Selective displacement and workforce restructuring during a mass layoff*

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Abstract

In this paper we investigate the role of firms when they face a mass layoff. We investigate a simple question: '*when things go bad, who gets fired first?*'. Using administrative and survey data for France, we first show that the companies that had a mass layoff used this event to restructure their workforce. We observe a small but significant increase in the composition of social skills and a decrease in manual skills and cognitive skills within the firm, as compared to the control group. The restructuring of the workforce demonstrates that firms use layoff strategically to recompose, and then selective displacement plays an important role. We also investigate the factors that determining who is fired. The results indicate that firms strategically chose which workers to displace, and that demographic characteristics, perceived cost and skills mismatch are determining factors.

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1 Introduction

In the aftermath of the great recession, the low-skilled have been affected considerably more than those with more skills at the macro level, both in terms of job loss and longer unemployment spells (OECD, 2013). The current economic downturn due to COVID-19 has led to a similar situation, with a potentially higher incidence for low skilled workers Mongey and Weinberg (2020). Policymakers need to know which factors determine job separations in order to create tailored programs for the displaced workers. This paper presents evidence of workforce restructuring at the firm level when downsizing occurs and characterizes the selective displacement of workers during a mass layoff, focusing on the role of skill mismatch.

A long stream of literature had studied the effects of job displacement on workers' labor market outcomes. The results of the seminal work of Jacobson, LaLonde and Sullivan (1993), where displacement had huge long term effects in labour earnings, have been confirmed across time (Davis and Von Wachter, 2011) and countries (Bertheau et al., 2021; Seim, 2019). The long-term effects on displaced workers' earnings have also been studied previously in France (Bender et al., 2002; Bertheau et al., 2021), and recent research tries to unveil the sources of such losses (Schmieder et al., 2018; Brandily et al., 2020). Previous literature has focused mainly on worker outcomes (except some research in which value-added per worker that is also an outcome that is taken into account). However, less is known on the firm's role and decisions around displacement when the firm does not disappear entirely (Gibbons and Katz, 1991). If displacement affects the composition of a firm's workforce, it will also affect the firm's productivity and its ability to absorb different types of labor.

This paper discusses mass layoffs from the firm's perspective and addresses two different questions. First, do firms use mass layoffs to restructure their workforces? Second, how do firms choose which workers to layoff? We focus on worker skills and, for this second question, we outline the importance of the factors that directly affect the value of the employment relationship and specifically the role of skills mismatch, defined as the difference between the skills the worker provides and the requirements of the job that he performs in the firm.

A comparison of workforce composition between 30 years ago and today shows that the skill composition of the workforce has changed. For example, there is evidence at the macro level that medium-skill routine jobs have disappeared (Autor and Dorn, 2009). Such a restructuring of the labor force is often explained by a change in the economic activity at the sector level (Goos et al., 2011). However, given that the firm's occupational structure plays an essential role in its productivity (Simon, 1962; Michaels et al., 2014), one could imagine that within variation should also be important. How the firm organizes the human capital it employs has an impact on how productive and competitive it is, and reorganization of the firm might occur due to a multitude of factors: the firm's life-cycle, its use of technology, offshorability, or managerial styles, for example. There is also evidence of workforce restructuring across Europe. Harrigan et al. (2020) shows that ICT occupations have increasing weight in the structure of occupations, and France is likely not an exception.

Often, long periods of time are required to evaluate changes in organization and the structural composition of employment. However, if firm uses mass layoff periods to adjust and restructure its workforce, we could see reorganization occur more rapidly. The strategic use of mass layoff to adjust workforce composition has been less studied, but given the legal constraints and the high cost of firing, once a firm has concluded that it is optimal to incur adjustment costs (especially fixed adjustment costs), it can use such moments to undertake adjustments that would have been too costly to make on continuous basis. In France, where the firing cost function is concave in the number of layoffs (Abowd and Kramarz, 2003), such behavior seems natural.

In order to examine the firm's strategic behavior during a mass layoff, we first test if the firm restructures its workforce in a shorter period when undergoing a mass layoff, or iff it lays off all workers with equal probability.To do this, we identify a set of mass layoff firms using french administrative data on the universe of private sector jobs and firms (DADS postes). In selecting this sample, we do not differentiate between separations for economic or other reasons, but we identify the mass layoff based on changes in the firm's workforce size. We then study how the occupational composition and average skill use within a firm changes during a mass layoff. We find evidence of firm reorganization in the firm's skill structure, finding a small and significant increase in the use of social skills, a small and significant reduction of manual skills, and cognitive skills. To explore how this mechanism operates, we then explore selective displacement.

How do firms decide which workers are fired when they decide they need to downsize? If firms use mass layoffs to re-organize their workforce, selecting the workers that must leave the firm becomes a strategic decision. What are the factors that enter into this decision? Bender et al. (2002) investigate the importance of age, tenure, and education for selective displacement for France. Seim (2019) studies the role of skills in determining layoff risk, finding that an increase in one standard deviation in cognitive and non-cognitive skills reduces the likelihood of being laid off by around 1%. Our results complement the literature on selective displacement, finding that skill *mismatch* and compensation cost plays an important role in determining who is fired. The result is robust to different specifications, even when we control for demographic characteristics, firm characteristics, and firm and year fixed effects. The results are also robust when calculated in a sub sample (one third of full sample size), where we observe family characteristics.

The paper proceeds as follows. Section 2 presents an economic analysis of why firms want to displace workers. Section 3 describes the data sources used, and describes the samples under consideration. Sections 4 and 5 presents the empirical results on firm re-organization and the role of skills mismatch in determining the selective displacement. Section 6 concludes the paper.

2 Why do firms want to downsize?

All firms face ups and downs during their life cycle. What are the main factors that induce firms to reduce their workforce? The economic and management literature has provided various explanations for the factors that determine mass layoffs, ranging from productivity shocks, a need for firm re-organization, to cost structure changes. Depending on the reason for the mass layoff, the firm will make different actual decisions and these will determine the resulting productivity and workforce structure after a layoff process.

How displacement works depends on the stability of the match. A static model of separations would consider firms and workers, calculating in each period the value of match continuation. Each party would compare its surplus share against its outside option of terminating the employment relationship. While employed, workers compare their share of the match surplus to the outside option value, which is the value of unemployment in a model without on-the-job search. Firms compare the value of production from the match to its net cost (wage plus other employment costs).

The stability of this relation can change with a productivity shock. When wages are negotiated in each period and the total value of production from the match is still positive, the firm will be willing to continue the employment relationship (after renegotiating wages and seeing the post-shock value of production) as long as its share of the surplus is positive. However, it may be the case that an acceptable renegotiated wage for the firm, although positive, would be lower than the outside option and would result in a voluntary separation. When dealing with multiple and heterogeneous skills, further consideration must be taken into account. How skills enter into a production function and how they affect productivity also influences the likelihood of separation, especially when workers have heterogeneous skills (Lise and Robin, 2017). Wage renegotiation might happen using several mechanisms that depend on the expected productivity, worker inputs considered in the match, and firm inputs that enter the match value function. For example, Postel-Vinay and Turon (2010) consider that the renegotiation will happen if one of the parties has a credible outside option and the new surplus generated is higher than the sum of outside options.

In practice, however, such types of wage adjustments may not be feasible due to regulation, long-term contracts, and the existence of internal labor markets. First, consider the case of regulation. A binding minimum wage will prevent too large of a downward wage adjustment, resulting in a layoff. As such, competitive labor market models in the literature (Mortensen and Pissarides, 1994) imply that an increase in minimum wages will increase separations since there will be fewer profitable matches. Such a view contradicts the findings of more general models such as Dube et al. (2016), where an increase in the minimum wage decreases the number of layoffs.

A wage cut could be also unfeasible in the presence of an agreement between the two parties. In case of a formal agreement (collective or individual), the contract establishes a level compensation that can not be unilaterally modified. Such agreements can be informal, i.e. implicit contracts in which the worker expects a wage increase conditional on good effort or performance and/or investment of specific human capital (Jovanovic, 1979). Internal labor markets are an example of informal contracts, where incentive mechanisms result in vertical mobility within the firm and increasing wage profiles (Dohmen et al., 2004). In face of a negative productivity shock and the absence of wage cuts or wage renegotiation, worker displacement may be a rational option for the firm. This behavior implies that firm employment over time fluctuates with the overall conditions of the economy (Davis et al., 2012).

Nevertheless, firms do not change size only because of productivity shocks. The life-cycle of the firm may also play a role in the composition and size of its workforce. The type of knowledge that the firm requires in each phase of its development would determine the optimal occupational structure, the organization of work, and its labor productivity. For example, consider a firm that was recently established. It would be reasonable to think that it would invest a lot of resources in research and development, hiring high-skill workers with that objective in the first phase. A later phase of production would require different types of tasks and skills for the production of goods and services, thus having a different occupational composition. How the firm is composed of self-organized elements and how these elements interact have consequences for firm performance. This is not a new idea in economics, and is pervasive to the management literature. It can be traced back to Simon (1962). The management decision of corporate structure and strategy would thus have an impact on workforce composition and firm size.

Another factor that could explain a modification in the structure of the firm is technological change. Implementing new technology requires the adaptation of workers' skills and knowledge and can potentially impact how the firm is organized. For example, Michaels, Natraj and Van Reenen (2014) document the occupational structure change due to the adoption of ICT in 11 countries (including France) during 25 years. Blinder and Krueger (2013) also analyze the effect of technology and offshorability on the structure of occupations, finding significant effects for both, with the effects being larger for technology. In France's case, Harrigan, Reshef and Toubal (2020) show an occupational shift in the composition of workers in the period 1994 - 2007, where firms that employed "techies" in 1994 realized an overall skill upgrade at the end of the analyzed period.

Given that structural reorganization is a slow process, it has always been analyzed over a long time span. A mass layoff, in which a large share of the firm is displaced in a limited period of time, could serve as an opportunity to change the composition and structure of the firm's workforce more rapidly. Thus, the selective displacement can play an important role in re-organizing the firm, especially in changing the skill composition.

Of course, mass layoffs entail adjustment costs. It is a known result that an increase in termination costs, in the form of employment protection legislation, tends to reduce layoffs, but at the same time can reduce job creation. Such costs provide an incentive for labor hoarding, in which non-profitable employment relationships are maintained because the separation costs exceed the present discounted value of the profit gains from ending the employment relation. If the cost of displacement is a function that exhibits decreasing returns to scale, a mass layoff is an opportunity for the firm to get rid of expensive matches. Abowd and Kramarz (2003) investigate the incidence of firing and hiring cost in France and find that the separation function cost is indeed concave, and therefore it makes more sense for the firm dismiss workers by in large groups as opposed to individually.

These last three factors that might influence displacement have a common characteristic: all of them highlight situations where a worker's productivity is low compared to his/her cost. These considerations provide firms with an incentive to monitor the quality of the match between workers and jobs. One measure to calculate *match quality* is in terms of the opportunity cost of a filled job. For instance, firms can identify if the worker is *"too expensive"*, comparing his/her wage to that of the best alternative worker, or comparing the requirements of a job with the capacity of its occupant to perform these tasks. This idea is at the heart of our calculation of *skills mismatch*, used throughout this paper. Using the notions of cognitive and social skills required for each job, we measure the extent to which workers' skills coincide with skill requirements and the degree to which such differences influence the probability of displacement during a mass layoff.

3 Data

This section describes the sources of information used and how they are combined for our estimation purposes.

3.1 French administrative data

The analysis presented here relies on French social security records (DADS - Déclaration Annuelle des Données Sociales) collected by social security and tax authorities and covering the universe of non public sector workers and firms. We use a sample covering the 2003-2015 period, comprised of the administrative declarations that all employers complete for each employment spell for each worker in each establishment in each year. The data set contains detailed information at the level of the firm, establishment, and worker, and includes the stand and end dates of employment spells, measured to the day. We use two different administrative data sources in this paper: the DADS postes, and DADS-EDP panel.

DADS postes This database contains the universe of employed individuals in the non-public sector and uniquely identifies each worker, firm and establishment. Each observation describes the employment relationship in the current and previous year[1], allowing us to follow employment relationships through time[2]. An observation in the data to which we had access presents one employment relation per year, in which each registry provides information on up to two employment spells during the year with the same worker-establishment combination. It also contains information on the overall duration

[1]The current or previous year information is missing if the person left the firm in the previous year or was hired by the firm in the current year, respectively.

[2]We are considering the firm true employment ("postes non annexes"). According to the information in the DADS guide, a job is considered in the DADS as non annex if the net remuneration is higher than 3 minimum wages (SMIC) per month, and the employment relationship is longer than 30 days, with an intensity of more than 120 hours.

of employment, sex, occupational information, and wage [3]. The establishment-level data is aggregated to the level of the firm in all of our analyses.

We use DADS postes for two purposes: first, it allows us to determine the sample of firms undertaking mass layoffs. We follow them before and after an event to evaluate a change in their skill composition using changes in occupational structure. Second, we use the unique identifiers to identify displaced and not displaced workers involved in a mass layoff.

The variables used in our analysis are:

- The firm's unique identifier (SIREN).
- The individual's unique identifier.
- The start and end dates of each job spell.
- The total duration of job spells in the year.
- The number of job spells per year.
- The occupation[4].

Using the above information, we construct a measure of skill requirements for each occupation using the skill contents of the Occupational Information Network (O*Net),

[3] We correct the start and end dates of the observed spells in case the spells are not consistent with the reported duration. Since each registry reports up to two employment spells per worker and firm, total employment duration does not coincide for some observations (around 5% of the total). As we know the number of distinct spells for each match, we correct such registries by adding the correct number of (approximately) equal length spells such that the total length of spells coincides with the reported length without making them overlap. Such correction allows us to calculate more precisely firm size and its variations.

[4] We construct a correspondence table that relates the french national occupation classification and the international occupation classification. We then re-categorize the occupation from PCS-82 and PCS-2003 to ISCO-08.

In cases when the occupation was missing or had errors, we use the information from the previous year. In case it is not available or it has errors, we rely on the socio-professional category (cs) (either in the year or the previous year). The CS is a more aggregated categorization that can be related to the occupation at an aggregate level. This makes missings in the occupation variable rare and sparse.

which contains information of job characteristics at the level of occupation. We merge a vector of skill requirements for each occupation into the DADS data, based on three types of skills: cognitive skills, social skills, and manual skills[5]. Aggregated to the firm level, these measures can give a sense of the firm's skill structure.

DADS-EDP panel This data set merges the panel version of DADS and the permanent demographic sample (EDP - Echantillon Démographique Permanent). The DADS panel contains around 1/12 of the workers, formed by retaining all workers born in October, following them through all of their jobs and organizing the observations into a panel. Apart from the worker demographic variables (age, sex, seniority) and job characteristic variables (firm characteristics, wage, and occupation) that come from the panel, the data provides additional information on the educational attainment, civil status, and birth age of children collected from the census or other administrative records, such as birth and marriage certificates.

BIC -RN The BIC-RN (Bénéfice Industriels et Commerciaux - Régime Normal) data includes fiscal year information from the tax declarations and balance sheets of firms. Using this information, we calculate some fundamental financial indicators: value-added, return on investment, return on equity, and EBITDA. The BIC-RN data shares the firm identifier with the DADS data, allowing us to merge these sources.

3.2 PIAAC

The French workers' skill endowment information comes from the Programme for the International Assessment of Adult Competencies (PIAAC). The OECD developed the survey, and the data was collected for France between September and November 2012. The PIAAC provides internationally comparable data about the skills of the adult populations in 24 countries. The sample consists of adults between 16 and 65 years of age. The survey

[5]We build the skill measures using all the skills information from O*NET, following Lise and Postel-Vinay (2020). Using principal component analysis (PCA) to reduce dimensionality, we construct a skill vector that describes every occupation's cognitive, social, and manual skill requirements. More details on how the occupation skills requirements are built can be found in appendix A.2.2.

assigns 10 plausible values to each individual in the survey for both literacy and numeracy. A weight accompanies each plausible value.

The survey includes an assessment of cognitive skills in two main domains: literacy and numeracy. For literacy, the survey assesses how well people comprehend, evaluate, use, and engage with written texts. For numeracy, it assesses a person's ability to solve a problem in a real-world setting by relating it to mathematical data and ideas. It is worth noting that these are not self-declared measures but are derived from directly assessed raw test responses and other personal characteristics. The test was designed to accurately assess cognitive abilities by adjusting the questions' complexity and specifying the thresholds based on the individual's educational level and whether or not they are a native speaker. To evaluate each cognitive component, the test is divided into two stages, the first with nine tasks and the second with eleven tasks. PIAAC is based on an incomplete balanced block design, so not all individuals are evaluated on the same components.

Furthermore, since the test is adaptive and the respondent's results determine the questions' complexity, raw responses have missing values by design. The OECD suggests that the plausible values be used. Social skills measures are derived from the answers to the background questionnaire (BQ) of the survey. In this part, six questions about attitudes and interest toward learning are asked. These measures are related to personality and interpersonal skill areas.

We build a person's vector of cognitive skills by combining knowledge on literacy and numeracy. The questions in the BQ are combined to form a social skills assessment. A Factor Analysis was used to determine the composition's weights[6]. By combining the information on the identified questions from the BQ, we construct a unique vector that expresses each individual's social skill ability in the survey. Using a principal component analysis, we find the optimal weights that capture the largest part of the variance (see appendix A.2.1 for details).

[6] See appendix A.2.1 for details.

3.3 Adding skills endowments into the DADS-EDP panel data

Due to the lack of skills measures in the French administrative data, direct calculation of the size of mismatch is practically impossible. To overcome such shortcomings, we therefore use the observable individual and firm characteristics common to the DADS-EDP and PIAAC data to combine the skill endowments of the individuals in the DADS - panel EDP. In order to combine the information of both data sets we follow Ridder and Moffitt (2007).

Such a proposal is made under the assumption that the joint distribution of skills and observable variables in the DADS-EDP and PIAAC samples is the same. Several reasons support this assumption. First, the PIAAC survey (the donor database) represents the French working population (as does the DADS-EDP data), so the relation between skills and observable characteristics should be maintained across the samples. Moreover, the PIAAC survey incorporates additional sources of uncertainty and variability, given that it provides plausible values and weights for the variables of interest. This allow us to avoid the risk that the imputed data variance is too small, as would be the case if the imputation were on conditional means and did not incorporate uncertainty (Little and Rubin, 2019)). Intuitively, the uncertainty derives from the error of the estimated combination model on the donor data set. In the case of multiply imputed surveys, we obtain the same number of estimated vectors as imputations. This makes PIAAC design more suitable for such combination, given that the plausible values account for uncertainty in the measurement. A final important consideration is that the two bases have common variables or variables that can be easily harmonized [7] across samples.

Using a stochastic regression imputation, we impute a conditional draw form the individual specific joint skills distribution into the DADS panel. The procedure is divided into the following steps:

(i) For each of the m multiple imputation samples in the PIAAC data, estimate a model that relates each one of the skills to the observable characteristics for each

[7] When referring to harmonization, we are taking into consideration the fact that both sources have the same categorizations and groupings and can be compared across samples. We also use the same level of detail of classification information and other adjustments.

record. We select the observable characteristics that are available in both data sets and can be harmonized to the same categories.

$$S_i^m = \beta X_i + \epsilon_i$$

For this regression, we take into account worker demographics, job and firm characteristics. The model includes as demographic characteristics sex, a sixth degree polynomial on age, a third degree polynomial on seniority, and educational level. As job characteristics we include the logarithm of monthly earnings and the occupation (2-digit ISCO-08 level); as firm characteristics we include the size of the firm. Note that this model is intended to be descriptive and not causal, so the endogeneity of earnings and occupation are less problematic in this setting.

(ii) As result of this imputation we obtain a vector of estimated residuals $\hat{e}_i^m$ for each one of the 10 plausible values m. We also obtain m vectors of estimated coefficients β. For the imputation we used the average of the 10 models calculated $\tilde{\beta}$. Tables C3 - C4 (in the appendix) report the estimated coefficients and calculate the adjusted standard errors[8].

(iii) For each individual in the DADS-EDP sample we draw a value from $\hat{e}_i^m$. We indicate such draw with $\bar{e}_i^p$. We then combine the samples as in the two sample instrumental variable approach (Ridder and Moffitt, 2007). The value of skills introduced into the DADS-EDP data then is:

$$\hat{S}_{it} = \tilde{\beta} X_{it}^p + \bar{e}_i^p$$

The combination in our case is divided then in two components. The first part correspond to the observable individual, job and firm characteristics in the DADS panel X^p, multiplied by $\tilde{\beta}$, the average coefficient across plausible values (this is the same approach that is advised by Avvisati and Keslair (2020), following the design of the PIAAC data). Even if this part seems deterministic, note that it already

[8]We adjust the standard errors to incorporate within and between variance.

incorporates the uncertainty of the plausible values and their weights. The second part is stochastic and allows us to avoid the risk that the imputed data variance is too small (Little and Rubin, 2019).

(iv) Considering the missingness patterns of the data in the DADS-EDP panel, we run five different models. One model includes all the explanatory variables common to both data sets, and the four others capture the most common patterns of missingness in the data: missing hourly wages[9], missing occupation, missing firm size, and missing education. We repeat steps (i) to (iii) for each of the five models.

Skills cannot be imputed for some observations in the DADS-EDP panel due to a pattern of missingness that is not considered. These observations account for the 3% of the values in the worker sample and are excluded from the subsequent analysis.

3.4 Sample Description and Estimation

In order to investigate the two hypotheses of the paper, we construct two different samples. To test the composition change within the firm, we use a panel of mass layoff firms. To study the selective displacement, we use a panel of workers that worked in firms prior to a mass layoff event. Identification of mass layoffs is very important for the construction of such samples.

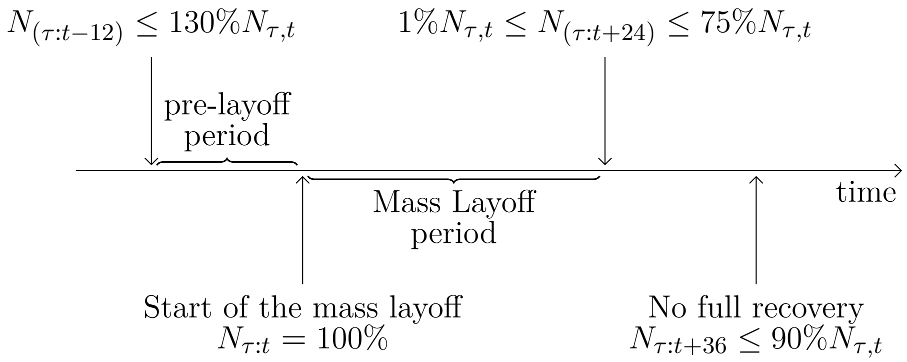
What is a mass layoff?

Both samples hinge entirely on the definition of mass layoff that is used. In this paper, we consider a mass layoff to have occurred when the following conditions are met: i) a firm at the start of the layoff period must have 50 employees or more[10], and ii) the firm's workforce contracts by between 25% and 99% in a two year period. The last condition

[9]In the PIAAC, the monthly wage is calculated from the hourly wage. To have an equivalent measure in the DADS panel, we use reported hours and wages. When reported hours are missing this can not be calculated and the value is missing.

[10]According to Davis and Von Wachter (2011) it is more challenging to identify mass layoffs in smaller firms as they are subject to higher percentage fluctuations. Since this paper is concerned with the firm's structure and composition, dropping small firms is less problematic.

Figure 1: Mass layoff definition



avoids the possibility that we consider firms that disappear from the administrative records because they are merged or acquired by other firms, or for other problems in the processing and compilation process of the data (for example, a change in the firm identification number in the sample). iii) Among these firms, we only consider those for which the maximum employment the year before the start of the layoff period is less than 130% of the employment level at the start of the layoff. Using this condition, we take out firms in a steady decline, which helps us avoid classifying them in the mass layoff event. iv) To avoid capturing temporary fluctuations in firm employment level, we consider only firms which do not recover recent employment levels a year after the end of the layoff period. In particular, we consider only firms for which the employment a year after the mass layoff is less than 90% of the employment level one year before the start of the mass layoff period. In case a firm presents multiple layoff events, we consider only the first four. These conditions are very similar to those considered in the displacement literature (Lachowska et al., 2018; Davis and Von Wachter, 2011). It is important to note that this definition relies exclusively on employment stocks and flows, and not on whether the firm designates a separation as a layoff or not, as firms may choose to spread layoffs over time to avoid needing to apply the layoff legislation and incur extra costs[11]. The description of the selected firms is summarized in figure 1.

Such definition is also comparable with the recent literature on separations in France,

[11]Not focusing on declared layoffs means that some employment variation can be due to voluntary departures, but the size threshold (at least a 25% reduction) should eliminate the risk of misclassification of voluntary departures as mass layoffs.

which defined a mass layoff as occurring when the workforce reduces year to year by 10% or more (Royer, 2011; Brandily et al., 2020). It is also comparable with the management literature in which the 10% threshold is a reference point. This threshold usually describes severe workforce reduction (Datta et al., 2010). We chose a 25% threshold, however, to remain close to the definition in Davis and Von Wachter (2011) (30%) and close to the cited literature when considered as a yearly change. Figures A.1-A.2 in the appendix show how variations in the threshold change the size of the sample with respect to the universe of firms in DADS postes. These figures also make clear that mass layoffs events are not distributed uniformly across months, especially when such thresholds are low, suggesting that low thresholds might disproportionately capture the seasonality of workforce variation.

Legal definition of a mass layoff in France

When we consider a mass layoff as a function of the size of the firm, there is not an equivalent definition in the French legislation. This makes that finding strictly comparable official statistics on firms that downsize impossible. The most similar legal indicator associated with a mass layoff, is the Employment Saving Plan ("Plan de Sauvegarde de l'emploi", or PSE). A PSE is an employment protection legislative requirement that is a function of the number of economic displacements in the firm that occur during a fixed period of time and the size of the firm. An economic displacement ("licencement economique") is a separation initiated by the firm, without the worker's consent, in which the firm must justify that the separation occurs for economic reasons (see Appendix A.3.1 for a detailed description of economic displacement). In practice, economic displacement is very costly.

To be required to propose a PSE, the firm must displace 10 or more employees for economic reasons during a period of 30 days. In order to reduce the risk that firms split their layoffs over a longer time span so as to remain under the threshold, the mechanism also requires a PSE if the firm lays off 10 workers in a 90 day period for economic reasons, or 18 during a calendar year. When the firm meets such conditions must put in place a

PSE[12].

A PSE is composed by all the actions that the firm must put in place to limit the number of layoffs, in particular through re-qualification, re-skilling, and the creation of favorable conditions in local labor markets. It includes the internal reallocation of employees to jobs in the same or equivalent categories (within the firm or other firms with the same company group), measures to create better conditions of employment in local labor markets, the redistribution of overtime hours across the shifts of all the workers of the firm, and programs for skill upgrading for the affected workers. The implementation of a PSE is costly in time and resources for the firm. It is even more expensive when the costs associated to the economic displacement and the potential legal costs are taken in consideration.

When we compare the number of mass layoffs using the size of the firm (see table A.5), and the number of PSEs in firms with more than 50 employees (table A.15) it seems that firms might use other mechanisms to reduce their workforce, perhaps due to the high cost of the mechanism. But what could be the other alternatives? In particular, firms might adjust their workforces using other channels due to the high cost that economic displacements imply for the firm. It has been previously suggested that the firm might adjust its size by reducing its hiring rate and not by increasing its separations rate (Abowd and Kramarz, 2003; Fraisse et al., 2015). Given this option is available to many firms, downsizing might take place through a combination of economic displacements and the adjustment of in- and outflows from the firm.

The economic displacement definition involves taking into consideration only involuntary separations. By using adjustments in firm size, we are considering all types of separations, including voluntary (worker initiated quits), accidental (deaths), or legal (termination of a fix term contract, by worker leaving the firm because he arrived to the pension age, or separation with cause). In all cases, we observe the destruction of a job in a specific occupation that is not filled again by other worker.

[12] Section A.3 in the Appendix, presents a detailed description of the institutional framework of economic displacements and its relation to mass layoffs in France.

Sample description

To calculate the firm size, we use the information on the start and end of each employment spell reported in the DADS postes data. We aggregate this information to the firm level to obtain the daily number of employees per firm[13]. With this information, we can calculate the day-to-day variation of the workforce. It is again worth mentioning that we observe only the size, and not the type, of separations that result in downsizing. Recent literature focuses on the identification of mass layoffs using involuntary separations only Brandily et al. (2020); Seim (2019). Such a choice is associated to the level of analysis and the research question, which in both cases is the displaced worker. This degree of specificity is less relevant when the unit of analysis is the firm, and when we want to understand skill restructuring during mass layoffs.

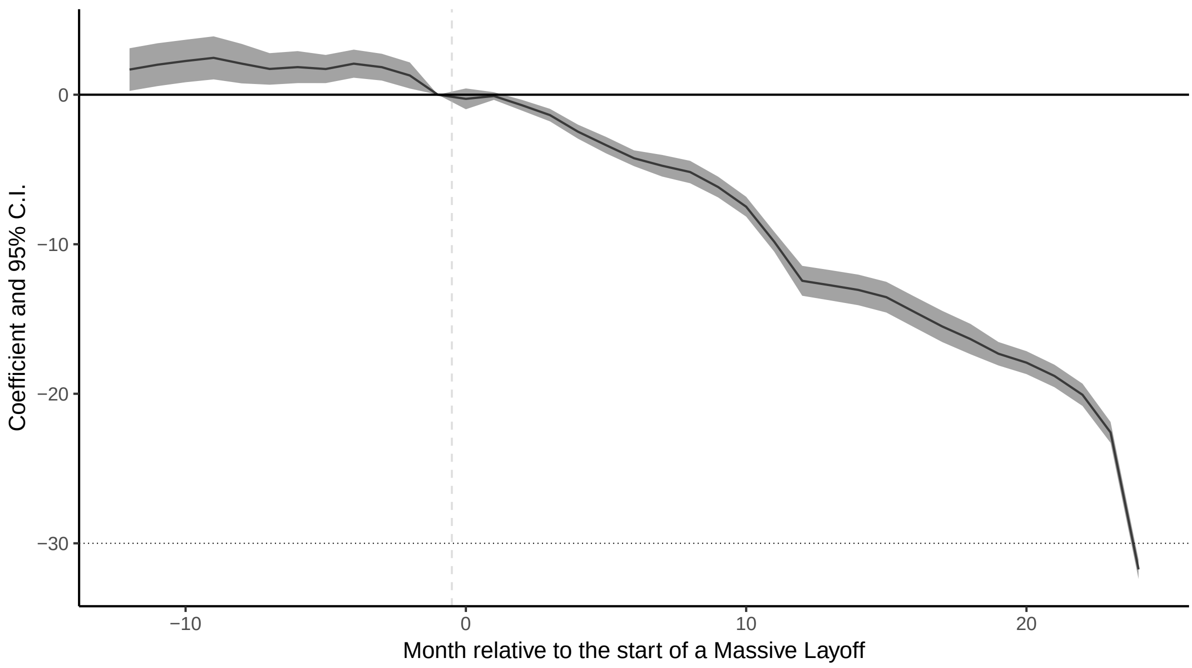
We use this data on the firm's daily size over the period 2004 - 2014 and conditions i) to iv) to identify the firms that undertake a mass layoff and assign a date to the mass layoff. We then construct a firm and a worker sample. The firm sample allows us to evaluate if there are changes in the firms' composition and structure. To examine selective displacement, we construct a worker sample containing worker demographic characteristics and firm characteristics.

Control group We construct a control group for the firms that experienced a layoff by selecting comparable units based on employment structure, firm sector, firm financial indicators two years prior to the start of displacement. The observable characteristics used to assess the employment structure are the size of the firm, the occupational composition and the number female of workers in the firm. We also use a set of financial indicators calculated using the balance sheet data that characterize the firm productivity (value added and labor productivity), profitability (fiscal year results), the wage profile of the firm (compensation costs), and the degree of indebtedness (debt ratio).

For each year, we match units on all firms that never experienced a mass layoff. We perform match with replacement, so the order of the matching does not change the result

[13]Note that our algorithm for introducing spells to the DADS postes data can lead to measurement error in this variable when observations refer to more than 2 spells within a year. This situation concerns less than 3% of the DADS postes observations.

Figure 2: Employment evolution in the mass layoff sample



of the algorithm Imbens (2015). The matching method used is nearest neighbor on the propensity score, which is calculated using a logistic regression. Table A.1 and figure A.3 present as an example the balance for the year 2009, where the quality of the matching can be assessed. The figures show that the selection method reduces the difference in covariates between the two constructed samples. Under conditional independence, an appropriate matching makes the robust estimation of the average treatment effects feasible, since the methods will not be exposed to specification choices or outliers. In the tables we present both the t-statistic and the standardized difference, since the latter is more adequate to assess the difference in the covariates (Imbens, 2015). Tables A.2-A.3 present the mean differences and the p-value of the t-statistic for the matching in all years in the sample. Table A.7 presents the difference for the treated and control samples for each covariate The normalized difference is under the 0.10 threshold, implying overlap of the covariates.

Firms characteristics The mass layoff sample contains information on 16.185 firms. Table 1 reports some financial indicators in the different years considered in the sample.

Mass layoffs are known to impact such financial indicators (Reynaud, 2010). Following the criteria summarized in figure 1, firm size in our mass layoff sample evolves as shown in Figure 2. Two years after the start of the layoff event, the firms in our mass layoff sample shrink their workforce by 35% on average. As can be seen in the figure, on average, this change is gradual. The layoff happens slowly in the first part and accentuates in the second half of the layoff period. This contrasts with the idea of a mass layoff as an event in which all the workers are displaced at the same time, and is visible in our data due to the precise dating of the start and end dates of employment at the match level. When we consider our sample's sector composition, the 55,1% of the observations belong to the service sector, 5.8 construction, 13.2% Retail, and 26.9% to Manufacturing.

Workers characteristics We filter the observations identified in our mass layoff firms sample from DADS-EDP panel to construct the worker sample. The worker sample includes all workers employed at the firm at some point during the layoff process and contains information on both displaced and not displaced workers. The sample contains information on 161.293 workers. Table 2 presents the sample's main characteristics, calculated both for displaced and non displaced workers[14].

4 Firm restructuring

This section provides evidence that firms that experience a mass layoff use this opportunity to restructure their skill requirements.

To identify their change, we perform an event study type analysis. The outcomes of interest are the average firm requirements for cognitive, social, and manual skills. Using such an approach allow us to identify changes in the firm's skill structure.

To understand how we capture skills change, imagine two identical firms: same sector, size, and occupational distribution. Imagine that ten managers compose the firms. Each of them supervises a team of ten workers (110 workers in each firm). The only difference between the firms is their behavior during a mass layoff. During a mass layoff, one firm

[14]The construction of the cognitive mismatch index, social mismatch index, and wage cost is presented in section 5.

Table 1: Firm financial indicators for mass layoff sample

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Commercial margin	−0.074	0.056	0.466	−0.019	0.015	0.144	0.175	0.041	0.178	−0.077	0.017	−0.196
Productivity	−0.235	−0.245	0.042	0.026	0.081	−0.267	−0.074	−0.276	−0.278	1.937	−0.283	−0.315
Value added	−0.336	−0.284	0.398	0.160	0.222	−0.341	−0.165	−0.321	−0.342	1.533	−0.348	−0.397
Gross operating surplus	−0.172	−0.109	0.014	0.132	0.083	−0.192	−0.043	−0.240	−0.251	1.994	−0.255	−0.283
Operating Results	−0.204	−0.192	0.205	0.346	0.105	−0.258	−0.043	−0.253	−0.251	1.692	−0.282	−0.307
Earnings before taxes	−0.193	−0.161	0.189	0.515	0.300	−0.189	−0.012	−0.231	−0.252	1.460	−0.255	−0.281
Exceptional Income	0.104	0.070	0.102	0.168	0.029	0.090	0.115	0.099	0.106	−3.004	0.102	0.104
Profits	0.027	0.021	0.188	0.443	0.240	−0.011	0.099	−0.023	0.008	−2.643	−0.013	−0.019
ROA	−0.002	0.014	0.015	0.144	0.069	−0.010	0.061	0.007	−0.060	−0.072	0.155	−0.173
ROE	−0.028	−0.044	−0.022	0.134	0.057	−0.036	0.024	−0.006	0.027	0.109	0.320	0.004
Sales	−0.215	−0.204	0.303	0.013	0.062	−0.251	−0.061	−0.270	−0.271	1.790	−0.269	−0.342
Purchase/Sales	0.298	0.251	−0.023	−0.109	−0.071	0.233	0.152	0.089	0.149	−0.011	0.342	0.424
Export/Sales	0.284	0.141	−0.113	−0.095	0.011	0.246	0.029	0.002	−0.038	−0.122	−0.102	−0.413
Debt Ratio	0.113	0.069	−0.016	0.007	−0.030	0.079	0.018	0.021	0.065	−0.075	0.140	0.476

Source: DADS-EDP panel merged with BIC-RN. The statistics are calculated relative to the start of the layoff event. The variables are winsorized and standardized for ease of interpretation in the regression.

Table 2: Descriptive statistics for the worker sample

	Non Displaced		Displaced		Differences	
	Mean	**St. Dev.**	**Mean**	**St. Dev.**	**t-stat**	**p-value**
Worker and job characteristics						
Age	33,614	11,447	37,621	10,890	-20.82	0.00
Tenure	2,206	2,886	3,387	3,976	-39.50	0.00
$\log\left(w_{ijt}/\tilde{w}_{to}\right)$	-0,012	0,153	-0,005	0,142	-4.83	0.00
Sex (Female)	0,391	0,488	0,364	0,481	7.98	0.00
Family characteristics						
Has an under age children	0,993	0,084	0,993	0,081	-0.09	0.93
Occupation						
Managers	0,046	0,210	0,077	0,267	-13.04	0.00
Professionals	0,107	0,309	0,136	0,343	-11.73	0.00
Technicians	0,450	0,497	0,429	0,495	3.08	0.00
Clerical support	0,012	0,111	0,012	0,103	-1.10	0.27
Service and sales workers	0,088	0,284	0,073	0,258	2.57	0.01
Skilled agri. workers	0,003	0,059	0,002	0,046	3.00	0.00
Craft and related workers	0,092	0,290	0,098	0,297	-0.53	0.59
Plant and machine operators	0,065	0,246	0,076	0,266	-1.97	0.05
Elementary occupations	0,136	0,343	0,099	0,299	13.57	0.00
Armed Forces	0	0	0	0	1	0
Education						
Lower secondary or less	0,184		0,187		8.64	0.00
Upper and Post Secondary	0,347	0,476	0,355	0,479	-7.14	0.00
Bachelor	0,340	0,474	0,332	0,471	-10.27	0.00
Higher Tertiary	0,129	0,335	0,126	0,332		
Mismatch						
Cognitive mismatch index	0,025	0,049	0,020	0,054	-7.43	0.00
Social mismatch index	0,087	0,124	0,100	0,136	-14.48	0.00
Number of workers per layoff episode						
1st mass layoff	20209		130311			
2nd mass layoff	13543		59826			
3rd mass layoff	13070		34181			
4th mass layoff	4975		14248			

Source: DADS-EDP panel. The descriptive statistics are calculated for demographic and firm characteristics relative to the start of the layoff event. The bottom part of the table presents the the number of workers when a firm has multiple layoff events.

had to downsize and laid off five of its managers and the teams under their supervision. At the end of the mass layoff, the final number of employees decreased by half, but its organization and structure did not change. For the second firm, instead, the mass layoff impacted mainly the team workers and not the managers, since it decides to keep the ten managers but only five of the workers' teams (60 workers). Even if workforce downsizing remains similar, its occupational structure and how the firm is organized has changed.

The model used to evaluate the hypothesis is standard to the displaced workers literature. We use an event study design of the form:

$$Y_{jt} = \alpha_j + \omega_t + \sum_{k=-12}^{24} \gamma_k 1_{\{K_{jt}=k\}} \times G_j + \epsilon_{jt} \tag{1}$$

where the outcome of interest Y_{jt} is the firm's average skills, the coefficient γ_k captures the change in the outcome variable with respect to the beginning of the mass layoff event[15]. We also include firm fixed effects α_j and year fixed effects ω_t. In the model we indicate the start of the layoff event with K_{jt}. Treatment (having a mass layoff) is indicated with the letter G_j, which is a dummy that takes the value of 1 for the mass layoff group ($G_j = 1$), and ($G_j = 0$) for the the control. We investigate the skill requirements (cognitive, social, and manual) associated with the occupations using the mass layoff sample from the DADS postes.

Figures 3, 4 and 5 illustrate the results of our analysis. They present the changes in the outcome variable and its 95% confidence interval for each month after the start of the mass layoff period. We can see that the restructuring effect is small but significant when observing the average effect of the difference in difference estimation (horizontal red line in the plots). We observe that, on average, the firm uses more social skills (+1.2% standard deviations) and less manual skills (−0.5% standard deviations). The effect on cognitive skills is also positive and small (ranges from 0.25% − 0.8% standard deviations). The difference in difference estimates are all significant, and all the p-values are under the 0.05 threshold. The magnitude of such results is expected to be small since we are analyzing the composition of large firms in a short time frame (24 months).

[15]Following Borusyak and Jaravel (2017) we drop the period $k = -1$ and $k = -12$ (the period most negative and distant to $k = -1$) are taken as reference for the estimation and are not included into the regression, so $\gamma_{k=-1}$ and $\gamma_{k=-12}$ are not identified.

Figure 3: Firm social skills per capita (full dynamic specification)

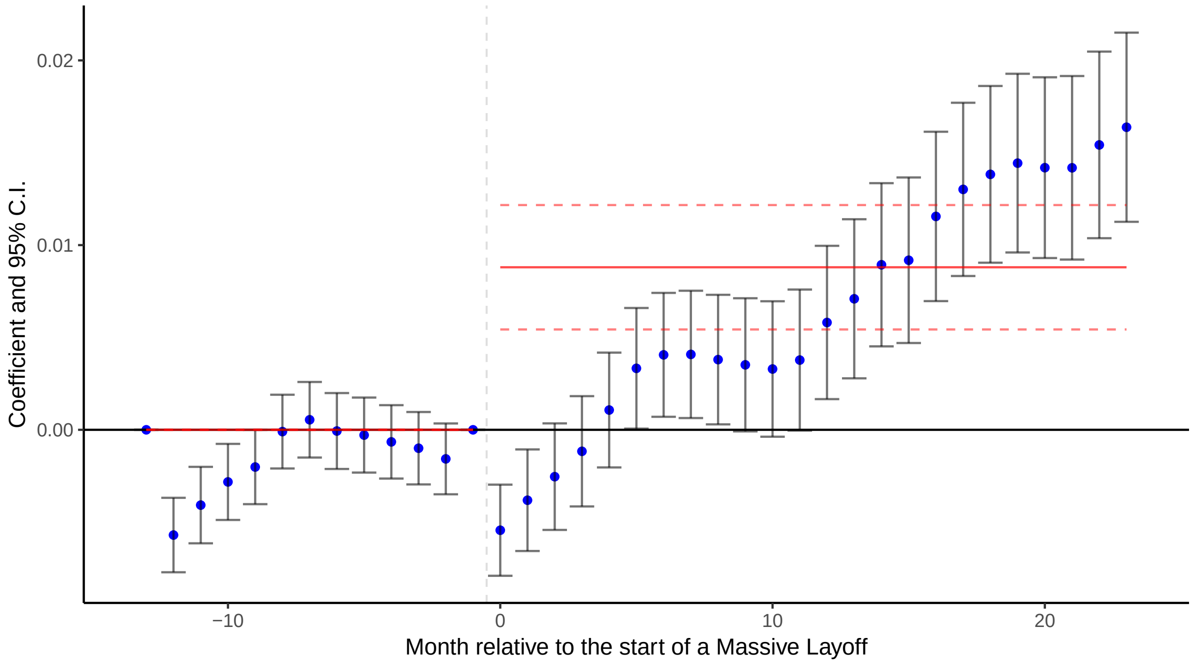


Figure 4: Firm manual skills per capita (full dynamic specification)

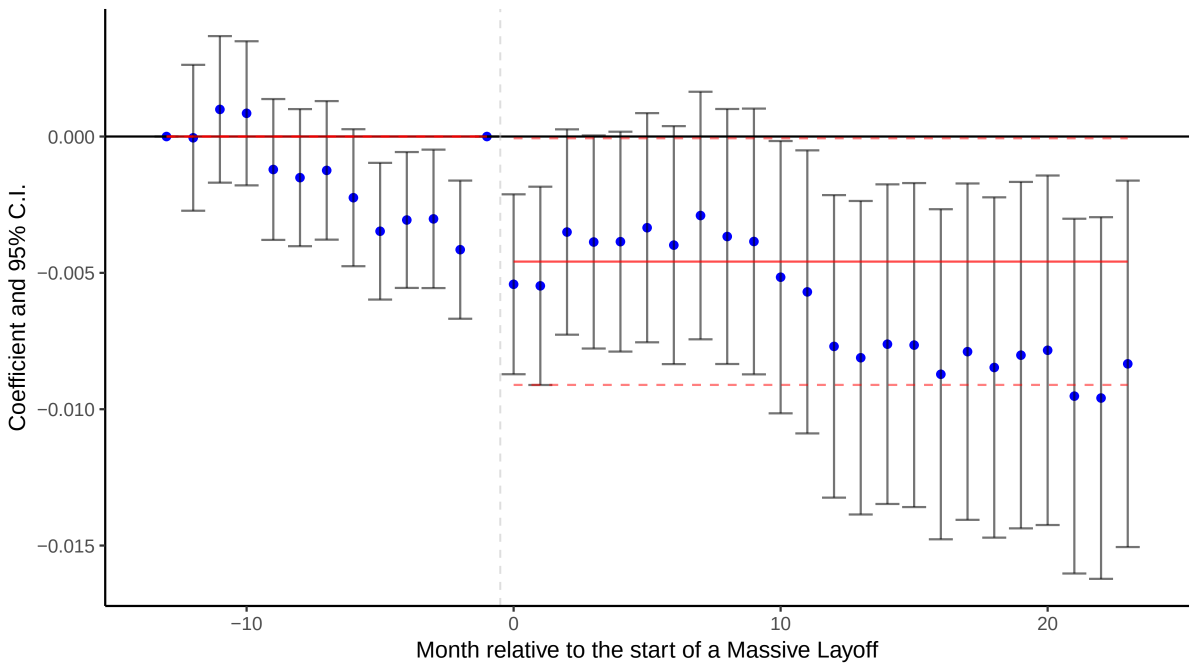
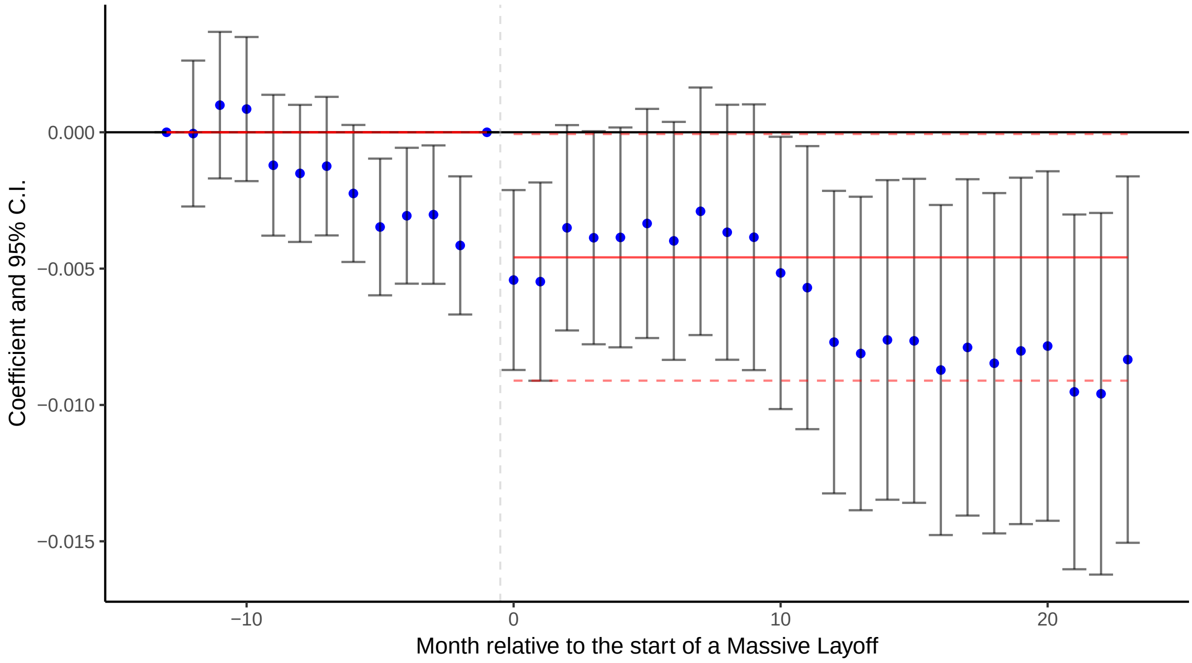


Figure 5: Firm cognitive skills per capita (full dynamic specification)



Matching has been under scrutiny recently in the statistical literature, since the method bases unit selection in observable characteristics. Non observable characteristics, when present and not homogeneous between samples, have the potential to make unfeasible the estimation of robust effects. The design used here has two components that help to deal with such unobserved characteristics: first, we match control units each single year, and assign to each unit the event date of the corresponding treated unit, so in the regression we use the same calendar with respect to the event. This allow us to include year and firm fixed effects, controlling for unobserved characteristics in the regression. Second, in order to test the robustness of our estimates, in the design we also calculate different weights[16] to make comparable the layoff firms and the matched control firms[17]. The coefficients of the difference in difference estimates, both unweighted and weighted, are significant and stable both in magnitude and sign across all the weighting schemes

[16]We calculate weights on different target populations. For the calculation of the weights we follow Li, Morgan and Zaslavsky (2018), for which we calculate ATE, ATT, ATC, ATO weights. We use the formulas in Table 1 of Li's paper.

[17]Combining weighting and matching is known as the *Tudor solution* in the statistical literature (Li et al., 2018).

(see table A.7).

The positive coefficients for social skills are in line with several sets of results in the literature, including the macro results on the growth of services in the overall economy. They are also consistent with the literature on changes in skill composition within sectors, such as the results for France, where Harrigan et al. (2020) find evidence of a change in the occupational composition at the macro and sector level and Crozet and Milet (2017) find changes within-firm for the manufacturing sector.

5 Skills mismatch and selective displacement

Understanding selective displacement is relevant for multiple domains. For policy, it is essential to understand who is displaced in order to formulate targeted programs for reemployment. From a theoretical point of view, understanding selective displacement complements our understanding of separations.

The selection of which workers to keep and which workers to lay off is a strategic decision. Considering the mechanism behind an employment separation, the layoff choice is associated with the elimination of matches whose cost must exceed their benefits. This section proposes two channels to define a "*too expensive match*" in terms of the match surplus-value and the worker's potential to perform his/her job. The first channel uses the notion of *skills mismatch*, considering the worker's skill endowments relative to the job's skill requirements. The second considers the extra cost that a firm pays in terms of compensation for a worker.

To investigate the role of expensive match characteristics on the layoff decision, we estimate the following linear probability model:

$$P_{ijt} = \alpha_j + \eta_t + \rho_r + \omega_a + \mathbf{x}_{itj}\beta + \epsilon_{ijt} \tag{2}$$

where P_{ijt} is an indicator function that describe if the worker is has been displaced or not for each period observed. α_j is a firm fixed effect, which takes into account the time-invariant firm characteristics[18]. We also include year fixed effects (η_t) that capture

[18]We include this since different sectors and sizes will imply a different productive organizations, and thus a different skill composition. Different management styles and human resources practices can also

macroeconomic events that could affect our estimates. This is very important for our sample since it covers the great recession. Another concern is that we identify layoffs using the firm level ("*entreprise*") measures, and not measures at the establishment level ("*établissement*"). To account for different labor market conditions that vary with a jobs' geographical location, we also included a worker region of residence fixed effect (ρ_r). Finally, the $\mathbf{x}_{itj}$ term includes all the variables of interest and additional time-varying controls. Recognizing that there could be also differences in the procedures for separations across collective agreements, we also include a set of collective agreement fixed effects (ω_a) to capture such differences.

We are interested in examining the impact of skills mismatch on the layoff decision. We construct an index of cognitive and social mismatch for each individual, taking into account the worker's skill level and his/her job requirements. When the worker's skill level is below the occupation's skill requirement, we calculate its euclidean distance. When the worker skills endowments are above the required level, the mismatch assigned is 0, since it does not represent a cost for the firm. Our index is not therefore symmetric around zero in the difference between skill requirements and endowments.

$$M\left(s_{it}, r_{ot}\right) = M_{it} = \begin{cases} \sqrt{\left(s_{it} - r_{ot}\right)^2} & \text{if} \quad s_{it} \leq r_{ot} \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

We then scale the M_{it} to lie between 0 and 1, where 0 is no mismatch, and 1 is the maximum mismatch level observed in the data. The resulting index I_{it} is calculated for cognitive and social skills. In order to assess the effect of labor cost, we also include a variable that measures the percent difference between the wage and the average wage in the same occupation that year.

Our models also include individual-specific demographic characteristics that have been shown to be related to worker displacement. Specifically, we are interested in seeing the role of sex, age and tenure on selective displacement. We are also interested in understanding if the firm considers other variables that do not directly affect the match-

affect our estimates, and insofar as they are invariant over time, the firm fixed effects absorb such practices.

specific surplus. We thus include a variable related to the worker's family composition, namely whether the household includes members under age 18. We only see this variable for a subset of the observations, mainly one-third of the sample. We also include a set of firm financial indicators: value-added, return on assets, return on equity, and EBITDA.

Table 3 presents the results for the estimation of Equation 2. The results indicate that the likelihood of being displaced increases with the skill mismatch. This relationship is particularly strong, positive and significant for cognitive skills mismatch in all the models compared. Social skills mismatch is also a good predictor when controlling for demographic characteristics and the relative wage. The coefficients for both skill mismatch indices remain significant and positive in all models once controlling for the relative wage. The magnitude of cognitive skills coefficient is comparable to that of social skills in the more complete specifications, however when we take in consideration the average mismatch for cognitive (0.021) and social skills (0.084), the expected effect on the probability of displacement in the sample is larger for social skills ($0.187 \times 0.084 = 1.58\%$) than for cognitive skills ($0.137 \times 0.021 = 0.29\%$). This result is consistent with the findings of Montana (2021), where the production function's structural coefficients are calculated and social skills are found to have a higher weight. One of the reasons social skills are more valuable for the firm is because they depend heavily on the worker endowment, which cannot easily be adjusted since social skills are difficult to learn and transfer (Deming and Kahn, 2018; Deming, 2017).

The second channel that we study is the perceived cost of the worker by the firm. This is expressed as the percent deviation of the observed wage for individual i, working at firm j at time t, versus its market reference, i.e. the average wage of the occupation o the same year t[19], controlling for demographic characteristics. When a worker's wage is 10% over the market wage, his/her likelihood to be displaced increases 4.29%.

This paper is not the first to consider the impact of skills on job displacement. Seim (2019) investigates how cognitive and not cognitive skills affect the displacement decision. His paper finds that cognitive and non cognitive skills are good predictors of displacement.

[19]Formally, we define the variable as: $\log\left(\frac{w_{ijt}}{\tilde{w}_{ot}}\right)$, where $\tilde{w}_{ot}$ is the average wage in the occupation o in year t.

Table 3: Selective displacement - Linear probability model

	(1)	(2)	(3)	(4)	(5)
Mismatch variables					
Mismatch Cognitive Skill	0.072^{**}	0.042	0.174^{***}	0.172^{***}	0.137^{*}
	(0.035)	(0.044)	(0.046)	(0.046)	(0.074)
Mismatch Social Skill	-0.026	-0.051^{**}	0.161^{***}	0.155^{***}	0.187^{***}
	(0.020)	(0.025)	(0.027)	(0.027)	(0.048)
Personal Characteristics					
Sex (Female)		-0.152	-0.152	-0.145	-0.084
		(0.094)	(0.097)	(0.098)	(0.169)
Age		0.014^{***}	0.010^{**}	0.009^{*}	0.024^{**}
		(0.005)	(0.005)	(0.005)	(0.011)
Age^2		-0.000^{***}	-0.000	-0.000	-0.000^{***}
		(0.000)	(0.000)	(0.000)	(0.000)
Seniority		0.058^{***}	0.055^{***}	0.055^{***}	0.067^{***}
		(0.002)	(0.002)	(0.002)	(0.003)
Seniority^2		-0.003^{***}	-0.003^{***}	-0.003^{***}	-0.003^{***}
		(0.000)	(0.000)	(0.000)	(0.000)
Upper and Post Secondary		0.186^{**}	0.216^{**}	0.220^{**}	-0.327^{*}
		(0.095)	(0.096)	(0.096)	(0.189)
Bachelor		0.061	0.058	0.060	-0.168
		(0.089)	(0.090)	(0.091)	(0.174)
Higher Tertiary		0.032	-0.040	-0.041	-0.079
		(0.118)	(0.124)	(0.125)	(0.233)
Perceived Cost					
$\log(w_{ijt}/\tilde{w_{to}})$			0.442^{***}	0.440^{***}	0.429^{***}
			(0.020)	(0.020)	(0.035)
Firm Characteristics					
Added value				-0.102^{***}	-0.065^{***}
				(0.010)	(0.018)
ROA				-0.003^{***}	-0.000
				(0.001)	(0.002)
ROE				-0.007^{***}	-0.009^{***}
				(0.001)	(0.002)
Purchases/Sales				-0.097^{***}	-0.087^{***}
				(0.005)	(0.009)
Family Characteristics					
Children under 18					-0.108
					(0.075)
Num. obs.	803543	546835	542657	537490	172418

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Source: DADS-EDP panel. The dependent variable is a dummy variable that indicates if the worker is displaced in period t. All the columns control for firm, year, collective agreement, and worker region of residence fixed effects. Robust standard errors are clustered at the worker level.

An increase in one standard deviation of cognitive or non cognitive skills decreases the probability of being laid off by 1%. Even if Seim's result highlights the importance of skills in selective displacement, it does not account for the firm's skill structure and the worker's occupation. Seim's result further differs from ours since we consider the mismatch with respect to the occupation requirements and wage costs, thus controlling for the extra cost incurred in maintaining expensive employment relationships.

The effect of age, seniority, and education on the likelihood of selective displacement is in line with previous literature for France and Germany from almost 20 years ago (Bender et al., 2002). Even though we are not considering only economic separations in our sample (and thus some separations may actually be retirements), the effect of age on separations is negative, in contrast to Bender et al. (2002) but similar to the estimates of Seim (2019) for Sweden. When considering education levels, the likelihood of being displaced decreases with high education levels conditional on the degree of skills mismatch. The effect of seniority is also non-linear, initially increasing to reach a maximum at around 10 years (in the most complete specification) before falling for workers with higher tenure.

The coefficient for sex is not significant in the proposed specification that includes time, firm, region, and collective agreement fixed effects. The gender dummy, whose coefficient implies that women have a lower risk of being displaced in a mass layoff event, is not significant in the specification when errors are clustered at the individual level, but it is when using standard robust standard errors (see Table A.8). When we control for the number of children under 18, the effect on sex disappears (see column 5 in Table A.8). This combination of results might be due to the effect of regulations since women cannot be fired while on maternity leave, but the gender effect disappears once we control for the presence of children. Even if the presence of children under 18 reduces layoff risk, it is not significant across specifications when we include clustered robust errors at the worker level. In the case we use robust heteroscedastic errors, the coefficient is significant at the 1% level. We investigate further the effect that gender plays in displacement by interacting it with the mismatch indices and the relative wage cost variables. Results in table A.9 suggest that women have a higher likelihood than men of being displaced when they are mismatch in social skills or if the wage is high with respect to the occupation average. When we interact the dummy with mismatch in cognitive skills the estimate is negative, implying a lower probability of being displaced, but it is not significant at the 5% threshold when standard errors are clustered at the individual level.

When we look at the influence of financial indicators[20] on the likelihood of displacement, all of them have negative and significant effects. When working in a firm with 1 additional standard deviation of value-added, the likelihood of being displaced is reduced by 10%. For the return on assets and equity the results are smaller in magnitude, and also negative, decreasing the likelihood in 0.3% and 0.7% respectively. We include an additional financial indicator that measures the ratio of purchases to sales in the firm, which is positively associated with the outsourcing of production[21]. A 1 additional standard deviation in the purchase over sales indicator decreases the likelihood of displacement by 9%.

Given that we can only observe the number of children under 18 for one-third of our sample[22], this variable's inclusion also serves as a robustness check for our results. The coefficients remain stable and significant in this sub-sample for skills mismatch, relative wage costs, firm and personal characteristics except for sex. Both of the mismatch coefficients and the relative wage cost are not significantly affected by restricting the sample and the inclusion of the additional household composition variable.

To further investigate the robustness of our results, we run the regression by sector to alloww all coefficients to vary across sectors. Table A.10 presents the results by sector, highlighting the heterogeneity, and the difference that the existing occupational structure might have in the results[23]. The result on mismatch on cognitive skills seems to be driven by the services sector, while social skills affect the displacement probability in all sectors.

Another source of heterogeneity is the collective agreement. Each collective agreement

[20]The financial indicators are winsorized. Moreover they are standardized for ease of interpretability of the results.

[21]The balance sheet item of purchases considers also the imports in the firm, so it controls for both domestic and foreign outsourcing activities.

[22]For the remaining two thirds of the sample the value is missing. Missing information on children does not necessarily imply that the individual does not have children.

[23]The results for the agricultural sector are not reported due to a relatively small sample and collinearity of covariates with the fixed effects.

might have particularities that affect the process and selection into displacement. As such, we also estimated the model on subsamples divided by an aggregate grouping of collective agreements Table A.11 shows the result by aggregated collective agreement. These results align with those by sector, except that workers in firms covered by the agriculture, commerce and (to a lesser extent) construction collective agreements are not more protected from displacement when their social skills are more aligned with the needs of their jobs. However, those workers in firms not covered by a collective agreement or whose collective agreements are not more constraining than standard labor law are the most subject to selective displacement when their cognitive skill mismatch is high, while the impact of social skills mismatch on their risk of selective displacement is similar to that of workers employed by firms covered by manufacturing or construction collective agreements.

6 Conclusion

Using a combination of linked employer-employee administrative data and survey data on skills,we have found that restructuring occurs in a time span that is very short (two years) compared to the long-term analysis of previous macro literature, although our results are consistent with those findings. The restructuring of the workforce provides evidence that firms use layoffs strategically, and selective displacement plays an important role.

When we investigate selective displacement directly, we find that skills mismatch and relative wages play an important role in determining who leaves the firm. The coefficients for both cognitive and social skills mismatch are significant and positive, implying that being mismatched increases the likelihood of being displaced. The result is robust across samples and specifications, even if we control for other demographic characteristics, firm characteristics, and firm and year fixed effects. The findings for firm characteristics also demonstrate how difference in firm performance can affect the likelihood of displacement.

Our findings may serve to highlight the value of re-employment initiatives for recently unemployed people. This group has the greatest levels of mismatch and programs based on skill upgrades could speed up re-employment into jobs similar to the ones that were lost. Moreover, policy makers could attempt to identify the occupations that are more employable and up-skill the unemployed workforce in order to reduce susceptibility to future mass layoffs.

This paper confirms the relevance of skills in selective displacement. It also opens the door to study how other dimensions could affect displacement risk beyond the characteristics of the specific match. These channels should be explored still further.

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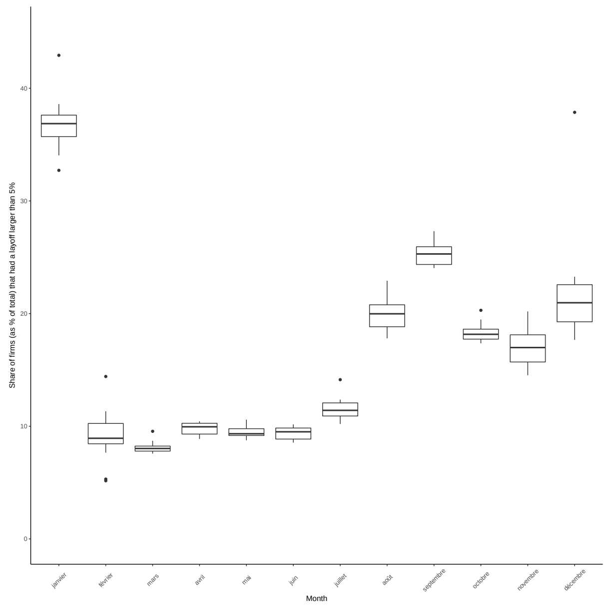
Appendix: Selective displacement and workforce restructuring during a layoff

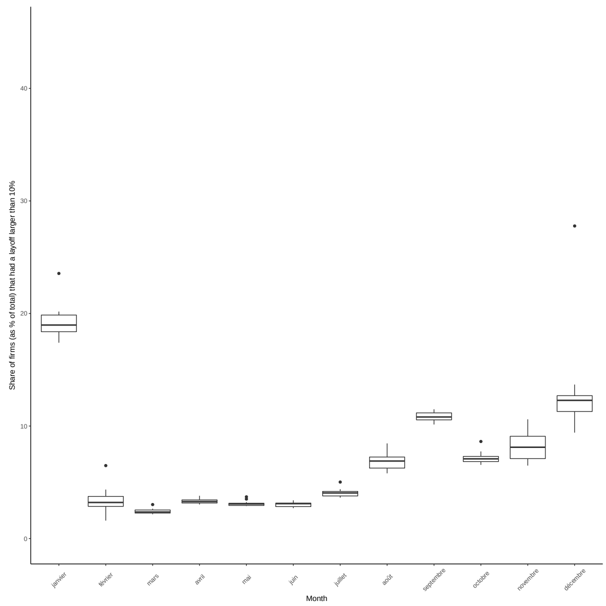
A.1 Additional tables and figures

Figure A.1: Firms that downsize - 5% threshold



Source: DADS Postes

Figure A.2: Firms that downsize - 10% threshold



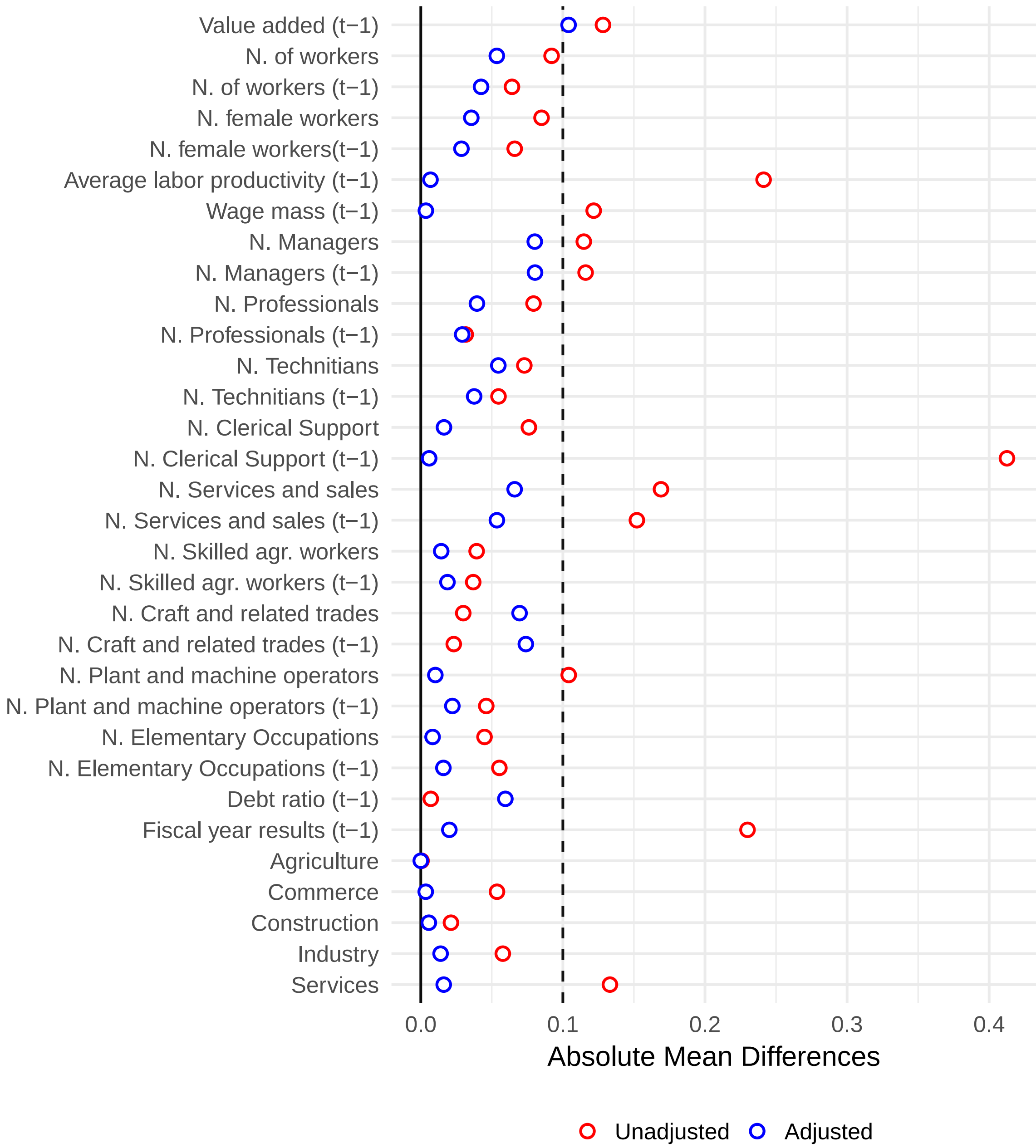
Source: DADS Postes

Table A.1: Matching balance for selected covariates 2009 - Standarized mean

Variable Name	Mean Control Unweighted	Mean Treated Unweighted	Difference Unweighted	t-test Unweighted	p-value Unweighted	Mean Control Adjusted	Mean Treated Adjusted	Difference Adjusted	t-test Adjusted	p-value Adjusted
Distance	0.07	0.09	0.36			0.09	0.09	-0.00		
N. of workers	186.28	151.68	-0.09	3.47	0.00	171.80	151.68	-0.05	-17.57	0.00
N. female workers	73.99	58.12	-0.08	3.30	0.00	64.75	58.12	-0.04	-13.63	0.00
N. Managers	19.88	13.86	-0.11	3.81	0.00	18.07	13.86	-0.08	-11.31	0.00
N. Professionals	28.49	21.74	-0.08	3.10	0.00	25.10	21.74	-0.04	-11.11	0.00
N. Technicians	74.50	61.68	-0.07	2.90	0.00	71.28	61.68	-0.05	-15.20	0.00
N. Clerical Support	7.31	2.59	-0.08	2.85	0.00	1.57	2.59	0.02	-1.90	0.06
N. Services and sales	17.16	10.20	-0.17	3.85	0.00	12.92	10.20	-0.07	-10.58	0.00
N. Skilled agr. workers	0.12	0.18	0.04	-1.78	0.08	0.20	0.18	-0.01	-5.49	0.00
N. Craft and related trades	14.19	12.96	-0.03	1.13	0.26	15.83	12.96	-0.07	-13.46	0.00
N. Plant and machine operators	12.66	9.39	-0.10	2.97	0.00	9.07	9.39	0.01	-13.27	0.00
N. Elementary Occupations	11.62	18.96	0.04	-2.05	0.04	17.60	18.96	0.01	-5.16	0.00
Agriculture	0.00	0.00	-0.00	3.87	0.00	0.00	0.00	0.00		
Commerce	0.21	0.16	-0.05	6.65	0.00	0.16	0.16	-0.00	-19.33	0.00
Construction	0.09	0.07	-0.02	3.71	0.00	0.07	0.07	0.01	-12.54	0.00
Industry	0.23	0.17	-0.06	6.99	0.00	0.16	0.17	0.01	-20.22	0.00
Services	0.46	0.59	0.13	-12.47	0.00	0.61	0.59	-0.02	-53.02	0.00
N. of workers (t-1)	183.01	158.57	-0.06	2.42	0.02	174.73	158.57	-0.04	-18.17	0.00
N. female workers(t-1)	72.08	59.99	-0.07	2.55	0.01	65.22	59.99	-0.03	-14.38	0.00
N. Managers (t-1)	19.39	14.22	-0.12	3.72	0.00	17.81	14.22	-0.08	-13.66	0.00
N. Professionals (t-1)	27.43	23.84	-0.03	1.35	0.18	27.15	23.84	-0.03	-9.17	0.00
N. Technicians (t-1)	76.19	65.97	-0.05	2.15	0.03	72.98	65.97	-0.04	-15.37	0.00
N. Clerical Support (t-1)	5.50	1.16	-0.41	5.16	0.00	1.23	1.16	-0.01	-4.89	0.00
N. Services and sales (t-1)	17.99	11.17	-0.15	3.53	0.00	13.57	11.17	-0.05	-10.69	0.00
N. Skilled agr. workers (t-1)	0.09	0.15	0.04	-1.65	0.10	0.19	0.15	-0.02	-3.93	0.00
N. Craft and related trades (t-1)	14.73	13.74	-0.02	0.86	0.39	16.90	13.74	-0.07	-13.79	0.00
N. Plant and machine operators (t-1)	12.19	10.28	-0.05	1.51	0.13	9.36	10.28	0.02	-11.06	0.00
N. Elementary Occupations (t-1)	9.34	17.90	0.06	-2.53	0.01	15.43	17.90	0.02	-5.17	0.00
Value added (t-1)	20183815.73	15076454.75	-0.13	5.80	0.00	19219910.01	15076454.75	-0.10	-16.29	0.00
Fiscal year results (t-1)	1221970.75	371842.29	-0.23	10.39	0.00	446163.08	371842.29	-0.02	-4.37	0.00
Average labor productivity (t-1)	153568.57	109908.05	-0.24	10.87	0.00	111142.95	109908.05	-0.01	-26.79	0.00
Wage mass (t-1)	43796.07	40928.15	-0.12	5.60	0.00	40844.05	40928.15	0.00	-76.05	0.00
Debt ratio (t-1)	1.15	1.18	0.01	-0.33	0.74	1.45	1.18	-0.06	-11.45	0.00

Source: DADS-EDP panel. The table show the difference in means for all the units in the DADS sample, and for the selected matching units. The treated sample are the firms who have a layoff in the year 2009, and the control the set of firm who do not. In the unadjusted sample the control are all firms in the DADS that do not have a mass layoff under the definition proposed. The adjusted control group consist of all the matched firms based on nearest neighbor matching. Column 3 and 8, compute the standardize mean difference for each of the selected observable covariates. Columns 4 and 9 present the t-statistics (the null hypothesis that there is no difference between the mean of both samples), and the corresponding p-value (columns 5 and 10).

Figure A.3: Matching balance for selected covariates 2009 - Absolute Standarized mean



The figure presents the absolute mean differences for the all the firms in DADS (red) and the matched units in year 2009 (blue). The vertical dashed line propose a 0.1 threshold to evaluate the distance. This threshold is very conservative, since in general the 0.25 threshold is used (Imbens, 2015).

Table A.2: p-values for the corresponding t-statistic - difference in means for matched and layoff units

Variable Name	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Distance										
N. of workers	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
N. female workers	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
N. Managers	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04
N. Professionals	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01
N. Technicians	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
N. Clerical Support	0.02	0.00	0.05	0.00	0.00	0.06	0.00	0.00	0.00	0.00
N. Services and sales	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
N. Skilled agr. workers	0.02	0.00	0.05	0.08	0.09	0.00	0.00	0.00	0.00	0.00
N. Craft and related trades	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01
N. Plant and machine operators	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.05
N. Elementary Occupations	0.01	0.00	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00
Agriculture	0.08		0.41	0.37	0.19		0.17	0.01	0.01	0.00
Commerce	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Construction	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Industry	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Services	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
N. of workers (t-1)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
N. female workers(t-1)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
N. Managers (t-1)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03
N. Professionals (t-1)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01
N. Technicians (t-1)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
N. Clerical Support (t-1)	0.05	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00
N. Services and sales (t-1)	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
N. Skilled agr. workers (t-1)	0.01	0.00	0.04	0.04	0.12	0.00	0.00	0.00	0.00	0.00
N. Craft and related trades (t-1)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01
N. Plant and machine operators (t-1)	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.06
N. Elementary Occupations (t-1)	0.01	0.00	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00
Value added (t-1)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fiscal year results (t-1)	0.16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.15
Average labor productivity (t-1)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wage mass (t-1)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Debt ratio (t-1)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Source: DADS-EDP panel. The table shows the p-values for the corresponding t-statistic, that calculates the difference in means for matched and mass layoff units for all periods between 2004 - 2015. The adjusted control group consists of all the matched firms based on nearest neighbor matching.

Table A.3: Standardized difference in means for matched and layoff units

Variable Name	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Distance	0.00	0.00	0.00	0.01	0.00	-0.00	0.00	0.00	0.00	-0.00
N. of workers	0.01	0.05	0.02	0.03	0.01	-0.05	0.02	0.02	-0.01	0.02
N. female workers	0.01	0.04	0.02	0.02	0.01	-0.04	0.01	0.01	-0.00	0.02
N. Managers	-0.03	0.02	-0.02	-0.00	-0.04	-0.08	-0.04	-0.06	-0.03	0.02
N. Professionals	0.01	0.03	0.03	0.03	-0.02	-0.04	-0.06	-0.00	-0.06	0.02
N. Technicians	0.01	0.05	0.03	0.03	0.01	-0.05	0.01	0.02	-0.01	0.02
N. Clerical Support	-0.00	-0.01	-0.02	0.01	0.00	0.02	-0.02	0.01	-0.00	-0.01
N. Services and sales	-0.03	0.02	-0.03	0.02	-0.02	-0.07	0.02	-0.07	0.01	0.02
N. Skilled agr. workers	0.03	-0.03	0.03	0.02	0.03	-0.01	0.03	0.02	-0.00	-0.03
N. Craft and related trades	0.01	0.07	0.03	0.03	0.02	-0.07	0.03	0.03	-0.04	0.03
N. Plant and machine operators	0.00	0.00	0.03	0.03	0.02	0.01	0.04	0.02	-0.01	0.01
N. Elementary Occupations	0.01	0.02	0.04	0.02	0.02	0.01	0.05	0.02	0.01	0.03
Agriculture	0.00	0.00	-0.00	0.00	-0.00	0.00	0.00	0.00	0.00	-0.01
Commerce	0.02	0.03	0.01	0.00	0.01	-0.00	-0.00	-0.00	0.00	0.02
Construction	-0.00	-0.00	-0.00	0.00	0.01	0.01	-0.00	0.01	0.01	-0.00
Industry	-0.01	0.03	0.03	0.02	0.02	0.01	0.02	-0.00	-0.01	0.01
Services	-0.01	-0.05	-0.04	-0.03	-0.03	-0.02	-0.01	-0.00	-0.01	-0.02
N. of workers (t-1)	0.01	0.01	0.02	0.03	0.01	-0.04	0.02	0.02	-0.01	0.02
N. female workers(t-1)	0.01	0.01	0.02	0.03	0.01	-0.03	0.01	0.02	0.00	0.02
N. Managers (t-1)	-0.02	-0.01	-0.02	-0.00	-0.04	-0.08	-0.05	-0.06	-0.03	0.02
N. Professionals (t-1)	0.01	-0.03	0.03	0.04	-0.01	-0.03	-0.07	0.03	-0.04	0.02
N. Technicians (t-1)	0.01	0.02	0.03	0.03	0.01	-0.04	0.01	0.02	-0.01	0.02
N. Clerical Support (t-1)	0.01	-0.02	-0.02	0.01	0.01	-0.01	-0.01	0.01	0.00	-0.01
N. Services and sales (t-1)	-0.02	0.03	-0.03	0.02	-0.02	-0.05	0.02	-0.07	0.01	0.02
N. Skilled agr. workers (t-1)	0.03	0.01	0.03	0.02	0.02	-0.02	0.03	0.03	0.00	-0.03
N. Craft and related trades (t-1)	0.02	0.05	0.03	0.04	0.02	-0.07	0.03	0.04	-0.03	0.03
N. Plant and machine operators (t-1)	0.01	0.00	0.03	0.03	0.02	0.02	0.04	0.03	0.00	0.01
N. Elementary Occupations (t-1)	0.02	0.01	0.04	0.02	0.02	0.02	0.05	0.02	0.01	0.03
Value added (t-1)	-0.07	0.06	-0.03	-0.01	-0.02	-0.10	-0.03	-0.03	-0.06	-0.02
Fiscal year results (t-1)	-0.02	-0.03	-0.03	-0.02	-0.01	-0.02	-0.04	-0.06	-0.03	-0.04
Average labor productivity (t-1)	-0.01	0.03	-0.01	-0.03	-0.02	-0.01	-0.01	-0.01	-0.01	-0.00
Wage mass (t-1)	0.02	0.04	0.02	0.04	0.02	0.00	0.02	0.07	0.06	0.03
Debt ratio (t-1)	-0.03	-0.02	-0.00	-0.05	-0.06	-0.06	0.00	0.01	-0.04	-0.01

Source: DADS-EDP panel. The table shows the standardized difference in means for matched and mass layoff samples for all periods between 2004 - 2015. The adjusted control group consists of all the matched firms based on nearest neighbor matching.

Table A.4: Standardized difference in means for matched and layoff units

Variable Name	Mean Control	Mean Treated	Normalized Difference
N. of workers	173.19	215.55	0.02
N. female workers	65.91	77.22	0.02
N. Managers	16.31	15.23	-0.01
N. Professionals	22.87	23.91	0.01
N. Technicians	72.08	92.14	0.02
N. Clerical Support	2.79	2.54	-0.00
N. Services and sales	15.50	14.70	-0.00
N. Skilled agr. workers	0.24	0.49	0.02
N. Craft and related trades	15.00	21.54	0.03
N. Plant and machine operators	11.60	16.74	0.02
N. Elementary Occupations	16.57	27.14	0.03
Agriculture	0.00	0.00	-0.00
Commerce	0.14	0.14	0.00
Construction	0.05	0.05	-0.00
Industry	0.20	0.20	0.01
Services	0.61	0.60	-0.01
N. of workers (t-1)	173.34	219.48	0.02
N. female workers(t-1)	65.82	78.68	0.02
N. Managers (t-1)	16.19	15.37	-0.00
N. Professionals (t-1)	23.71	25.20	0.01
N. Technicians (t-1)	73.54	96.09	0.02
N. Clerical Support (t-1)	2.62	2.34	-0.00
N. Services and sales (t-1)	15.10	14.68	-0.00
N. Skilled agr. workers (t-1)	0.22	0.48	0.03
N. Craft and related trades (t-1)	14.64	21.26	0.03
N. Plant and machine operators (t-1)	11.57	16.97	0.02
N. Elementary Occupations (t-1)	15.47	25.99	0.03
Value added (t-1)	15606849.62	14432028.29	-0.03
Fiscal year results (t-1)	531332.06	365594.83	-0.05
Average labor productivity (t-1)	104622.31	99609.86	-0.03
Wage mass (t-1)	38142.44	38382.08	0.01
Debt ratio (t-1)	1.25	1.16	-0.02

Source: DADS-EDP panel. The table shows the standardized difference in means for matched and mass layoff sample. The control group consists of all the matched firms based on nearest neighbor matching.

Table A.5: Number of firms that start a mass layoff periods

Finalization year of layoff	Total number of firms
2006	$1,999$
2007	$1,982$
2008	$2,272$
2009	$2,870$
2010	$2,697$
2011	$1,997$
2012	$1,932$
2013	$2,227$
2014	$2,132$
2015	$1,690$

A.2 Cognitive and social skills

A.2.1 PIAAC

Cognitive skills In order to construct the cognitive skills measure we use the information on two dimensions evaluated in the Programme for the International Assessment of Adult Competencies (PIAAC) survey: literacy and numeracy. We use the PIAAC's constructs instead of the raw responses due to the test administration methodology.

The definition of literacy is broad. It includes the evaluation of the comprehension of texts at different levels, from the most basic (understanding) to the most complex (how to use information from a text for self development). The design of the questions that evaluate literacy take into account the ability to interpret texts in different contexts (personal, health, or occupation related), trying to capture literacy level in job related activities.

The definition of numeracy evaluates not only the comprehension of mathematical

Table A.6: Difference in difference estimates for all weighted and unweighted specifications

	Dependent variable:				
	Average Cognitve requirement				
	Unweighted	ATE	ATT	ATC	ATO
after × treatment	−0.0061***	−0.0058**	−0.0057**	−0.0058**	−0.0059**
	(0.0023)	(0.0025)	(0.0025)	(0.0024)	(0.0025)
	Average Manual skills				
	Unweighted	ATE	ATT	ATC	ATO
after × treatment	−0.0053**	−0.0053**	−0.0054**	−0.0050**	−0.0052**
	(0.0022)	(0.0023)	(0.0023)	(0.0023)	(0.0023)
	Average social skills				
	Unweighted	ATE	ATT	ATC	ATO
after × treatment	0.0116***	0.0115***	0.0115***	0.0115***	0.0116***
	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)

Note: *p<0.1; **p<0.05; ***p<0.01

Source: DADS-EDP panel. Each value presents the estimate of the difference in difference models. The top of the table presents the estimate for the model in which the dependent variable is the average cognitive skills requirement in the firm, in the center the dependent variable is the average manual skills in the firm, and in the bottom the average social skills requirements in the firm. The formulas to calculate the different weightings follow table 1 in Li, Morgan and Zaslavsky (2018).

Table A.7: Standardize difference in means for matched and layoff units

Variable Name	Mean Control	Mean Treated	Normalized Difference
N. of workers	173.19	215.55	0.02
N. female workers	65.91	77.22	0.02
N. Managers	16.31	15.23	-0.01
N. Professionals	22.87	23.91	0.01
N. Technicians	72.08	92.14	0.02
N. Clerical Support	2.79	2.54	-0.00
N. Services and sales	15.50	14.70	-0.00
N. Skilled agr. workers	0.24	0.49	0.02
N. Craft and related trades	15.00	21.54	0.03
N. Plant and machine operators	11.60	16.74	0.02
N. Elementary Occupations	16.57	27.14	0.03
Agriculture	0.00	0.00	-0.00
Commerce	0.14	0.14	0.00
Construction	0.05	0.05	-0.00
Industry	0.20	0.20	0.01
Services	0.61	0.60	-0.01
N. of workers (t-1)	173.34	219.48	0.02
N. female workers(t-1)	65.82	78.68	0.02
N. Managers (t-1)	16.19	15.37	-0.00
N. Professionals (t-1)	23.71	25.20	0.01
N. Technicians (t-1)	73.54	96.09	0.02
N. Clerical Support (t-1)	2.62	2.34	-0.00
N. Services and sales (t-1)	15.10	14.68	-0.00
N. Skilled agr. workers (t-1)	0.22	0.48	0.03
N. Craft and related trades (t-1)	14.64	21.26	0.03
N. Plant and machine operators (t-1)	11.57	16.97	0.02
N. Elementary Occupations (t-1)	15.47	25.99	0.03
Value added (t-1)	15606849.62	14432028.29	-0.03
Fiscal year results (t-1)	531332.06	365594.83	-0.05
Average labor productivity (t-1)	104622.31	99609.86	-0.03
Wage mass (t-1)	38142.44	38382.08	0.01
Debt ratio (t-1)	1.25	1.16	-0.02

Source: DADS-EDP panel. The table shows the standardized difference in means for the matched and mass layoff samples. The control group consists of all the matched firms based on nearest neighbor matching.

Table A.8: selective displacement - Linear probability model with robust standard errors

	(1)	(2)	(3)	(4)	(5)
Mismatch variables					
Mismatch Cognitive Skill	0.072***	0.042	0.174***	0.172***	0.137***
	(0.022)	(0.028)	(0.029)	(0.029)	(0.046)
Mismatch Social Skill	−0.026**	−0.051***	0.161***	0.155***	0.187***
	(0.013)	(0.015)	(0.017)	(0.017)	(0.029)
Personal Characteristics					
Sex (Female)		−0.152***	−0.152**	−0.145**	−0.084
		(0.059)	(0.060)	(0.061)	(0.134)
Age		0.014***	0.010***	0.009***	0.024***
		(0.003)	(0.003)	(0.003)	(0.009)
Age^2		−0.000***	−0.000**	−0.000*	−0.000***
		(0.000)	(0.000)	(0.000)	(0.000)
Seniority		0.058***	0.055***	0.055***	0.067***
		(0.001)	(0.001)	(0.001)	(0.002)
Seniority^2		−0.003***	−0.003***	−0.003***	−0.003***
		(0.000)	(0.000)	(0.000)	(0.000)
Upper and Post Secondary		0.186***	0.216***	0.220***	−0.327**
		(0.062)	(0.062)	(0.063)	(0.139)
Bachelor		0.061	0.058	0.060	−0.168
		(0.062)	(0.063)	(0.063)	(0.141)
Higher Tertiary		0.032	−0.040	−0.041	−0.079
		(0.075)	(0.076)	(0.076)	(0.205)
Perceived Cost					
$\log\left(w_{ijt}/\tilde{w_{to}}\right)$			0.442***	0.440***	0.429***
			(0.012)	(0.012)	(0.021)
Firm Characteristics					
Added value				−0.102***	−0.065***
				(0.005)	(0.008)
ROA				−0.003***	−0.000
				(0.001)	(0.001)
ROE				−0.007***	−0.009***
				(0.001)	(0.001)
Purchases/Sales				−0.097***	−0.087***
				(0.003)	(0.006)
Family Characteristics					
Children under 18					−0.108***
					(0.042)
N. Obs.	803543	546835	542657	537490	172418

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Source: DADS-EDP panel. The dependent variable is a dummy variable that indicates if the worker is displaced in period t. All the columns control for firm, year, collective agreement, and worker region of residence fixed effects. Robust standard errors are reported.

Table A.9: Gender heterogeneity in selective displacement - Linear probability model

	Clustered error		*Robust errors*	
	(1)	(2)	(3)	(4)
Mismatch variables				
Mismatch Cognitive Skill	0.172***	0.227***	0.172***	0.227***
	(0.046)	(0.056)	(0.029)	(0.036)
Mismatch Social Skill	0.155***	0.103***	0.155***	0.103***
	(0.027)	(0.034)	(0.017)	(0.021)
Personal Characteristics				
Sex (Female)	−0.145	−0.154	−0.145**	−0.154**
	(0.098)	(0.098)	(0.061)	(0.061)
Perceived Cost				
$\log\left(w_{ijt}/\tilde{w_{to}}\right)$	0.440***	0.404***	0.440***	0.404***
	(0.020)	(0.025)	(0.012)	(0.014)
Interactions with gender				
Female × Mismatch Cognitive		−0.165*		−0.165***
		(0.098)		(0.062)
Female × Mismatch Social		0.149***		0.149***
		(0.056)		(0.035)
Female × $\log\left(w_{ijt}/\tilde{w_{to}}\right)$		0.100**		0.100***
		(0.042)		(0.025)
Num. obs.	537490	537490	537490	537490

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Source: DADS-EDP panel. The dependent variable is a dummy variable that indicates if the worker is displaced in period t. All the columns control for firm, year, collective agreement, and worker region of residence fixed effects. Columns (1) and (2) report the errors clustered at the individual level. Columns (3) and (4) reports robust standard errors. All the model includes all the covariates for individual, firm characteristics (Column (4) of table 3. The estimated models include firm, year, collective agreement, and worker region of residence fixed effects.)

Table A.10: selective displacement by sector - Linear probability model

	Dependent variable: Worker is displaced			
	Industry	Services	Construction	Commerce
	(1)	(2)	(3)	(4)
Mismatch Cognitive Skill	-0.058	0.201^{***}	0.305	0.101
	(0.089)	(0.061)	(0.191)	(0.112)
Mismatch Social Skill	0.232^{***}	0.149^{***}	0.273^{**}	0.145^{*}
	(0.060)	(0.034)	(0.135)	(0.076)
$\log{(w_{ijt}/\tilde{w_{to}})}$	0.413^{***}	0.473^{***}	0.582^{***}	0.329^{***}
	(0.047)	(0.024)	(0.083)	(0.065)
R^2	0.563	0.517	0.595	0.565
Adjusted R^2	0.451	0.404	0.485	0.442

Note: *p<0.1; **p<0.05; ***p<0.01

Source: DADS-EDP panel. The dependent variable is a dummy variable that indicates if the worker is displaced in period t. All the columns control for firm, year, collective agreement, and worker region of residence fixed effects. Robust standard errors are reported.

Table A.11: selective displacement by collective agreement - Linear probability model

	Dependent variable: Worker is displaced						
	Missing	No Binding Agreement	Agriculture and wood	Manufacturing	Services	Construction	Commerce
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mismatch Cognitive Skill	-0.169	0.411***	0.089	-0.029	0.285***	0.138	-0.081
	(0.313)	(0.105)	(0.142)	(0.079)	(0.084)	(0.160)	(0.241)
Mismatch Social Skill	0.243	0.156***	0.122	0.155***	0.339***	0.187*	0.094
	(0.178)	(0.052)	(0.090)	(0.057)	(0.055)	(0.104)	(0.136)
$\log(w_{ijt}/\tilde{w_{to}})$	0.283***	0.676***	0.339***	0.362***	0.476***	0.574***	0.302***
	(0.102)	(0.045)	(0.069)	(0.043)	(0.038)	(0.067)	(0.098)
R^2	0.819	0.514	0.576	0.545	0.561	0.585	0.617
Adjusted R^2	0.629	0.393	0.480	0.423	0.452	0.473	0.480

Note: *p<0.1; **p<0.05; ***p<0.01

Source: DADS-EDP panel. The dependent variable is a dummy variable that indicates if the worker is displaced in period t. All the columns control for firm, year, and worker region of residence fixed effects. Robust standard errors reported.

concepts, but also the ability to locate, interpret and communicate mathematical ideas in real contexts (among them work contexts).

Table A.12 shows the result of the factor analysis for the two PIAAC-constructed interest variables. The factor analysis methodology allows us to reduce the dimensions and express the information in a unique vector of weights that captures the largest amount of variance. In this calculation, the resulting vector is rotated such that the weights can be interpreted easily[24]. The results suggest that the numeracy value explains a larger proportion of the total variability, and thus is attributed a higher weight in the composite cognitive skill measure.

In the publicly available PIAAC data, literacy and numeracy are provided as plausible values and a set of 10 values is proposed for each dimension. Following the multiple imputation methods (Little and Rubin, 2019), from the set of ten plausible values of each sub-measure proposed, we can calculate a set of 10 cognitive skills measures for each observation in the sample.

Table A.12: Factor loadings for the construction of cognitive skills

Dimension	PIAAC variable name	Weight
Numeric	numer	0.763
Literacy	liter	0.646

Source: PIAAC France 2012.

Social skills As stated previously, the social skills measures are derived from the answers to the background questionnaire (BQ) of the survey. In this part, six questions about attitudes and interest toward learning are asked. These measures are related to personality and interpersonal skill areas. Following the same methodology as before, we

[24] I used the standard rotation option, 'varimax'.

combine the results of the six questions into a unique vector using principal component analysis (PCA). The only difference between the PCA and the factor analysis (FA) is that FA implies a rotation of the components that might help one to interpret the role of each component. Since in this case the interpretation is not straightforward, we use the PCA weights directly. Table A.13 presents the estimated loadings for the first factor on each of the questions.

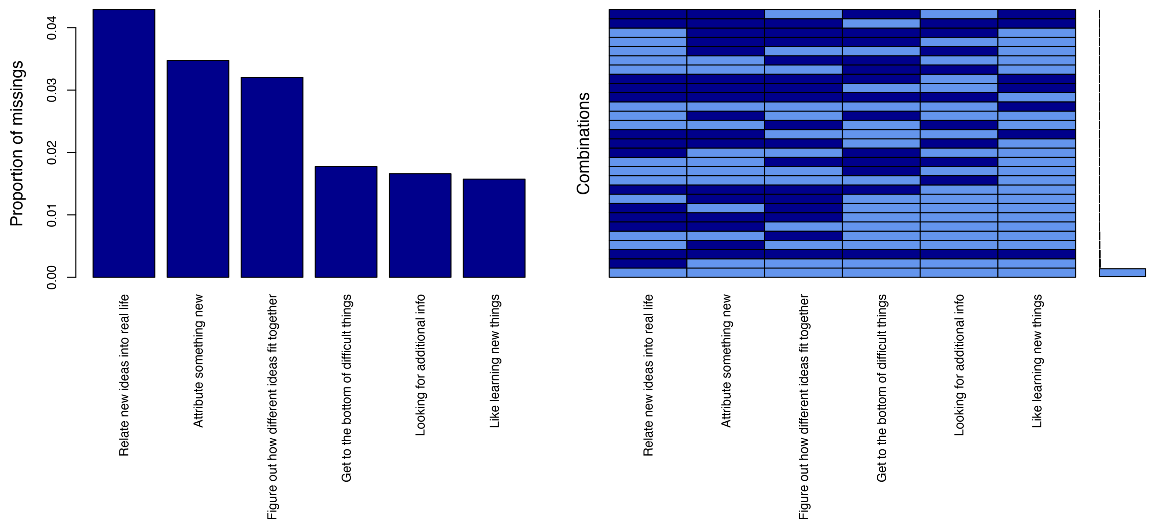
Table A.13: Factor loadings for the construction of social skills

	Variable	Factor1
Relate new ideas into real life	I_Q04b	0.581
Like learning new things	I_Q04d	0.681
Attribute something new	I_Q04h	0.485
Get to the bottom of difficult things	I_Q04j	0.723
Figure out how different ideas fit together	I_Q04l	0.728
Looking for additional info	I_Q04m	0.612

Source: PIAAC France 2012.

One of the worries in the construction of the social measure is the rate of the missingness for some questions in the background questionnaire. Unlike the numeracy and literacy measures, these are self-reported responses, and a systematic pattern of missing values could be problematic when building a unique measure of social skills. Figure A.4 presents a visualization that helps analyze the distribution of missing values across questions. The rate of missing values is very low. If we analyze separately each of the questions, the maximum rate of missing values is around 4%. When considering patterns for missingness (right part of the figure), we can see there are no visible patterns.

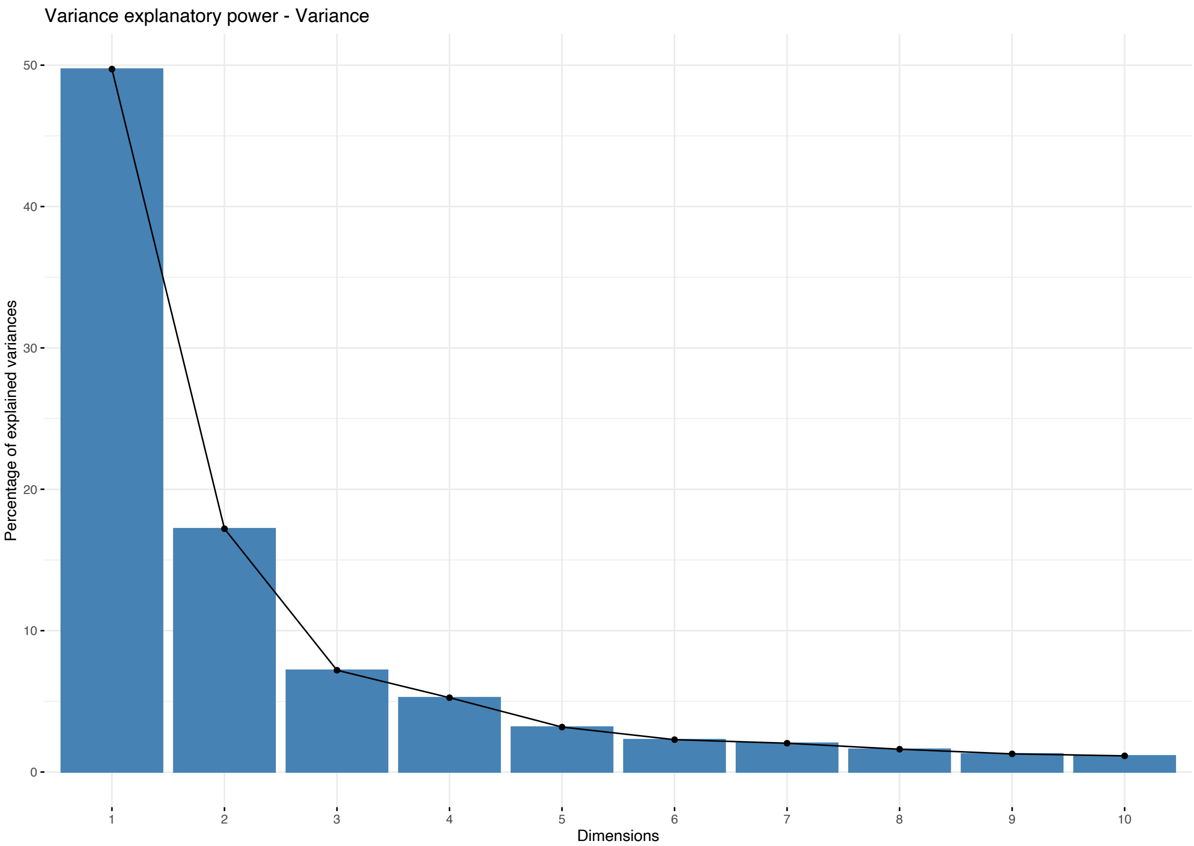
Figure A.4: Patterns of missingness for Non Cognitive questions



Source: PIAAC France 2012

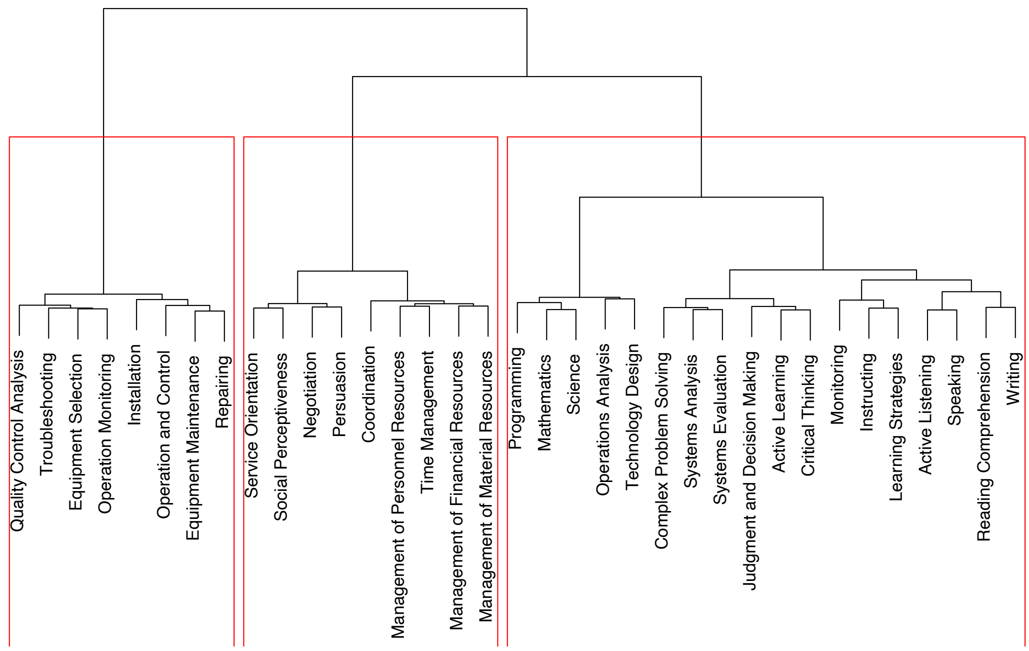
A.2.2 O*NET - Skills requirements

Figure A.5: Explanatory power of variance - PCA



Source: O*NET Skills

Figure A.6: Cluster selection based on PCA and hierarchical clusters based on Ward distance



Source: O*NET Skills

Table A.14: Factor loadings for three principal components (PCA) on skills measures - O*NET

	Comp.1	Comp.2	Comp.3
Active Learning	0.219	0.066	0.092
Active Listening	0.217	−0.045	0.027
Complex Problem Solving	0.208	0.143	0.101
Coordination	0.180	0.026	−0.291
Critical Thinking	0.217	0.084	0.085
Equipment Maintenance	−0.122	0.302	−0.130
Equipment Selection	−0.105	0.319	−0.056
Installation	−0.055	0.229	−0.082
Instructing	0.192	0.033	−0.049
Judgment and Decision Making	0.217	0.095	0.045
Learning Strategies	0.197	0.034	−0.010
Management of Financial Resources	0.135	0.065	−0.215
Management of Material Resources	0.130	0.123	−0.235
Management of Personnel Resources	0.186	0.086	−0.245
Mathematics	0.132	0.135	0.277
Monitoring	0.195	0.097	−0.113
Negotiation	0.188	−0.043	−0.241
Operation and Control	−0.130	0.249	−0.127
Operation Monitoring	−0.105	0.304	−0.083
Operations Analysis	0.157	0.123	0.198
Persuasion	0.199	−0.041	−0.191
Programming	0.068	0.140	0.338
Quality Control Analysis	−0.073	0.343	−0.035
Reading Comprehension	0.214	0.020	0.152
Repairing	−0.116	0.300	−0.131
Science	0.128	0.128	0.299
Service Orientation	0.159	−0.111	−0.209
Social Perceptiveness	0.189	−0.086	−0.199
Speaking	0.219	−0.055	0.011
Systems Analysis	0.204	0.151	0.073
Systems Evaluation	0.207	0.147	0.051
Technology Design	0.066	0.224	0.239
Time Management	0.196	0.064	−0.190
Troubleshooting	−0.107	0.341	−0.087
Writing	0.213	−0.005	0.112

Source: O*NET.

A.3 Institutional framework of mass layoff in France

This section describes and compiles the institutional information concerning how the layoff process works in France in the case of displacement for economic reasons - (ED). It presents the legal environment of economic displacement, the process timing, and the implications for the identification of mass layoffs in the project from the data point of view.

The process for layoffs for economic reasons is heterogeneous and includes numerous thresholds. First, a firm has more or fewer obligations depending on its size. Second, the size of the layoff can affect the timing of various obligations. As noted by Cahuc and Carcillo in 2007:

"The individual redundancy procedure is not very different from other individual redundancy procedures, and lasts on average 15 days. However, it involves informing the labor administration, in order to avoid "saucissonnage". The procedure for collective layoffs of less than ten employees over a period of 30 days lasts at least 3 days longer, as it entails, in addition to the individual procedures and the information of the administration, a consultation for opinion and the information of the staff representatives, who must be provided with a summary document explaining the reasons for the layoffs and specifying the details (persons and positions concerned, timetable, etc.) On the other hand, the procedure for large-scale economic layoffs is particularly complex (see Cahuc and Kramarz, 2005, for a detailed description), and lasts much longer: a minimum of three months, in practice around six months, and can reach nine or twelve months for a large company when negotiations are difficult or when there is a failure to fulfill the requirements."[25]

[25]"La procédure individuelle de licenciement économique se distingue peu des autres procédures de licenciement individuel, et dure en moyenne 15 jours. Elle implique néanmoins d'informer l'administration du travail, afin d'éviter le "saucissonnage". La procédure de licenciement collectif de moins de dix salariés sur 30 jours dure au minimum 3 jours de plus, car elle entraîne, outre les procédures individuelles et l'information de l'administration, une consultation pour avis et l'information des représentants du personnel auxquels il faut fournir un document de synthèse motivant et précisant les licenciements (personnes et postes concernés, calendrier, etc.) En revanche, la procédure en cas de grand licenciement économique est particulièrement complexe (voir Cahuc et Kramarz, 2005, pour une description détaillée), et dure beaucoup plus longtemps : au minimum trois mois, en pratique autour de six mois, et pouvant atteindre neuf ou douze mois pour une grande entreprise lorsque les négociations sont difficiles ou qu'il y a eu constat de carence." (Cahuc and Carcillo (2007) - page.8-9, own translation)

We begin by presenting the definition of economic displacement, followed by the definition of a mass layoff.

A.3.1 Definition of economic displacement

This type of separation involves some particularities in the definition:

- It is an *involuntary* separation (the decision follows the employer's will and not the employee).
- The displacement happens because the job is destroyed or *transformed in its nature* (by changing previous mutual agreements reflected in the job contract). The worker does not accept such changes.[26]

Both points share a characteristic of economic displacement. It is *non-consensual*. From the economic point of view, the surplus of the employment relation changes, and the employer no longer benefits from continuing the match. In the paper, we examined how changes in productivity could explain value of production from a match could change. Given that the legal arrangement happens between the firm and the employer, such a process occurs at the firm level. From the legal standpoint, such change could arise from:

i Economic performance was poor in comparison to the previous years;

ii The firm's technology changed;

iii The firm made a strategic decision to reorganize to improve its competitiveness[27]. According to the jurisprudence, it may not be used to improve it but only to maintain it;

[26]" A dismissal for economic reasons is a dismissal carried out by an employer for one or more reasons not inherent to the person of the employee resulting from the elimination or transformation of a job or from a modification, refused by the employee, of an essential element of the employment contract" (Article L1233-3 - Code du travail) https://www.legifrance.gouv.fr/codes/article_lc/LEGIARTI000036762081/ .["Constitue un licenciement pour motif économique le licenciement effectué par un employeur pour un ou plusieurs motifs non inhérents à la personne du salarié résultant d'une suppression ou transformation d'emploi ou d'une modification, refusée par le salarié, d'un élément essentiel du contrat de travail"]

[27]This aspect is crucial in the conception of the law, but is very difficult to interpret. Following Cahuc (2012), the French case is extreme when compared to other European countries, since an interpretation of the law that does not allow firms to fire to improve productivity, but just to maintain it, is jurisprudence in labor courts. Still, the *maintenance* of productivity is very difficult to proof and is conditional on the judge's interpretation.

iv The firm will shut down operations and will disappear.

Another level of complexity in the application of the law has to be considered since, conditions (i) to (iii) could happen and be calculated at a level different from the firm's, including that of the conglomerate to which it belongs. Judges could consider the level of the group that controls the firm or the performance of the sector as a whole, and examine its performance to justify the ability of the firm to use the mechanism. There have been cases in which a firm that is having economic difficulties but belongs to a group that is performing well has found it difficult to motivate an economic displacement. Consider for example some recent jurisprudence of the Court de Cassation: *"But whereas the economic cause of a dismissal is assessed at the level of the company or, if it is part of a group, at the level of the sector of activity of the group in which it operates; whereas the perimeter of the group to be taken into consideration for this purpose is all of the companies united by the control or influence of a dominant company under the conditions defined in article L. 2331-1 of the Labor Code, without there being any reason to restrict the group to the companies located on national territory."* (Court de Cassation, 6 novembre 2016, 14-30.063)[28]. The definition of the reach (perimeter) of the group in this sense is far from the context of the firm, which could make the mechanism difficult to access. A firm, to be able to use the economic separation mechanism, has to comply with any of the conditions listed above.

The accessibility of the economic displacement mechanism in France has three barriers. First, the motivation of the reasons to layoff can be easily disputed since they have to be interpreted by an authority using a concept which can be subject to subjective interpretation. Second, the perimeter of the group can be disputed, and this can limit the ability to access the mechanism. Finally, the mechanism can not be used to improve productivity, but only to maintain it, which could make it unsuitable for firm reorganization.

The next section details the process of economic displacement. It differs by the size of the firm, the number of workers involved in the layoff, and the concentration of layoffs in time.

[28]https://www.legifrance.gouv.fr/juri/id/JURITEXT000033429110/[*Mais attendu que la cause économique d'un licenciement s'apprécie au niveau de l'entreprise ou, si celle-ci fait partie d'un groupe, au niveau du secteur d'activité du groupe dans lequel elle intervient ; que le périmètre du groupe à prendre en considération à cet effet est l'ensemble des entreprises unies par le contrôle ou l'influence d'une entreprise dominante dans les conditions définies à l'article L. 2331-1 du code du travail, sans qu'il y ait lieu de réduire le groupe aux entreprises situées sur le territoire national*].

A.3.2 The process of economic displacement

There is a well established timeline for firms that intend to use economic displacement. The procedure differs slightly if the firm is large or by the number of employees firing. Below a summary of the process, which depends on the number of layoffs by the firm.

A.3.2.1 In the case of an individual layoff

Ind.1 A firm recognizes itself in a situation where an economic displacement could be justified (conditions (i) to (iv). It is crucial that it can demonstrate such a condition in front of a judge since the employee could contest it, increasing the time and cost of the layoff. Fraisse et al. (2015) provide evidence that the legal procedure affects the job flow of firms. An increase in the amount of litigation decreases firings. Such evidence suggests that firms might adopt this mechanism essentially in cases where the underlying economic motivation can not be contested at all.

Ind.2 The firm must organize an interview in which it informs the employee that she will be fired. The law defines the minimum contents of the interview. The firm notifies the employee of the interview at least five days in advance[29].

Ind.3 In this meeting, the employee is told the decision and the causes. The firm offers him the possibility of getting a "contrat de sécurisation professionnelle (CSP)". When the separation is for economic reasons, some rules must also be considered, specifically which employees to lay off in which order, accounting for family responsibilities, seniority, age and disabilities, and others[30]. If there exists a collective agreement, it also needs to be taken into consideration.

Ind.4 Seven days after the meeting, the employer sends a letter of dismissal. The employee has 12 months to dispute this decision with the authorities. The letter offers him the "contrat de sécurisation" professionnelle (CSP) if the firm has less than 1000 employees or a retraining period if the firm (or economic group) has more than 1000 employees[31]. If the employee accepts the option of retraining, it can last from 4 to 12 months .

[29] Article L1233-11 - Code du travail. https://www.legifrance.gouv.fr/codes/article_lc/LEGIARTI000006901023/

[30] Article L1233-5 - Code du travail https://www.legifrance.gouv.fr/codes/article_lc/LEGIARTI000036261856/.

[31] These requirements cost around 65% of the wage in addition to the cost of the training. More details can be found in https://travail-emploi.gouv.fr/emploi/accompagnement-des-mutations-economiques/article/conge-de-reclassement.

Ind.5 The firm communicates the decision to the french administration (Dirrecte).

Ind.6 The interruption of the contract occurs when the notification arrives, after a specified advanced notice period ('preavis') that changes as a function of the seniority of the employee[32].

A.3.2.2 Layoff of two or more employees (below nine)

A similar procedure as the one stated before should be implemented. Still, before the interview with the employer, the firm must also meet with the employee's representatives and communicate to them all the details of the workforce restructuring. In case the firm has more than 50 employees, it must notify the Ministry of Labor.

The communication involves the design and presentation of a restructuring plan. It requires the economic reasons that motivate the plan to be well described (financial, economic, or technical reasons). There is a precise number of separations proposed, the occupations considered, and the expected calendar.

A.3.2.3 Mass layoff (over ten economic displacements)

If the firm has less than 50 employees (strictly) and wants to perform a mass layoff, it must comply with the above conditions. Additionally, the consultation procedure with the employee representative changes and must be done twice in 14 days before proceeding to the interview. This has to be communicated to the administrative authorities (DIRECCTE), and 30 days after that, the firm can send the letters to the employees.

If the firm has 50 or more employees, the firm has to put in place an Employment Saving Plan, PSE (plan de sauvegarde de l'emploi). The content of a PSE has to be in agreed upon with the employee representatives. It has to be presented to them in (at least) 2 meetings, and the employee representatives have some time to reply to its points and evaluate its contents (they have a window of 2 to 4 months to respond to the proposed content). The proposal and response are communicated to the administration before the layoffs can continue. The administration validates the plan (it has around 21 days to do it), during which the firm can organize the interviews and proceed with the process. The firm can send the letters around 30 days after it communicates the PSE to the Direccte (French Ministry of Labor).

[32] The length of the *preavis* is one (1) month for a worker with less than two years of seniority and two (2) months for a seniority equal or superior to two years.

We can thus use the number of PSEs to have a sense of what could be the order of magnitude of mass layoffs in France. According to information of the French ministry of labor, table A.15 presents the number of PSE for the period 2005 to 2013. As we can see, the number of events is pretty low compared to the reported number of events per year using our definition based on the size of the firm, suggesting that the the economic displacement is not the principal channel by which a firm reduces its workforce. A revision of the legislation suggests that the cause for this is related to the barriers to use the mechanism, and the high cost that it has (which includes the cost in time).

Table A.15: Number of PSE notifications to the French Ministry of labor 2005 - 2013

Year	Number of PSE notifications (more 50)	All PSE notifications
2005	396	1270
2006	412	1305
2007	351	957
2008	393	1061
2009	764	2245
2010	372	1195
2011	270	952
2012	307	914
2013	237	583
2014		772
2015		768
2016		721
2017		562
2018		561
2019		491
2020		871

Source: French Ministry of Labor. The second column indicates the number of PSEs notified to the French Ministry of labor for firms with more than 50 employees at the moment of the notification. Column 3 presents the total number of notifications including small firms. There is a series break in 2013 since the source of the data changes.

A.4 Coefficients for multiple imputation samples in PIAAC

Table A.16: Average coefficient for multiple imputation samples, PIAAC - FR, Cognitive skills

	No seniority	No firm size	No occupation	No education	No wage	Complete
Intercept	−3.017	−0.063	−2.423	1.641	1.286	−2.072
	(9.668)	(9.692)	(10.146)	(9.526)	(9.516)	(9.750)
Sex (female)	0.084	0.089	0.057	0.034	0.109	0.085
	(0.027)	(0.027)	(0.024)	(0.028)	(0.028)	(0.027)
Monthly earnings	−0.132	−0.134	−0.228	−0.237		−0.124
	(0.032)	(0.030)	(0.029)	(0.040)		(0.031)
Isco Group 02	−0.343	−0.425		0.275	−0.396	−0.361
	(0.253)	(0.250)		(0.288)	(0.256)	(0.256)
Isco Group 03	−0.540	−0.584		0.139	−0.564	−0.554
	(0.213)	(0.211)		(0.213)	(0.228)	(0.212)
Isco Group 11	−0.335	−0.353		−0.121	−0.360	−0.355
	(0.194)	(0.197)		(0.213)	(0.223)	(0.198)
Isco Group 12	−0.335	−0.373		−0.016	−0.422	−0.364
	(0.178)	(0.179)		(0.201)	(0.195)	(0.182)
Isco Group 13	−0.386	−0.436		−0.137	−0.453	−0.416
	(0.166)	(0.166)		(0.189)	(0.187)	(0.169)
Isco Group 14	−0.333	−0.348		0.193	−0.416	−0.362
	(0.183)	(0.180)		(0.197)	(0.203)	(0.184)
Isco Group 21	−0.326	−0.395		−0.031	−0.385	−0.357
	(0.175)	(0.177)		(0.199)	(0.196)	(0.179)
Isco Group 22	−0.175	−0.248		0.056	−0.213	−0.210
	(0.175)	(0.180)		(0.195)	(0.193)	(0.184)
Isco Group 23	−0.358	−0.373		−0.135	−0.365	−0.375
	(0.167)	(0.170)		(0.183)	(0.186)	(0.171)
Isco Group 24	−0.262	−0.314		0.055	−0.333	−0.294
	(0.163)	(0.164)		(0.183)	(0.187)	(0.169)
Isco Group 25	−0.412	−0.478		−0.170	−0.459	−0.444
	(0.173)	(0.181)		(0.201)	(0.192)	(0.181)
Isco Group 26	−0.063	−0.100		0.134	−0.125	−0.090
	(0.174)	(0.181)		(0.194)	(0.197)	(0.182)
Isco Group 31	−0.102	−0.151		0.508	−0.134	−0.131
	(0.164)	(0.168)		(0.180)	(0.187)	(0.169)

Isco Group 32	−0.163	−0.208	0.213	−0.197	−0.196
	(0.177)	(0.184)	(0.193)	(0.196)	(0.183)
Isco Group 33	−0.226	−0.280	0.224	−0.253	−0.257
	(0.166)	(0.170)	(0.183)	(0.190)	(0.172)
Isco Group 34	−0.174	−0.210	0.237	−0.210	−0.205
	(0.168)	(0.170)	(0.190)	(0.187)	(0.173)
Isco Group 35	−0.165	−0.217	0.243	−0.208	−0.191
	(0.211)	(0.214)	(0.229)	(0.225)	(0.216)
Isco Group 41	−0.144	−0.192	0.369	−0.133	−0.175
	(0.168)	(0.172)	(0.189)	(0.188)	(0.175)
Isco Group 42	−0.266	−0.271	0.157	−0.266	−0.290
	(0.194)	(0.199)	(0.214)	(0.217)	(0.201)
Isco Group 43	−0.169	−0.221	0.303	−0.204	−0.199
	(0.166)	(0.168)	(0.179)	(0.188)	(0.169)
Isco Group 44	−0.140	−0.170	0.386	−0.083	−0.157
	(0.224)	(0.224)	(0.242)	(0.244)	(0.226)
Isco Group 51	0.239	0.170	0.892	0.238	0.206
	(0.175)	(0.181)	(0.183)	(0.191)	(0.180)
Isco Group 52	0.046	−0.008	0.625	0.032	0.013
	(0.171)	(0.177)	(0.189)	(0.191)	(0.178)
Isco Group 53	0.078	−0.006	0.731	0.076	0.040
	(0.180)	(0.184)	(0.195)	(0.199)	(0.186)
Isco Group 54	−0.118	−0.191	0.552	−0.136	−0.153
	(0.192)	(0.200)	(0.215)	(0.212)	(0.202)
Isco Group 61	0.211	0.140	0.879	0.214	0.175
	(0.194)	(0.200)	(0.220)	(0.215)	(0.202)
Isco Group 62	0.142	0.079	0.805	−0.142	0.104
	(0.444)	(0.450)	(0.456)	(0.362)	(0.442)
Isco Group 71	0.566	0.497	1.403	0.500	0.528
	(0.199)	(0.202)	(0.211)	(0.217)	(0.203)
Isco Group 72	0.087	0.035	0.749	0.065	0.057
	(0.193)	(0.198)	(0.208)	(0.215)	(0.199)
Isco Group 73	−0.032	−0.092	0.607	−0.067	−0.061
	(0.231)	(0.241)	(0.246)	(0.248)	(0.241)
Isco Group 74	−0.272	−0.341	0.359	−0.311	−0.307
	(0.221)	(0.229)	(0.221)	(0.236)	(0.226)

Isco Group 75	0.262	0.194		0.979	0.283	0.227
	(0.185)	(0.198)		(0.201)	(0.207)	(0.196)
Isco Group 81	0.306	0.255		1.062	0.256	0.272
	(0.178)	(0.180)		(0.196)	(0.201)	(0.184)
Isco Group 82	0.067	0.054		0.817	0.023	0.038
	(0.213)	(0.211)		(0.222)	(0.230)	(0.217)
Isco Group 83	0.190	0.136		0.895	0.162	0.155
	(0.183)	(0.186)		(0.204)	(0.204)	(0.189)
Isco Group 91	0.401	0.382		1.166	0.419	0.365
	(0.172)	(0.179)		(0.190)	(0.194)	(0.180)
Isco Group 93	0.132	0.108		0.846	0.127	0.100
	(0.180)	(0.178)		(0.201)	(0.196)	(0.183)
Isco Group 94	0.479	0.371		1.266	0.508	0.437
	(0.239)	(0.236)		(0.276)	(0.249)	(0.244)
Isco Group 95	−0.124	0.046		0.484	0.378	−0.179
	(0.276)	(0.374)		(0.292)	(0.420)	(0.287)
Isco Group 96	−0.043	−0.091		0.634	−0.029	−0.072
	(0.179)	(0.178)		(0.192)	(0.209)	(0.180)
age	0.958	0.451	0.959	0.239	0.111	0.794
	(1.669)	(1.674)	(1.754)	(1.662)	(1.637)	(1.686)
age^2	−0.072	−0.036	−0.069	−0.036	−0.016	−0.061
	(0.116)	(0.116)	(0.122)	(0.116)	(0.113)	(0.117)
age^3	0.003	0.001	0.002	0.002	0.001	0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
age^4	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
age^5	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
age^6	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lower secondary	−0.545	−0.616	−0.597		−0.588	−0.551
	(0.078)	(0.081)	(0.081)		(0.074)	(0.078)
Upper and Post Secondary	−0.911	−0.996	−1.048		−0.955	−0.918
	(0.069)	(0.072)	(0.072)		(0.063)	(0.069)
Bachelor	−1.343	−1.441	−1.668		−1.413	−1.355
	(0.074)	(0.078)	(0.073)		(0.068)	(0.074)

Higher Tertiary	−1.468	−1.584	−1.869		−1.568	−1.490
	(0.079)	(0.088)	(0.081)		(0.077)	(0.083)
11 to 50 workers	0.026		0.004	0.001	0.025	0.028
	(0.032)		(0.034)	(0.033)	(0.032)	(0.033)
51 to 250 workers	−0.029		−0.037	−0.061	−0.030	−0.023
	(0.036)		(0.037)	(0.038)	(0.035)	(0.037)
250 to 1000 workers	−0.039		−0.052	−0.085	−0.035	−0.029
	(0.039)		(0.040)	(0.042)	(0.039)	(0.040)
More than 1000 people	−0.129		−0.162	−0.142	−0.136	−0.115
	(0.046)		(0.050)	(0.050)	(0.046)	(0.048)
Tenure		−0.007	−0.006	0.003	−0.005	−0.004
		(0.010)	(0.010)	(0.010)	(0.009)	(0.009)
Tenure^2		0.000	−0.000	−0.000	0.000	0.000
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Tenure^3		−0.000	0.000	0.000	−0.000	−0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R2	0.456	0.461	0.413	0.376	0.444	0.456
BIC (null)	-1791	-1880	-1816	-1293	-1797	-1765
N	3702	3772	3700	3698	3875	3697

Table A.17: Average coefficient for multiple imputation samples, PIAAC - FR, Social skills

	No seniority	No firm size	No occupation	No education	No wage	Complete
Intercept	21.392	21.812	22.503	16.921	21.667	23.323
	(13.035)	(12.968)	(13.693)	(13.003)	(12.896)	(13.240)
Sex (female)	0.018	0.025	0.048	0.043	0.001	0.024
	(0.035)	(0.035)	(0.030)	(0.036)	(0.036)	(0.036)
Montly earnings	0.069	0.113	0.151	0.135		0.099
	(0.033)	(0.031)	(0.029)	(0.032)		(0.032)
Isco Group 02	−0.654	−0.764		−0.983	−0.756	−0.777
	(0.406)	(0.407)		(0.413)	(0.412)	(0.409)
Isco Group 03	−0.051	−0.160		−0.413	−0.157	−0.165
	(0.423)	(0.425)		(0.428)	(0.423)	(0.427)
Isco Group 11	−0.033	−0.175		−0.234	0.000	−0.166
	(0.386)	(0.386)		(0.405)	(0.385)	(0.392)
Isco Group 12	−0.015	−0.186		−0.284	−0.113	−0.176
	(0.357)	(0.362)		(0.382)	(0.356)	(0.366)
Isco Group 13	−0.050	−0.219		−0.292	−0.196	−0.206
	(0.357)	(0.360)		(0.382)	(0.349)	(0.364)
Isco Group 14	0.006	−0.144		−0.315	−0.116	−0.144
	(0.382)	(0.374)		(0.389)	(0.374)	(0.382)
Isco Group 21	0.044	−0.123		−0.214	−0.106	−0.116
	(0.368)	(0.372)		(0.392)	(0.362)	(0.375)
Isco Group 22	−0.031	−0.189		−0.283	−0.197	−0.211
	(0.364)	(0.369)		(0.387)	(0.363)	(0.372)
Isco Group 23	0.059	−0.077		−0.128	−0.091	−0.063
	(0.354)	(0.357)		(0.379)	(0.352)	(0.362)
Isco Group 24	0.021	−0.149		−0.251	−0.134	−0.145
	(0.359)	(0.362)		(0.381)	(0.356)	(0.366)
Isco Group 25	−0.402	−0.546		−0.621	−0.530	−0.541
	(0.350)	(0.359)		(0.378)	(0.353)	(0.363)
Isco Group 26	0.092	−0.096		−0.141	−0.008	−0.065
	(0.374)	(0.375)		(0.396)	(0.363)	(0.379)
Isco Group 31	−0.139	−0.304		−0.492	−0.298	−0.292
	(0.358)	(0.363)		(0.375)	(0.354)	(0.366)

Isco Group 32	−0.230	−0.401		−0.520	−0.411	−0.401
	(0.353)	(0.356)		(0.373)	(0.350)	(0.360)
Isco Group 33	−0.192	−0.353		−0.499	−0.351	−0.348
	(0.346)	(0.351)		(0.369)	(0.346)	(0.355)
Isco Group 34	−0.078	−0.229		−0.378	−0.289	−0.240
	(0.356)	(0.357)		(0.376)	(0.354)	(0.363)
Isco Group 35	0.021	−0.115		−0.249	−0.065	−0.118
	(0.394)	(0.393)		(0.411)	(0.377)	(0.396)
Isco Group 41	−0.304	−0.462		−0.634	−0.511	−0.470
	(0.368)	(0.375)		(0.390)	(0.371)	(0.379)
Isco Group 42	−0.081	−0.211		−0.360	−0.207	−0.222
	(0.361)	(0.365)		(0.384)	(0.358)	(0.370)
Isco Group 43	−0.346	−0.493		−0.644	−0.515	−0.491
	(0.356)	(0.362)		(0.378)	(0.356)	(0.365)
Isco Group 44	−0.261	−0.365		−0.562	−0.386	−0.375
	(0.365)	(0.370)		(0.388)	(0.366)	(0.375)
Isco Group 51	−0.323	−0.499		−0.715	−0.564	−0.493
	(0.359)	(0.362)		(0.382)	(0.363)	(0.369)
Isco Group 52	−0.246	−0.425		−0.610	−0.445	−0.415
	(0.351)	(0.355)		(0.369)	(0.357)	(0.360)
Isco Group 53	−0.217	−0.421		−0.619	−0.443	−0.401
	(0.369)	(0.368)		(0.386)	(0.369)	(0.376)
Isco Group 54	−0.280	−0.455		−0.680	−0.454	−0.458
	(0.351)	(0.356)		(0.369)	(0.352)	(0.360)
Isco Group 61	−0.239	−0.422		−0.629	−0.429	−0.415
	(0.374)	(0.380)		(0.393)	(0.376)	(0.384)
Isco Group 62	0.793	0.580		0.415	0.306	0.645
	(0.554)	(0.576)		(0.590)	(0.570)	(0.585)
Isco Group 71	−0.591	−0.784		−1.052	−0.755	−0.773
	(0.371)	(0.374)		(0.387)	(0.369)	(0.379)
Isco Group 72	−0.351	−0.511		−0.734	−0.512	−0.508
	(0.358)	(0.360)		(0.375)	(0.357)	(0.364)
Isco Group 73	−0.207	−0.364		−0.579	−0.403	−0.362
	(0.389)	(0.387)		(0.406)	(0.386)	(0.395)
Isco Group 74	−0.230	−0.396		−0.614	−0.392	−0.400
	(0.395)	(0.399)		(0.410)	(0.388)	(0.401)

Isco Group 75	−0.394	−0.577		−0.813	−0.592	−0.573
	(0.368)	(0.369)		(0.382)	(0.362)	(0.372)
Isco Group 81	−0.522	−0.689		−0.954	−0.699	−0.693
	(0.352)	(0.354)		(0.365)	(0.354)	(0.358)
Isco Group 82	−0.459	−0.567		−0.860	−0.601	−0.610
	(0.387)	(0.385)		(0.404)	(0.380)	(0.393)
Isco Group 83	−0.389	−0.556		−0.808	−0.591	−0.561
	(0.370)	(0.374)		(0.390)	(0.372)	(0.379)
Isco Group 91	−0.298	−0.491		−0.745	−0.525	−0.480
	(0.370)	(0.373)		(0.387)	(0.369)	(0.377)
Isco Group 93	−0.371	−0.498		−0.792	−0.571	−0.539
	(0.373)	(0.379)		(0.394)	(0.375)	(0.381)
Isco Group 94	−0.467	−0.660		−0.930	−0.664	−0.663
	(0.420)	(0.415)		(0.431)	(0.410)	(0.425)
Isco Group 95	−0.751	−0.959		−1.198	−1.102	−1.006
	(0.376)	(0.383)		(0.407)	(0.372)	(0.388)
Isco Group 96	−0.319	−0.480		−0.710	−0.486	−0.478
	(0.421)	(0.434)		(0.444)	(0.430)	(0.436)
age	−4.142	−4.173	−4.438	−3.400	−4.091	−4.443
	(2.197)	(2.194)	(2.322)	(2.195)	(2.187)	(2.237)
age^2	0.311	0.309	0.327	0.262	0.307	0.329
	(0.150)	(0.150)	(0.159)	(0.150)	(0.149)	(0.153)
age^3	−0.012	−0.012	−0.012	−0.010	−0.012	−0.012
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)
age^4	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
age^5	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
age^6	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lower secondary	0.000	−0.024	−0.000		0.004	−0.014
	(0.084)	(0.082)	(0.082)		(0.084)	(0.082)
Upper and Post Secondary	0.214	0.192	0.247		0.241	0.195
	(0.084)	(0.081)	(0.081)		(0.083)	(0.082)
Bachelor	0.388	0.354	0.536		0.421	0.350
	(0.090)	(0.087)	(0.083)		(0.085)	(0.086)

Higher Tertiary	0.442	0.386	0.620		0.472	0.369
	(0.096)	(0.091)	(0.082)		(0.091)	(0.092)
11 to 50 workers	0.082		0.089	0.107	0.088	0.093
	(0.038)		(0.037)	(0.037)	(0.034)	(0.037)
51 to 250 workers	0.074		0.072	0.107	0.089	0.094
	(0.049)		(0.050)	(0.049)	(0.047)	(0.050)
250 to 1000 workers	0.058		0.063	0.108	0.090	0.089
	(0.048)		(0.047)	(0.047)	(0.044)	(0.048)
More than 1000 people	0.053		0.081	0.108	0.099	0.096
	(0.064)		(0.064)	(0.066)	(0.064)	(0.066)
Tenure		−0.018	−0.018	−0.024	−0.023	−0.022
		(0.012)	(0.012)	(0.011)	(0.011)	(0.011)
Tenure^2		0.001	0.001	0.001	0.001	0.001
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Tenure^3		−0.000	−0.000	−0.000	−0.000	−0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R2	0.114	0.117	0.095	0.109	0.122	0.119
BIC (null)	29	2	-199	43	-3	34
N	3542	3594	3540	3538	3699	3537