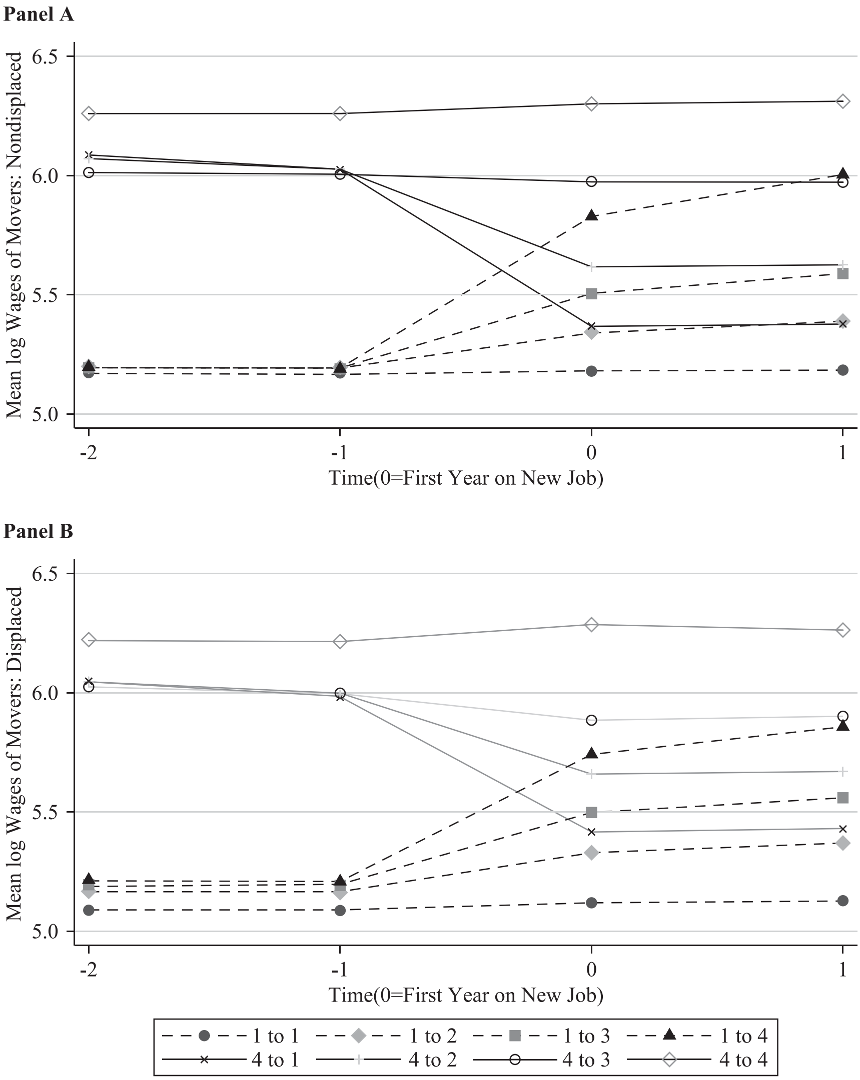


**Figure A1**

*Mean Log Wages of Firm Movers, Classified by Quartile of Mean Coworker Wage at Origin and Destination Firm*

Notes: The classification of workers into quartiles is based on the mean log wage of all coworkers (displaced and nondisplaced) in the last year of the old job and in the first year on the new job.

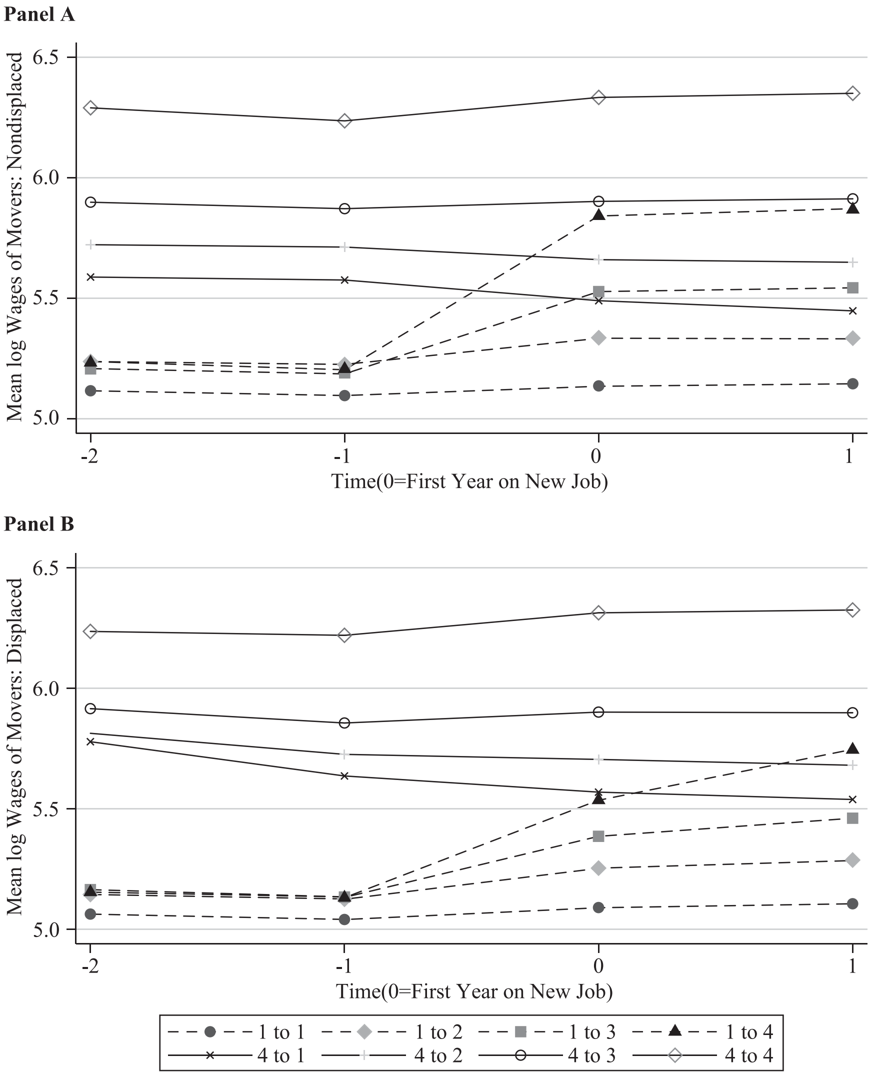


**Figure A2**

*Mean Log Wages of Job Title Movers, Classified by Quartile of Mean Coworker Wage at Origin and Destination Job Title*

Notes: The classification of workers into quartiles is based on the mean log wage of all coworkers (displaced and nondisplaced) in the last year of the old job title and in the first year on the new job title.

## Appendix 2

### *Estimating a Multiway, High-Dimensional Fixed-Effects Regression Model*

In this appendix we describe the procedure that allows the estimation of a wage equation that incorporates two high-dimensional fixed effects—the worker–firm fixed effect and the job title fixed effect. For this exercise we need to use a modified version of the methodology initially developed by Abowd, Kramarz, and Margolis (1999) and Abowd, Creecy, and Kramarz (2002) and extended and simplified by Guimarães and Portugal (2010) to work with large data sets.

We start with the full model specification given in Equation 9:

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta}_1 + \mathbf{M}\boldsymbol{\phi}_1 + \mathbf{J}\boldsymbol{\lambda}_1 + \mathbf{D}\boldsymbol{\delta}_1 + \boldsymbol{u}_1,$$

where $\mathbf{Y}$ represents (log) wages, $\mathbf{X}$ denotes the matrix of control variables (in our case, time dummies and a quadratic in age), $\boldsymbol{\beta}_1$ is a vector of regression coefficients, $\mathbf{D}$ contains the displacement dummies, $\boldsymbol{\delta}_1$ represent the (conditional) wage losses, $\mathbf{M}$ is a matrix collecting all the worker–firm dummies, the vector $\boldsymbol{\phi}_1$ denotes the regression coefficients of the worker–firm fixed effects, $\mathbf{J}$ is a matrix collecting all the job title dummies, the vector $\boldsymbol{\lambda}_1$ denotes the regression coefficients of the job title fixed effects, and $\boldsymbol{u}_1$ stands for the error term.

To simplify matters, $\mathbf{X}\boldsymbol{\beta}_1 + \mathbf{D}\boldsymbol{\delta}_1$ can, of course, be collapsed into $\mathbf{X}^*\boldsymbol{\beta}_1^*$, encompassing the covariates of the model. The stacked system has now the following form:

$$\mathbf{Y} = \mathbf{X}^*\boldsymbol{\beta}_1^* + \mathbf{M}\boldsymbol{\phi}_1 + \mathbf{J}\boldsymbol{\lambda}_1 + \boldsymbol{u}_1, \tag{14}$$

The Least Squares estimators of $\boldsymbol{\beta}_1^*$, $\boldsymbol{\phi}_1$, and $\boldsymbol{\lambda}_1$ solve the following equations:

$$\begin{bmatrix} \mathbf{X}^{*\prime}\mathbf{X}^* & \mathbf{X}^{*\prime}\mathbf{M} & \mathbf{X}^{*\prime}\mathbf{J} \\ \mathbf{M}'\mathbf{X}^* & \mathbf{M}'\mathbf{M} & \mathbf{M}'\mathbf{J} \\ \mathbf{J}'\mathbf{X}^* & \mathbf{J}'\mathbf{M} & \mathbf{J}'\mathbf{J} \end{bmatrix} \begin{bmatrix} \hat{\boldsymbol{\beta}}_1^* \\ \hat{\boldsymbol{\phi}}_1 \\ \hat{\boldsymbol{\lambda}}_1 \end{bmatrix} = \begin{bmatrix} \mathbf{X}^{*\prime}\mathbf{Y} \\ \mathbf{M}'\mathbf{Y} \\ \mathbf{J}'\mathbf{Y} \end{bmatrix}. \tag{15}$$

It is computationally difficult, or unfeasible, to invert the left matrix due to the large number of worker–firm and job title fixed effects. Herein, an iterative solution that alternates between $\hat{\boldsymbol{\beta}}_1^*$, $\hat{\boldsymbol{\phi}}_1$, and $\hat{\boldsymbol{\lambda}}_1$, can be used:

$$\begin{bmatrix} \hat{\boldsymbol{\beta}}_1^* \\ \hat{\boldsymbol{\phi}}_1 \\ \hat{\boldsymbol{\lambda}}_1 \end{bmatrix} = \begin{bmatrix} (\mathbf{X}^{*\prime}\mathbf{X}^*)^{-1}\mathbf{X}^{*\prime}(\mathbf{Y} - \mathbf{M}\hat{\boldsymbol{\phi}}_1 - \mathbf{J}\hat{\boldsymbol{\lambda}}_1) \\ (\mathbf{M}'\mathbf{M})^{-1}\mathbf{M}'(\mathbf{Y} - \mathbf{J}\hat{\boldsymbol{\lambda}}_1 - \mathbf{X}^*\hat{\boldsymbol{\beta}}_1^*) \\ (\mathbf{J}'\mathbf{J})^{-1}\mathbf{J}'(\mathbf{Y} - \mathbf{M}\hat{\boldsymbol{\phi}}_1 - \mathbf{X}^*\hat{\boldsymbol{\beta}}_1^*) \end{bmatrix}.$$

It is clear from the previous equations that at each iteration the estimates of the fixed effects are simply computed as averages of the residuals. For an example, $(\mathbf{J}'\mathbf{J})^{-1}\mathbf{J}'$ is simply a demeaning operator for the job title fixed effect. The iterative solution proceeds as follows. First, the algorithm makes use of the Frish–Waugh–Lovell theorem to remove the influence of the two high-dimensional fixed effects from each individual variable. Through the recursive algorithm, the current value of $\hat{\boldsymbol{\beta}}_1^*$ can be used to estimate the current value of $\hat{\boldsymbol{\phi}}_1$. In estimating $\hat{\boldsymbol{\lambda}}_1$ the previous values of $\hat{\boldsymbol{\phi}}_1$ and $\hat{\boldsymbol{\beta}}_1^*$ are used. Then, the algorithm restarts and will converge because the parameter updates are chosen according to the Equation 15. Next, we estimate the regression using the transformed variables with a correction to the degrees of freedom. This approach yields the exact least squares solution for the coefficients and standard errors. The main advantage of this methodology is that it can be applied even to very large data sets, in particular those requesting memory allocation that would make other procedures unfeasible (for example, those based on sparse matrixes). Another advantage of this algorithm is that it can be straightforwardly extended to more than two high-dimensional fixed effects (Guimarães and Portugal 2010). In this study, the "reghdfe" stata procedure was used to estimate the high-dimensional fixed effect regression models (Correia 2017).

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