Who gets to stay?
How mass layoffs reshape firms' skills structure

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Abstract

This paper contests the traditional view of layoffs as solely reactive to negative economic conditions. Using survey and administrative French data, we provide evidence on how firms strategically utilize mass layoffs to restructure their workforce composition. First, we investigate if firms use layoffs to shift their skill requirements. Analyzing both layoff and matched non-layoff firms, we find firms significantly increase the requirements for social skills while decreasing dependence on manual and cognitive skills requirements after layoffs. This suggests a premeditated reshaping of the workforce instead of a cost-cutting practice. Secondly, we explore the factors influencing selection into displacement during layoffs. We focus on three key aspects: skills mismatch, relative worker quality, and perceived monetary cost. Our findings highlight the significant role of skill mismatch and worker quality in determining dismissal, suggesting firms actively select based on strategic needs. By revealing the strategic nature of mass layoffs and their impact on skills composition and worker selection, this paper offers valuable insights into the understanding of workforce adjustment. Such insights are relevant for policy design.

Keywords: Skills, Layoffs, Mismatch, Firm reorganization
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1 Introduction

Recent layoff announcements challenge our understanding of workforce reduction. Traditionally, we often see firm downsizing as a natural adjustment to bad economic conditions and financial difficulties (Davis and Haltiwanger, 1992, 1999; Lise and Robin, 2017). While financial constraints undoubtedly play a role, the large part of tech layoffs during the past years paint these events as strategic choices, opportunities to reshape firms for the future.[1] We focus on studying firm behavior and structure during mass layoffs. While there is abundant literature on the costs of displacements and its sources across the U.S. and the European Union (Jacobson et al., 1993; Lachowska et al., 2020; Bertheau et al., 2022), less is known about the active role of firms, and how they trim their workforce in bad times. Are mass layoffs a sign of weakness, or a strategic power play? Do firms trim their workforce to survive or to compete? Or both?

This paper investigates how firms strategically utilize mass layoffs to restructure their workforce composition. To do so, we build a unique dataset combining information on multidimensional skills supply with multidimensional skills demand, employment and other variables drawn from linked employer-employee data from France. The French context is often perceived as rigid and worker-protective due to its protective labor laws, which provides us with the opportunity to explore a situation in which labor force adjustment might be particularly "lumpy", although our findings also offer insights applicable to labor markets where firms may have more room to continuously adjust their labor force composition. This paper discusses mass layoffs from the firm's perspective, addressing two different questions. First, do firms use mass layoffs to restructure their workforces? Second, what criteria do firms employ when selecting individuals for layoff?

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, 2023) shows that ICT occupations have

[1] For example, Spotify's 17% staff reduction in December 2023 memo, contained a section titled *"Looking ahead"*, in which the layoff aims to become a *relentlessly resourceful* organization.

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 layoffs 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 terminations (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, relative to the counterfactual in which it lays off all workers with equal probability. We offer evidence on how firms change their workforce composition following mass layoffs by combining information on skill requirements by occupation with daily headcounts across the occupation distribution in the window of time around a mass layoff in order to provide detailed insights into these dynamics. Our identification of the set of mass layoff firms uses French administrative data on the universe of private sector jobs and firms (DADS postes) and is based on changes in the firm's workforce size[2].

We then study how the occupational composition and average skill use within a firm changes during a mass layoff. By tracking monthly changes in the firm's skill requirements, we can identify shifts in organizational structure. Using a combination of matching and reweighting techniques and a difference-in-differences approach (Li et al., 2018), we employ an event study framework to track the evolution of firms' skill requirements before, during, and after layoffs in terms of their demand for cognitive, social, and manual skills. This allow us to document the short and medium-term stability of post-layoff skill requirements changes. Our findings present a clear picture: firms actively adjust their skills composition after mass layoffs. On average, firms increase their demand for social skills while decreasing their reliance on both manual and cognitive skills, suggesting that firms use mass layoffs to strategically adjust the skills composition of their workforces.

Having established that firms adjust the skills composition of their workforce during

[2]In selecting this sample, we do not differentiate between separations for economic or other reasons. French data sources that would allow us to distinguish the reasons for separation (e.g. the DMMO) do not provide information at a daily frequency and do not systematically cover firms with fewer than 50 workers. Being able to measure the number of separations in a sliding 30-day window is necessary to identify mass layoffs according the definition in French labor law; see section 3.2.2 for details.

a mass layoff, we turn to how firms decide which workers are fired when they decide to downsize. If the adjustments in workforce composition we document simply reflect differences in the cost of labor across categories, then there might be no efficiency-improving or forward-looking strategic component at all in layoff behavior, only a cost-saving reaction to negative shocks. We therefore analyze in detail *which* workers are laid off, allowing for multiple motives. In particular, we focus on three key factors directly influencing the value of the employment relationship. First, the role of skills mismatch, which captures the degree to which a worker's skills align with the particular requirements of the firm. Second, the relative monetary cost of a worker, comparing his or her ongoing monetary cost to that of a counterfactual worker who would performs the same tasks at the market rate. Finally the relative worker quality, as measured by comparing worker fixed effects to those of their peers in the relevant labor market. By analyzing these factors, we aim to shed light on the strategic decision-making processes behind mass layoffs and their implications for both firms and workers.

Using a linear probability model with firm, collective agreement and region high dimensional fixed effects, centered at the time of displacement, we model selection into displacement, and quantify the role of the cost associated to each factor. The effect of skills mismatch in the likelihood of displacement is sizeable. The expected effect on the probability of displacement in the sample of a one standard deviation increase in mismatch along the social skills dimension (1.23%) is larger than that for mismatch along the cognitive skills dimension (1.00%). Although it is also a relevant factor for determining layoffs, the quantitative effect of a one standard deviation in the relative cost of a worker is smaller than the effects along the skills mismatch dimension, increasing only slightly (0.13%) the likelihood of being displaced. Finally, the most important effect comes from the relative worker quality. An increase in one standard deviation decreases the likelihood of being displaced in 2.99%.

Related Literature We contribute to four strands of the literature. First, we contribute to the literature investigating changes in the occupational structure of the firm. The structure and composition of the firm is determined in part by its stage of growth (Simon, 1962; Lucas, 1978; Calvo and Wellisz, 1978). In each stage, the firm requires a specific type of knowledge (Handwerker et al., 2021; Garicano and Rossi-Hansberg, 2015). Changes in the organizational structure can be a response to implementation of new technologies, or changes in the production technologies of the firm (Autor et al., 2003; Acemoglu and Restrepo, 2019; Acemoglu et al., 2022). We provide evidence that part of this reorganization takes place via mass layoffs, in that firms change their skill composition around mass layoffs and that this adjustment takes time. While there is evidence that skills requirements differ across labor markets (Deming and Kahn, 2018), our paper is the first to show how the structure of skill requirements evolves over time in the aftermath of a mass layoff[3].

Second, we contribute to the recent literature highlighting the importance of multidimensional skills in labor market (Lise and Postel-Vinay, 2020). Allowing for multiple skills dimensions modifies how one thinks about the overall behavior of workers and firms (Lindenlaub, 2017), including how they are impacted by shocks (Lise and Robin, 2017), and how they modify their structure over time (Deming and Noray, 2020; Tan, 2023; Deming, 2023). We contribute to this literature by adopting a reduced-form estimation approach and highlighting the role of mass layoffs in this process.

Third, our paper relates to the causes of separation literature, and selection into displacement. While Bender et al. (2002) provides evidence on how demographic characteristics affect the likelihood of displacement, more recently Seim (2019) introduce the importance of skills in such a decision. Our paper complements this literature not only by incorporating skills mismatch, but also by comparing the effect of mismatch with other factors that could affect the likelihood of selective displacement, highlighting the important role of worker quality and skills mismatch to determine this likelihood.

Last, our study relates to the literature on combining data for causal analysis. While there are ongoing efforts to link observational and experimental data for causal inference (Athey et al., 2020; Colnet et al., 2023; Hünermund and Bareinboim, 2023), this study proposes to combine survey data with administrative data when common identifiers are missing. We base our approach on unique features of the survey data used that allow us to link both sources and apply double multiple imputation to stochastic regression imputation methods.

Outline The remainder of the paper is organized as follows. Section 2 lays out the conceptual framework as a motivation for our empirical analysis. Section 3 describes our primary data sources and presents descriptive statistics. This section also details how we combine the worker skill survey data with the French employer-employee data. Section 4 presents evidence on how firms use mass layoff to recompose their workforce and organization. Section 5 presents the factors that affect the individual-level displacement decision and quantifies their importance. Section 6 concludes.

[3] On a related question, Margolis (2005) and Margolis (2006) consider the time path of changes in workforce composition following mergers and acquisitions.

2 The determinants of downsizing

This section reviews contributions from the personnel economics literature which provide a variety of explanations for the determinants of mass layoffs. These explanations range from productivity shocks, to a forward-looking need for organizational restructuring, to changes in the structure of input costs. The underlying reason for a mass layoff drives the firm's decision-making process, ultimately determining the firm's productivity and workforce structure change after the layoff process.

The decision to continue or terminate a working relationship is fundamentally economic, guided by a cost-benefit analysis that considers both immediate and long-term implications. This fundamental concept underpins contemporary labor market models (Pissarides, 1985; Mortensen, 1998; Burdett and Mortensen, 1998). The economic nature of this decision is further underscored by the fact that it can be influenced by the management style and future plans of the firm. In the earlier models, workers compared their share of the match surplus (the economic gains to maintaining the employment relation relative to each party's outside option) to their outside option value, typically searching for another job in a different firm, and would quit when the outside option exceeded their share of the match surplus. Likewise, firms compare their share of the match surplus against the value of firing the worker and searching a new worker, with all relevant adjustment costs included. By comparing these scenarios, each party determines whether continuation or separation offers a more favorable outcome, and the employment relation only continues when both sides prefer to maintain it.

The role of productivity Consider an exogenous shock to firm-level productivity. When wages are flexible, productivity changes translate directly into wage changes at any time. When wages are not flexible (for example if wages are set and negotiated in a contract), changes in productivity will affect the value of the match both for the worker and the firm. If the remaining in the match is not profitable for the firm, it will terminate it. We refer to this as a '*involuntary*' separation since the worker did not initiate it. If, however, the value to the worker of remaining in the match is lower than the value of the outside option, the worker will dissolve the match. We refer to this as a '*voluntary*' separation since is initiated by the worker. As formalized by Cahuc et al. (2006), the firm can prevent voluntary separation with wage adjustments. More productive matches, or increases in the outside option, generally are translated in higher compensation in the form of higher wages.

In settings where workers possess diverse skill sets, the same productivity shock may affect differently according to the nature of the production process and the degree of mismatch between skill demand and skill supply. When worker and firm types are complementary, the same shock can significantly impact the match valuation of both workers and firms, thereby influencing the likelihood of separation (Lise and Robin, 2017). Wage renegotiation might happen using several mechanisms that depend on 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, wage adjustments may not be feasible in the face of a negative productivity shock due to regulatory, contractual, and internal labor market factors. Regulatory constraints, such as binding minimum wage laws, can prevent firms from making significant wage cuts, potentially leading to layoffs instead. As suggested by competitive labor market models, an increase in the minimum wage could also increase the outside option value for workers, consequently prompting more voluntary separations as fewer matches become profitable (Mortensen and Pissarides, 1994).

Even without minimum wage regulations, wage cuts may be impractical due to existing contractual agreements. Formal employment contracts often stipulate fixed compensation levels that cannot be unilaterally modified by either party. Moreover, wage floors at the occupation level —sectoral and collective agreements —are prevalent in many European countries, further restricting firms' ability to make downward wage adjustments (Card and Cardoso, 2022). Informal employment contracts, such as implicit contracts based on worker performance or investment in specific human capital, can also contribute to wage rigidity (Jovanovic, 1979; Lazear and Rosen, 1981). Internal labor markets, characterized by vertical mobility and increasing wage profiles, serve as another example of informal contracts that discourage downward wage adjustments (Dohmen et al., 2004; Huitfeldt et al., 2023). Finally, behavioral factors, such as worker perceptions of fairness, can prevent wage reductions (Kaur, 2019). Collectively, these nominal wage rigidities are often associated with mass layoff decisions (Ehrlich and Montes, 2024).

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 (Fallick, 1996; Martin and Scarpetta, 2012; Raposo et al., 2021). When making layoff decisions, management weighs the trade-offs associated with search, hiring, and firing costs (Hamermesh, 1993; Abowd and Kramarz, 2003; Kramarz and Michaud, 2010), along with the potential impact on overall firm productivity across time. This behavior leads to firm employment that fluctuates over time with the broader economic environment (Davis and Haltiwanger, 1992, 1999; Davis et al., 2012; Duhautois and Petit, 2023).

The role of firm organization A second factor influencing layoff decisions is the organizational structure of the firm. The firm's life cycle may also play a crucial role in determining the composition and size of its workforce (Simon, 1962; Lucas, 1978; Calvo and Wellisz, 1978). The type of knowledge required by the firm at each stage of its development dictates the optimal occupational structure, work organization, and productivity (Handwerker et al., 2021; Garicano and Rossi-Hansberg, 2015). For instance, a newly established firm would likely invest heavily in research and development, hiring high-skilled workers specialized in this area during the initial phase. Subsequently, the production phase would demand different types of tasks and skills, resulting in a different occupational composition. The internal elements of a firm's organization and the interactions among these elements have implications for firm performance Simon (1962). Management decisions, the firm's long-term vision and growth strategy can thus impact workforce composition and firm size.

Technological innovation is another key determinant that shapes the organizational structure of firms. The implementation of new technologies often necessitates the adaptation of workers' skills and knowledge and can potentially impact how the firm organizes its operations (Autor et al., 2003; Acemoglu et al., 2022). For instance, Michaels et al. (2014) documented the transformation of occupational structures resulting from the adoption of information and communication technologies (ICT) across 11 countries (including France), over a 25 years period.

Firm organization, including managerial decisions regarding production locations and product offerings, also plays a role in shaping workforce size and composition. For example, Blinder and Krueger (2013) analyze the effect of technology and offshorability on the structure of occupations, finding significant effects for both, with the effects being larger for technology. The implementation of such processes often leads to changes in the type of skills and tasks required (Hershbein and Kahn, 2018). In France's case, Harrigan et al. (2020) demonstrated an occupational shift in the composition of French workers between 1994 and 2007, in which firms employing "techies" in 1994 experienced an overall skill upgrade by the end of the study period. They show how the type of technology employed can orient demand for a specific type of worker, and that appropriately modifying the composition of occupations and skills in the workforce can significantly impact productivity (Harrigan et al., 2023). For preexisting firms, this strategic modification of the composition and structure of the firm's workforce can be done particularly rapidly in the context of a mass layoff.

The role of the cost structure As noted above, mass layoffs entail adjustment costs. These costs are primarily determined by job security provisions, such as employment protection legislation (EPL), which regulates the costs of dismissal. It is well established, for example, that increasing severance pay tends to reduce layoffs at the expense of job creation, suggesting that higher firing costs can influence hiring decisions (Boeri et al., 2017; Garibaldi and Violante, 2005). When these costs become substantial, firms may prefer to retain less productive workers than to fire them and incur the adjustment costs. This "labor hoarding" occurs when the separation costs outweigh the present discounted value of the profit gains from terminating the employment relationship. However, in cases where firms can aggregate the costs of dismissal and these costs exhibit decreasing returns to scale (Abowd and Kramarz, 2003), mass layoffs can allow firms to bundle displacements and reduce the per-worker adjustment costs relative to repeated individual layoffs (Signoretto and Valentin, 2019), giving them an incentive to eliminate less productive matches in bulk.

The factors highlighted above demonstrate the interplay between economic shocks, strategic decisions, and the quality of the match between workers and jobs. While external shocks undoubtedly influence firm behavior, employers also make proactive choices that shape their workforce composition and organizational structure. By carefully considering their future plans, strategic investments, and the constraints and costs imposed, firms strive to optimize their workforce to achieve their long-term objectives. In this context, assessing the costs associated with employing a worker, and thereby how many and which workers will be dismissed in a mass layoff, goes beyond simply evaluating their wage. It necessitates a model that can accommodate skill compatibility, job requirements, and the firm's overall strategic objectives.

3 Data

This section describes the data sets and variables employed in our analysis. To provide readers with a comprehensive understanding of how we utilize the data, we initially outline the data sources, then detail the process of combining them, and finally present descriptive statistics on the analysis sample.

3.1 Data sources

Our empirical analysis draws upon four primary data sources. First, we use the DADS (*Déclaration Annuelle des Données Sociales*), a linked employer-employee dataset covering salaried workers in France constructed from firm payroll tax contribution information. We also utilize the BIC-RN (*Bénéfices Industriels et Commerciaux - Régime Normal*), which furnishes balance sheet information on French firms with at least 50 employees, alongside the French PIAAC (*Programme for International Assessment of Adult Competencies*), a survey run by the OECD that provides a characterization into adults' skills and competencies. Finally, we exploit information from the O*Net database of occupational requirements and characteristics. This section provides a description of each data source, along with the specific information we extract from each.

3.1.1 DADS: linked employer-employee of French social security records

Our primary data source for employment and earnings data is the DADS, a linked employer-employee database compiled from employers' payroll declarations to social security and tax authorities. This dataset is available in several formats that differ in their sample characteristics and usage. Each version possesses its unique advantages and drawbacks.

DADS Postes: This version of the database compiles information annually at the establishment-employee match level, and covers the universe of non-public sector employees in France. We utilize the sample spanning the period 2003-2017. The dataset provides information at the firm, establishment, and worker levels. For any existing labor relationship, a record comprises firm and establishment identifiers, basic worker and firm demographic characteristics, and information specific to the match.

Although each record uniquely identifies the firm and the establishment, which allows us to follow them over time, this is not the case for employees, whose identifiers change annually. This limitation restricts our ability to track workers using the time panel dimension. However, the dataset's unique structure, encompassing detailed information for each worker's current and previous year, permits identifying and tracking the evolving composition of firm and workforce characteristics at the firm level over time.

Each data record provides basic demographic characteristics, including occupation, age, and gender. When the occupation variable, which is key for our analysis, is missing, we impute the missing occupation directly using information from other fields such as the socio-professional category and occupation from the current and previous year. This approach reduces the frequency and sparsity of missingness. Additionally, we recode the occupational information from the French classification systems (PCS-82 and PCS-ESE 2003) to the international standard (ISCO-08) to ensure consistency and comparability with the data from other sources.

Each record also provides detailed information about the employment relationship, encompassing wage, contract type, first and last days of paid employment in the calendar year[4], and collective agreement coverage. Given our objective of calculating firm size at

[4]For calendar years in the middle of a multiple-year employment spell, the first day of paid employment will be day 1 and the last day will be day 360, as the DADS coding adopts a 30-day months for all months and all years. This implies that day 60 never has any observations and day 30, for example, will include events that occur on

a very high frequency, we employ a data cleaning procedure to correct inconsistencies in start and end dates when there are more than two spells for the same individual in the same establishment of the same firm in the same calendar year (approximately 5% of all observations).[5] Additionally, each record details basic firm characteristics, such as region and sector.

We apply several basic restrictions to our sample. First, we focus on the "true" employment, using the French Institute of Statistics definition.[6] We remove observations for which we can not identify the gender, occupation, age, and sector. We also restrict our sample to the the firms that have financial information (see section 3.1.3 below).

DADS EDP Panel: This data set combines the panel version of the DADS database with the permanent demographic sample (EDP - *Echantillon Démographique Permanent*). The DADS EDP panel covers approximately $1/12$ of the French workforce, selecting all individuals born in October and tracking their employment history across multiple jobs. The resulting panel structure provides comprehensive longitudinal data at the firm, establishment, and worker levels. Each record uniquely identifies both firms and workers, enabling us to follow their evolution over time and potentially control for unobserved firm and worker characteristics. In addition to standard worker demographic variables (age, sex, seniority) and job characteristic variables (firm characteristics, wage, and occupation), the data set offers valuable information on educational attainment, marital status and the birth ages of children, drawn from the census and administrative records such as birth and marriage certificates.

3.1.2 O*Net: Occupation characteristics

To gauge the skill requirements of firms, we rely on detailed occupation descriptors from the O*Net database. O*Net provides up-to-date information on several dimensions of each occupation, including knowledge, skills, abilities, tasks, work activities, and work context. Unlike traditional occupational classifications, which are fixed and serve as a method of

January 30 and January 31.

[5] Since we know the number of distinct spells for each match and the start and end dates of up to two spells per match per year (including the earliest start date and the latest end date when multiple spells are present), we adjust these observations by adding the correct number of (approximately) equal length spells such that the total length of spells coincides with the number of days of paid employment, as reported in the data, without making them overlap. This correction facilitates precise calculations of firm size and its fluctuations.

[6] Our analysis focuses on "postes non annexes". According to the DADS guide, a job is classified as "non annex" if the net remuneration exceeds three times the minimum wage (SMIC) per month or if the employment relationship persists for more than 30 days and 120 hours with an average of at least 1.5 hours worked per day over the interval.

classification, O*Net is a taxonomy that links each occupation to a set of detailed descriptors. The O*Net database contains information for 965 occupations and, while constructed for the US, has proven useful for other countries (Galbis, 2020). For skill measures, O*Net provides granular information on 35 skills, clustered into groups based on the aspect of work covered. These range from basic skills like reading and writing to complex skills like judgment and decision-making. Sections 3.1.4 and A.1 in the appendix provide more details on how we reduce the number of skills to three and aggregate them at the firm level to describe the firm's skill requirements.

3.1.3 BIC-RN: balance sheet information on firms

The BIC-RN dataset encompasses fiscal year information gathered from firms' tax declarations and balance sheets. The accounting data originates from firms' tax filings, systematically collected by the Ministry of Finance. Leveraging this information, we derive key financial indicators: value-added, return on investment (ROI), return on equity (ROE), and EBITDA. The BIC-RN dataset shares the firm identifier with the matched employer-employee data, enabling us to seamlessly merge these data sources. However, the records are in the form of one record per fiscal year, which does not necessarily align with calendar years. Fortunately, the start and end dates of each fiscal year are provided, which allows us to match on a day-by-day basis with the information in the DADS data.

3.1.4 Calculating firm-level skill requirements

Using the occupation information from the DADS Postes file and the O*Net database, we provide a quantitative measure that describes the skill requirements of the firm in three dimensions: manual, cognitive and social skill requirements. To construct this skill requirement metric we follow Lise and Postel-Vinay (2020). Using the information on the O*NET skills, using a principal component analysis (PCA) we reduce the dimensionality of the available 35 skills into a matrix of dimension three. Each of the vectors is then normalized to be comprised between 0 and 1. Following Autor et al. (2003), we apply a crosswalk between the International Standard Classification of Occupations in its 2008 version (ISCO-08) and the Standard Occupational Classification (SOC), which allow us to connect the O*NET skill requirements to the DADS Postes data at the record level.[7] Using the detailed information on start and end dates of individual employment spells within the firm and summing across individuals employed on each day within each firm, we are able to construct daily information on firm size and workforce characteristics. In addition, our analysis enables us to map the daily skills requirement composition of firms and its evolution over time. This high-frequency headcount calculation allows us to identify and precisely date instances of

[7] Further details on how the occupation skills requirements are built can be found in appendix A.1.

mass layoffs.

3.1.5 PIAAC: French adults' skills and competencies

The French workers' skill endowment information stems from the PIAAC data. This survey, developed by the OECD, collected data for France occurred between September and November 2012. The PIAAC provides internationally comparable data on the skills of adult populations in 24 countries. The sample covers adults between the ages of 16 and 65.

The PIAAC survey includes a rigorous assessment of cognitive skills in two primary domains, literacy and numeracy. For literacy, the survey evaluates individuals' ability to comprehend, evaluate, utilize, and engage with written materials. For numeracy, it assesses an individual's capacity to solve real-world problems by connecting them to mathematical data and concepts. It is crucial to emphasize that these measures are not self-reported but are derived from directly assessed raw test responses and other personal characteristics. To accurately assess cognitive abilities, the test was designed to adjust the questions' complexity and establish thresholds based on an individual's educational background and native language proficiency. To evaluate each cognitive component, the test is divided into two stages: the first consists of nine tasks, and the second consists of eleven tasks. PIAAC utilizes an incomplete balanced block design, meaning that not all individuals are assessed on the same components.

Furthermore, due to the adaptive nature of the test, the complexity of the questions is determined by the respondent's responses and raw responses are inherently incomplete by design. The OECD recommends employing plausible values to address this issue and provides 10 plausible values for each individual and each measure in the publicly available data. Social skills measures are derived from the responses to the Background Questionnaire (BQ) of the survey. In this section, six questions pertaining to attitudes and interests related to learning are posed. These measures are associated with personality and interpersonal skill domains.

We build our cognitive and social skills indices by combining multiple components in the PIAAC data, employing factor analysis to determine the optimal weights[8] for the construction of the skills indices. To construct a person's cognitive skills index, we combine their literacy and numeracy scores. To construct the social skills measure, we use a subset of questions specifically identified from the BQ[9].

[8] The weights are optimal in the sense that they allow us to capture the largest share of variation common to all components of the index in a single weighted average. We present more detail on the procedure and optimal weights in appendix A.2.

[9] The questions used were: Relate new ideas into real life, Like learning new things, Attribute something new,

3.1.6 Adding skill demand and supply to the DADS-EDP for measuring skills mismatch

We replicate the same corrections in the DADS-EDP data as we applied to the occupations in the DADS Postes data, and further augment the dataset with skill requirements information as described in section 3.1.4 above. Additionally, we add in information on worker skill endowments using data from the French PIAAC data. This process is explained in detail in Appendix B. Given the dataset's longitudinal nature, this allows us to identify dismissed workers and non-dismissed workers, and investigate the causes of displacement. The data's structure also enables us to control for worker type, skill mismatch, and the financial cost of each employment relationship, which will be used in section 5 to identify factors that influence displacement.

3.2 Sample description

Our empirical analysis leverages two distinct samples tailored to match each of the hypotheses of the paper. First, to examine compositional changes within firms amidst mass layoffs, we construct a panel dataset specifically focusing on firms experiencing such events. Second, to study the selective worker displacement, we utilize a panel of workers employed by firms prior to mass layoffs. Accurate identification of mass layoff events is crucial for both sample constructions, ensuring robust analysis.

3.2.1 What is a mass layoff?

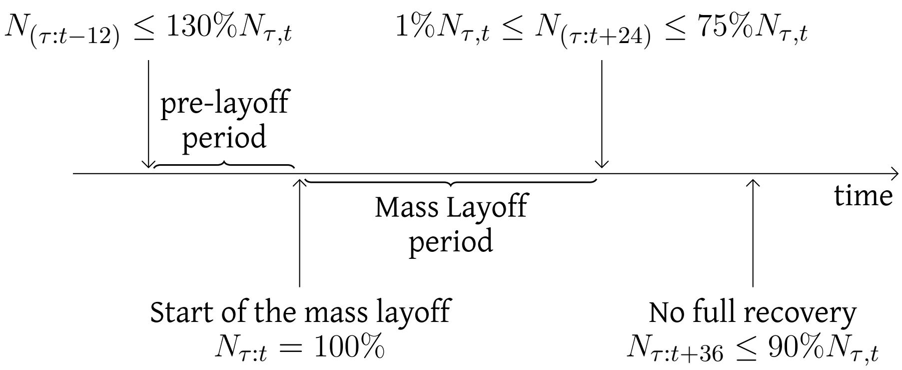
In this paper, we consider a mass layoff to have occurred when the following conditions are met: i) a firm at the start of the layoff period must have 50 employees or more[10], and ii) the firm's workforce contracts by between 25% and 99% in a two year period. The last condition avoids the possibility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

Get to the bottom of difficult things, Figure how different ideas fit together, Looking for additional information.

[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. This definition also aligns with our firm financial data, which reports information only for this sample of firms.

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 were chosen to correspond as closely as possible, given our data constriants, to those considered in the displaced workers literature (Lachowska et al., 2020; 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.

Figure 1: Mass layoff definition



Note: The figure illustrates the conditions for a firm to be considered in the mass layoff sample.

The choice of a minimum decline of 25% for characterizing a workforce reduction as a mass layoff represents an arbitrage between several thresholds found in the literature. In particular, the recent literature on separations in France has defined a mass layoff as occurring when the workforce reduces year to year by 10% or more (Royer, 2011; Brandily et al., 2020). The management literature also uses the 10% threshold is a reference point, considering such a drop to be a severe workforce reduction (Datta et al., 2010). However, our choice of a 25% threshold is close to the definition in Davis and Von Wachter (2011) (30%) and close to the above-cited literature when considered as a yearly change. Figures A4-A5 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

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

that low thresholds might disproportionately capture the seasonality of workforce variation.

3.2.2 Legal definition of a mass layoff in France

Although we define 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 a legislative requirement that depends on the number of economic displacements in the firm that occur during a fixed period of time, according to the size of the firm. An economic displacement ("licenciement économique") 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 C.1 for a detailed description of economic displacement). In practice, economic displacement in France can be particularly costly (Abowd and Kramarz, 2003).

A PSE comprises all of 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 direct costs associated with the economic displacement and the potential legal costs are taken in consideration.

Whenever a firm displaces 10 or more employees for economic reasons during a period of 30 days, it is required to propose a PSE. 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, a PSE must be put in place[12].

The definition of economic displacement underlying the PSE requirements only takes into consideration involuntary separations. However, firms might adjust their workforces using other channels due to the high cost that economic displacements impose on 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.,

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

2015) or by using a separation by common accord ("rupture conventionnelle") (Signoretto, 2013; Batut and Maurin, 2019) instead of an economic displacement. Given these options are available to many firms, downsizing might take place through a combination of economic displacements, common-accord separations and the adjustment of in- and outflows from the firm. By using adjustments in firm size, our definition are considers all types of separations, including voluntary (worker initiated quits), accidental (deaths), or legal (termination of a fixed term contract, mandatory retirement, separation for cause). In all cases, our definition allows us to observe the destruction of a job in a specific occupation that is not filled again by other worker. The effects of broadening the definition of mass layoffs beyond PSEs are visible when comparing to official statistics. When we compare PSEs to our measure that uses the size of the firm (see table C1), we find many fewer PSEs, suggesting that firms use other mechanisms besides firm-labelled economic displacements to reduce their workforce.

3.2.3 Sample description

We use our data on the firm's daily size over the period 2003 - 2017 and conditions i) to iv) from section 3.2.1 to identify the firms that undertake a mass layoff between 2004 and 2015 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. The worker sample, containing worker demographic characteristics and firm characteristics, allows us to examine selective displacement.

Control group We construct a control group for the firms that experienced a layoff by selecting comparable units based on employment structure, firm sector, and firm financial indicators measured 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. The financial indicators used balance sheet data to 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 firms that experienced a mass layoff with all firms that never experienced a mass layoff using single nearest neighbor matching based on a propensity score calculated with a logistic regression. We perform the match with replacement, so the order of the matching does not change the result of the algorithm (Imbens, 2015). Table A5 and figure A6 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, matching that generates well-balanced samples reduces the risk that our results will be sensitive to specification choices and outliers. In the tables we present both the t-statistic and the standardized difference, since the latter is more appropriate to assess the difference in the covariates (Imbens, 2015). Table A6 presents the normalized mean differences in all years in the sample. Table A7 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.

Firm 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 directly (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 have reduced their workforces by 35% on average. As can be seen in the figure, on average, this change is gradual. The layoffs initially start slowly and accelerate 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, is not due to our specific criteria for defining a mass layoff (which impose no constraints on the evolution of employment during the two years following the start of the layoff) 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% Manufacturing.

Worker characteristics To study how firms select workers into displacement, we construct from DADS-EDP panel a sample utilizing our identified mass layoff firms. The worker sample includes all workers employed at the firm during the layoff event, regardless of displacement status. Including both displaced and non-displaced workers, allows for a richer understanding of firm-level restructuring dynamics. We focus on the year of identification of the mass layoff and the preceding year, aligning with the displacement literature that acknowledges potential early exits of high-skilled workers (Schwerdt, 2011). Our analysis sample is further restricted to the observations for which the hourly wage is larger than 70% of the minimum wage and where the covariates of interest are non missing. We also only include workers that have worked in the firm for more than 8 months, to avoid including workers that are in their trial period. Table 2 presents the sample's main characteristics. We use information on age, seniority, education, regional location, collective agreements, and associated labor costs. As discussed in Section 5.1, these costs can be further disaggregated into skill mismatch, relative worker cost, and relative worker quality.

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

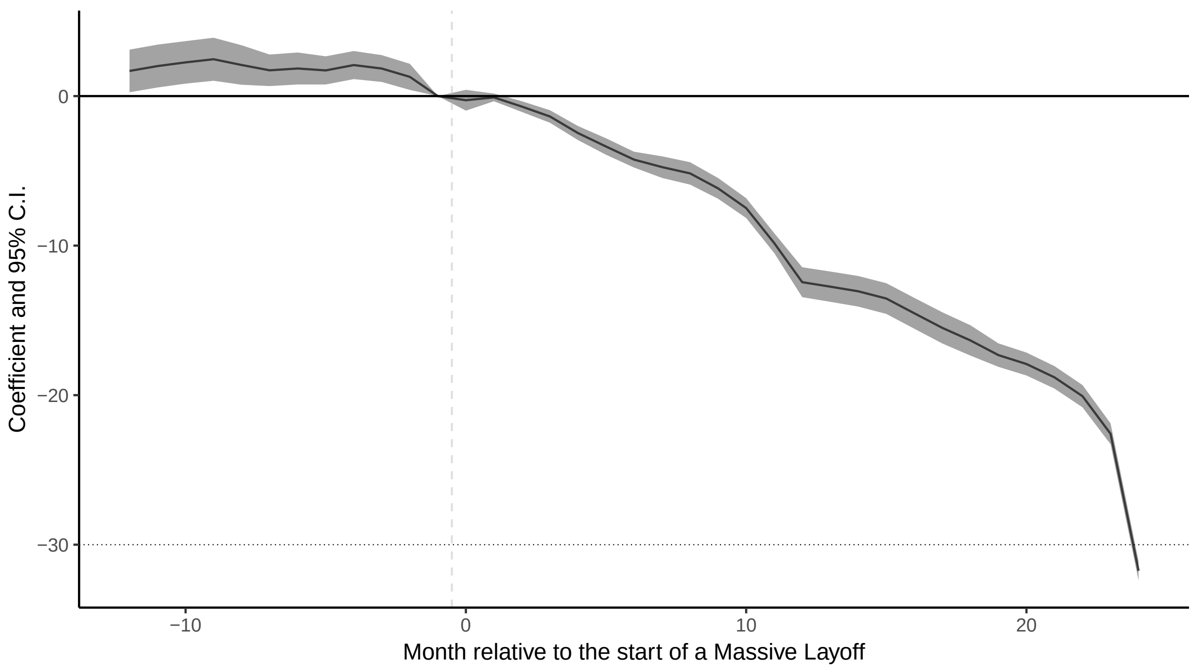
Source: DADS-EDP panel merged with BIC-RN. The statistics are calculated relative to the start of the layoff event. The variables are winsorized and standardized for ease of interpretation in the regression.

Table 2: Summary statistics

	Non Displaced		*Displaced*		
	Mean	St. Dev.	Mean	St. Dev.	Difference
Mismatch					
Cognitive	0.690	0.825	0.681	0.782	0.010
Social	0.657	0.727	0.763	0.754	-0.106
Demographic characteristics					
Male	0.64	0.47	0.59	0.49	0.05
Age	38.33	9.55	36.16	9.58	2.17
Relative Wage $\log\left(\frac{w_{it}}{\tilde{w}_{ot}}\right)$	3.85	3.80	2.48	2.92	1.37
Worker quality	0.03	0.30	0.00	0.31	0.03
Education					
Lower secondary or less	16.8%		20.9%		-4.14%
Upper and Post Secondary	35.7%		36.8%		-1.11%
Bachelor	34.4%		30.8%		3.55%
Higher Tertiary	13.1%		11.4%		1.70%
Occupation - ISCO major groups					
Clerical and Sales (4,5)	8.0%		8.7%		-0.72%
Crafts, operators and alike (6 to 9)	26.6%		31.7%		-5.17%
Managers (1)	8.8%		5.8%		3.04%
Professonals and technicians (2,3)	56.6%		53.8%		2.83%
Firm characteristics					
Value added	0.49	0.27	0.50	0.27	-0.02
ROA	-0.01	1.00	0.10	1.04	-0.10
ROE	-0.01	1.00	0.13	1.00	-0.15
Purchases/Sales	-0.01	1.01	0.04	0.94	-0.05
Sector					
Industry	28.3%		16.4%		11.86%
Construction	4.7%		2.6%		2.09%
Commerce	13.2%		10.0%		3.24%
Services	53.8%		71.0%		-17.20%

Source: DADS-EDP panel.

Figure 2: Employment evolution in the mass layoff sample



4 Firm restructuring

This section investigates whether mass layoffs serve as an opportunity for firms to restructure their skill requirements. To understand how we capture skills changes at the firm level, imagine two identical firms: same sector, size, and occupational distribution. Each firm has ten managers, and each manager supervises a team of five workers (60 workers in each firm). The only difference between the firms is their behavior during a mass layoff. During a mass layoff, one firm had to downsize and laid off five of its managers and the teams under their supervision (30 layoffs). 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, the mass layoff impacted exclusively the team workers, since it decides to keep all ten managers but only two workers per team (30 layoffs). In this example, both firms downsize by the same amount, but the second firm restructures its workforce while the workforce structure of the first firm remains constant.

To examine the effect of a mass layoff on the skills composition of firms, we adopt an event study approach. Specifically, we map skill requirements obtained from O*NET to each worker's occupation and then aggregate them to the firm level as described in section 3.1.4, generating a vector of average skill requirements for each firm at each day in our sample. This approach allows us to track and analyze changes in average firm-level skill requirements following mass layoff events. These aggregated skills scores serve as our principal outcome variables for subsequent analysis. We isolate the effect of layoffs by comparing changes in skill intensity between affected firms and similar unaffected firms before and after the layoff event. This aggregated skill score serves as our principal outcome variable for subsequent analysis.

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

$$Y_{jts} = \alpha_{js} + \omega_{ts} + \sum_{k=-12}^{24} \gamma_{ks} 1_{\{K_{jt}=k\}} \times G_j + \epsilon_{jts} \tag{1}$$

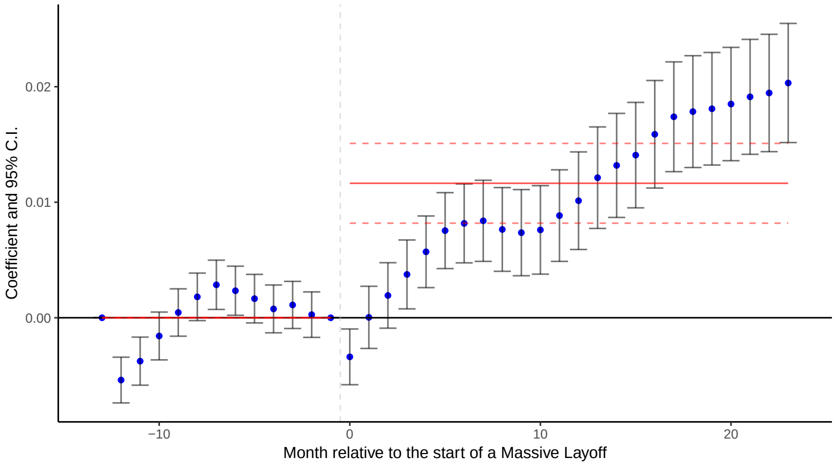
where the outcome of interest Y_{jts} is the average amount of skill s in firm j at time t, the coefficient γ_{ks} captures the change in the outcome variable with respect to the beginning of the mass layoff event[13]. We also include firm fixed effects α_{js} and year fixed effects ω_{ts} that can vary with the skill type. 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 (see section 3.2.3 for details on the construction of the control group). In terms of skill types, we consider separately cognitive, social, and manual skills and define the layoff event with the criteria listed in section 3.2.1.

Figure 3 illustrates the results of our analysis. The figure depicts the estimated changes in the outcome variable (average firm skill requirements) and their 95% confidence intervals across the 24 months following the start of the mass layoff events. The horizontal red line represents the average difference-in-differences (DID) estimate, capturing the overall impact of layoffs on skill composition. We observe that, on average, the firm uses more social skills ($+1.2$ standard deviations) and less manual skills (-0.5 standard deviations) over the 24 months following the start of the mass layoff. The effect on cognitive skills is also negative and quantitatively small (ranges from -0.25 to 0.8 standard deviations). The difference-in-differences estimates are all significant, and all the p-values are under the 0.05 threshold. Furthermore, there do not appear to be significant pre-trends, although the results for social skills somewhat resemble a pre-trend that was interrupted in the quarter prior to the mass layoff[14] As might be expected, the magnitude of our results is expected to be small since we are analyzing changes in the skill composition of large firms over a relatively short time frame (24 months).

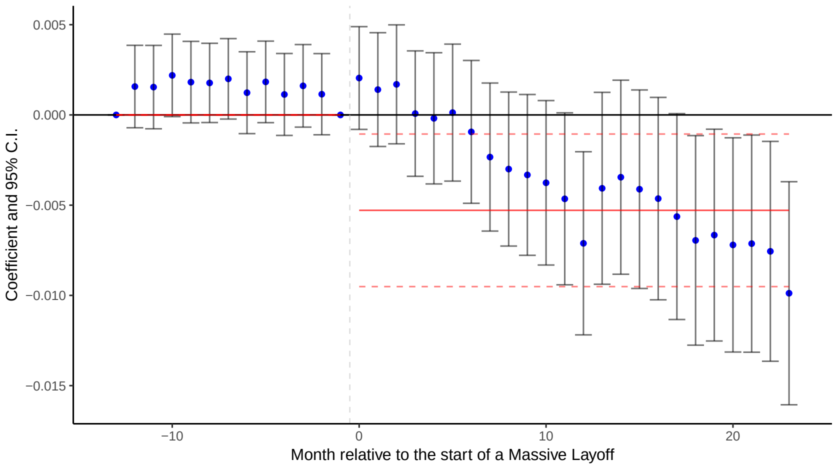
[13]Following Borusyak and Jaravel (2017) we drop the period $k = -1$ and $k = -12$ (the period furthest in the past relative to the reference period of $k = -1$). This implies that $\gamma_{k=-1}$ and $\gamma_{k=-12}$ are not identified.

[14]Recent literature (Roth, 2022) cautions against simply considering the significance of the coefficients in the period before treatment as a validation of the common trends assumption needed for causal interpretation.

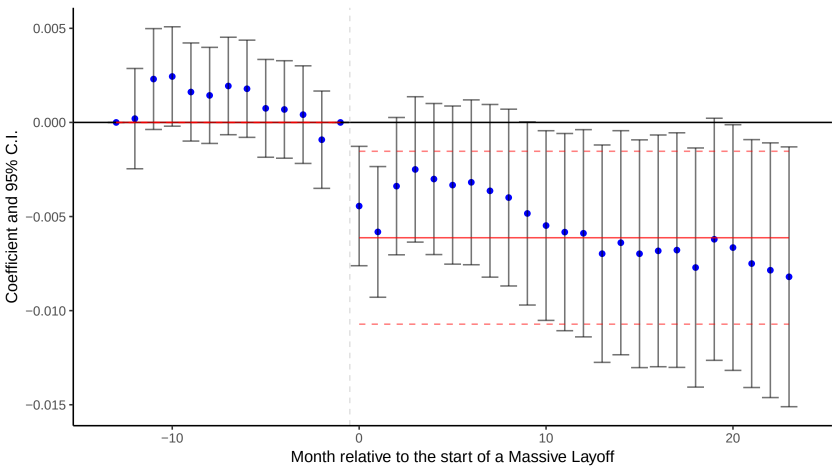
Figure 3: Skills requirements evolution after a mass layoff



(a) Social skills requirements



(b) Manual skills requirements



(c) Cognitive skills requirements

Note: Panels (a), (b) and (c), present the average social, manual, and cognitive skill requirements across firms before and after mass layoff events, normalized around the event date (time 0). The estimates are the results of estimating equation 1. The horizontal red line represents the difference-in-differences (DID) estimate, reflecting the average change in skill composition following a mass layoff. Given that the time unit is expressed in months, the DID estimator captures medium-term effects. *Source:* DADS Postes.

Recent debates in statistical literature highlight potential limitations of using matching methods to obtain robust estimates of treatment effects (King and Nielsen, 2019; Guo et al., 2022). Unobservable characteristics, when present and not homogeneous between the treated and control samples, can introduce bias to the estimates. Our research design incorporates two strategies to mitigate this concern. First, we conduct year-specific matching and assign the matched treated unit's event date to each control unit. This allows us to include year and firm fixed effects in the regression, controlling for time-invariant and firm-specific unobservables. Second, to further strengthen the reliability of our findings, we employ various weighting schemes to ensure comparability between layoff firms and matched controls.[15] We combine the selection of units using matching with re-weighting, also known as the *Tudor* solution in the statistical literature. Following Li, Morgan and Zaslavsky (2018), we calculate different weights on different target populations (ATE, ATT, ATC, ATO), and weight the estimations, to test the robustness of our estimates after matching the units. The coefficients of the difference-in-differences estimates, both unweighted and weighted, are significant and robust across specifications. The estimates are stable in magnitude and sign across all the weighting schemes (see table 3).

The positive coefficients for social skills are in line with several sets of results in the literature, including the macroeconomic results on the growth of services in the overall economy (Deming, 2017; Weidmann and Deming, 2021). 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, 2023) 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.

[15] Table A7 presents the differences for the covariates of interest between the matched and treated units.

Table 3: Difference in difference estimates for all weighted and unweighted specifications

	Dependent variable: 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)
	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 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)

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

Source: DADS postes. 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 et al. (2018).

5 Selective displacement

Understanding selective displacement is relevant for several reasons. In policymaking, identifying the specific individuals disproportionately affected by displacement is crucial for designing effective reemployment programs. These targeted interventions can then provide tailored support, maximizing the chances of reemployment and reducing the duration of unemployment for laid off individuals. From a theoretical perspective, understanding selective displacement improves our comprehension of labor market dynamics. It highlights the factors that influence worker retention and separation decisions within firms, enriching our knowledge of worker flows across diverse populations.

Insofar as economic principles underpin job separations, cost-benefit calculations that consider both immediate and long-term impacts of layoffs can be a determining factor. Based on a match's perceived value, firms can strategically select which workers to retain and which to displace. In the context of layoffs, this translates to eliminating matches where the perceived costs outweigh the (current or expected future) benefits. In order to investigate the role of "*too expensive*" matches in displacement likelihood, we proxy cost by three measures. First, we use a measure of skills mismatch (see section 5.1.1), which quantifies the discrepancy between the skills a worker supplies and skills a firm requires, capturing the extent to which the provided skill is inadequate. Second, we rank workers in their relative labor market as a proxy for their overall "quality" and use this measure to assess how worker type affects the layoff decision. We expect that better (higher-ranked) workers to be less likely to be laid off and more likely to be able to adapt to future plans. Finally, we directly assess the relative cost of employing each worker in the firm, providing a monetary measure of their perceived value. These criteria, the measurement of which we detail below, allow us to quantitatively examine the importance assigned to each dimension when firms decide which workers to select for displacement.

5.1 Measurement of costs and benefits of an employment relationship

The following dimensions capture, in part, the costs and benefits associated with an employment relationship, encompassing both monetary and non-monetary components. While the relevance of monetary aspects like wages results is evident, we expand our analysis to include non-monetary factors such as worker skill adequacy and perceived worker quality.

5.1.1 Skills mismatch

We construct indices of cognitive and social skills mismatch for each individual, taking into account the worker's skill levels 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 thus (intentionally) asymmetric around zero in the difference between skill requirements and endowments.[16]

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

where $r_{o(i,t)}^{k}$ is the amount of skill k required by the occupation that individual i occupies at time t and s_{it}^{k} is the amount of skill k supplied by individual i at time t. The resulting indices are calculated separately for cognitive and social skills.

5.1.2 Worker quality

To account for unobserved worker quality, we leverage a worker's estimated wage premium. Specifically, we estimate the following wage regression using the multi-level non-nested fixed effects model by Abowd, Kramarz and Margolis (1999), in which the wage is linearly additive with worker, firm and time components.

$$w_{it} = \alpha_i + \psi_{j(i,t)} + \tau_t + \epsilon_{it} \tag{3}$$

where w_{it} is the real hourly log wage observed in period t, α_i is a worker effect which captures the time-invariant unobserved characteristics of each worker, and $\psi_{j(i,t)}$ is a firm effect, capturing time-invariant, unobserved firm characteristics for the firm j where worker i is employed at time t. We also include time fixed effect to control for shocks common to all workers at a point in time. Estimation of this model yields worker-specific fixed effects $\hat{\alpha}_i$, which can be interpret as unobserved worker quality[17]. For identification purposes, we restrict our sample to the largest connected set, which gives the largest sample in which all firms are connected by worker mobility (Abowd et al., 2002). Finally, we define relative worker quality within each relevant labor market (a combination of 2-digit occupation and year) by the normalized ranking of workers based on their estimated unobserved quality $\hat{\alpha}_i$, which we

[16]We also calculated three alternative measures of skills mismatch: the asymmetric difference in the percentile rank of an individual's skills relative to the percentile rank of the skills required for the occupation (percentile), a measure with separate indicator variables for having a skill mismatch more than one standard deviation above or below the means skill mismatch ($\mathbb{1}$-Asymmetric), and a measure that is quadratic in the size of the underskilled mismatch (Quadratic). The results for these estimates, using the PSE definition of mass layoffs, are presented in table A8.

[17]As noted in Abowd et al. (1999), the estimator $\hat{\alpha}_i$ is asymptotic in t_i, the number of observations available for an individual, and thus will be more precisely estimated for individuals with more observations in the DADS-EDP data.

denote $r(\hat{\alpha}_i)$. We thus define the relative worker quality as:

$$Q_{it} = \frac{r(\hat{\alpha}_i) - \min\limits_{l \in L(i,t)} r(\hat{\alpha}_l)}{\max\limits_{l \in L(i,t)} r(\hat{\alpha}_l) - \min\limits_{l \in L(i,t)} r(\hat{\alpha}_l)} \tag{4}$$

where $L(i,t)$ is the relevant labor market of worker i at time t. Observe that the measure varies across time, since the composition of the relevant labor market varies. The proposed measure allows us to compare the type of worker with workers performing similar tasks at any point in time, providing us with a normalized measure of relative worker quality. Inasmuch as worker adaptability is compensated in the labor market, this measure can also serve as a proxy for the ability of a worker to fit with a firm's future plans[18].

5.1.3 Perceived cost

In order to assess the effect of labor cost, we also include a variable that measures the percent difference between the real wage and the average real wage in the same occupation that year. The relative wage is defined as:

$$\bar{w}_{\Delta it} = \log\left(\frac{w_{it}}{\tilde{w}_{ot}}\right) \tag{5}$$

where $\tilde{w}_{ot}$ is the *leave-one-out* average wage in the occupation o in year t. The leave one out mean calculates the average in the relevant group excluding the wage of worker i. This measure reflects the extent to which a given worker is highly paid relative to the unconditional average of other workers doing the same job, and can serve as a proxy for the direct role that labor cost plays in the dismissal decision.

5.2 Empirical strategy and results

To investigate the role of match characteristics on the layoff decision, we estimate the following linear probability model using the information of the workers present the year of the mass layoff and the preceding year. We restrict our sample to workers with more than 8 months of experience to exclude individuals still in their trial period, as stipulated by French

[18] In the absence of a first-stage model linking worker quality to a measure of adaptability, the results of our estimates should only be thought of in terms of the reduced form, and other mechanisms besides adaptability could also underlie any results we find linking worker quality to layoff risk.

labor law[19]. The model we estimate is given by:

$$P_{it+1} = \underbrace{\rho_r + \omega_a + \psi_{j(i,t)}}_{\text{Fixed effects}} + \underbrace{\mu^k M_{it}^k + \delta \bar{w}_{\Delta it} + \xi Q_{it}}_{\text{Match value cost}} + \underbrace{\mathbf{x}_{it}\beta}_{\text{Controls}} + \epsilon_{it} \tag{6}$$

where P_{it+1} is an indicator function equal to one if the worker i has separated from the firm $j(i,t)$ and zero otherwise, for each period $t+1$. $\psi_{j(i,t)}$ is a time-invariant firm fixed effect, which takes into account the fact that firms different sectors and of different sizes have different productive technologies, and thus different skill compositions. $\psi_{j(i,t)}$ also captures different management styles and human resource management practices, as well as the fact that we identify layoffs using the firm level ("*entreprise*") measures, and not measures at the establishment level ("*établissement*")[20]. To account for different labor market conditions that vary with a jobs' geographic location, we also included a worker region of residence fixed effect (ρ_r). Recognizing that there could be 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[21]. Note that we include worker fixed effects via a transformation of the estimated worker pay premium from the AKM estimates (see section 5.1.2), where we use the relevant market definition at the year and occupation level when building the relative worker quality measure.

Our model also includes the three measures of the costs and benefits of the match defined in section 5.1 in order to see if they are predictive of the selection into displacement. This allows us to quantify the role of skills mismatch, of worker quality and the perceived cost to the firm. Finally, the $\mathbf{x}_{it}$ term includes financial variables (value added, ROA, ROE and purchases/sales), demographic variables of interest and additional time-varying controls that have been shown to be related to worker displacement, specifically sex, age, education and job seniority.

Table 4 presents the results for the estimation of Equation 6. Our findings reveal that the three match value cost-related components are are helpful for understanding selection into

[19]Technically, managers ("*cadres*") can have a trial period of up to 4 months, renewable one time. Technicians ("*agents de maîtrise*") have a maximum trial period of 3 months (once renewable) and less-qualified workers ("*ouvriers*") have a maximum trial period of 2 months (renewable once).

[20]As noted in section 3.2.2, the legal definition of a mass layoff applies to employment changes at the firm, not establishment, level. Furthermore, an individual who leaves a job in one establishment of a firm to move to another establishment of the same firm cannot be considered to be part of a mass layoff.

[21]In France, collective agreements can cover multiple firms in multiple regions, and firms can also have establishments in multiple regions and be signatories to multiple collective agreements. This implies that the set of fixed effects is non-nested, although the set of fully identified collective agreement effects depends on the connectedness of the network of agreements and firms. As these fixed effects are incidental parameters to the main model, we do not focus on the the conditions for their identification here and simply note that the parameters of the "match value cost" part of the model remain consistent even when certain collective agreement effects are unidentified.

Table 4: Selective displacement - Linear probability model

	(1)	(2)	(3)	(4)	(5)
Skills mismatch					
Cognitive	0.003^{**}	0.007^{***}	0.007^{***}	0.007^{***}	0.009^{***}
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Social	0.008^{**}	0.010^{***}	0.010^{***}	0.010^{***}	0.009^{***}
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
Worker characteristics					
Male		-0.029^{***}	-0.031^{***}	-0.031^{***}	-0.026^{***}
		(0.002)	(0.002)	(0.002)	(0.002)
Age		0.002^{***}	0.002^{***}	0.002^{***}	-0.004^{***}
		(0.001)	(0.001)	(0.001)	(0.001)
Age^2		-0.000^{***}	-0.000^{***}	-0.000^{***}	0.000
		(0.000)	(0.000)	(0.000)	(0.000)
Seniority		-0.008^{***}	-0.009^{***}	-0.009^{***}	-0.008^{***}
		(0.001)	(0.001)	(0.001)	(0.001)
Seniority^2		0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}
		(0.000)	(0.000)	(0.000)	(0.000)
Upper and Post Secondary		-0.015^{***}	-0.016^{***}	-0.016^{***}	-0.016^{***}
		(0.003)	(0.003)	(0.003)	(0.003)
Bachelor		-0.027^{***}	-0.029^{***}	-0.029^{***}	-0.026^{***}
		(0.003)	(0.003)	(0.003)	(0.003)
Higher Tertiary		-0.013^{***}	-0.015^{***}	-0.015^{***}	-0.006
		(0.004)	(0.004)	(0.004)	(0.004)
Perceived cost					
$\frac{w_{it}}{\tilde{w}_{ito}}$			0.017^{***}	0.018^{***}	0.060^{***}
			(0.003)	(0.003)	(0.004)
Firm characteristics					
Value added				-0.012^{*}	-0.012^{*}
				(0.007)	(0.007)
ROA				-0.001	-0.001
				(0.002)	(0.002)
ROE				-0.000	-0.000
				(0.001)	(0.001)
Purchases/Sales				0.001	0.002
				(0.005)	(0.005)
Relative quality					
Relative w. quality					-0.129^{***}
					(0.009)
R2	0.324	0.328	0.328	0.328	0.329
N	171120	171120	171120	171120	171120

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

Source: DADS-EDP panel. The table presents the average coefficient and standard errors estimated from the $k-$regressions presented in equation 6. All regressions include firm, region, and collective agreement fixed effects.

displacement. When we consider skills mismatch, the results suggests that workers with a larger mismatch between their skills and the job requirements are more likely to be laid off. This relationship is positive and significant for cognitive and social skills mismatch in all the models compared. This association persists even after controlling for individual worker and firm characteristics. A one standard deviation increase in our measure of cognitive skills mismatch is associated with a 0.7[22] percentage point increase in the likelihood of being displaced in our most complete specification, which is quantitatively almost identical to the effect of a one standard deviation increase in social skills mismatch[23]. These effect sizes are relatively invariant to the introduction of additional regressors, with the exception of the effect of cognitive skills in the model with no controls other than fixed effects.[24].

Our results also show that the probability of being laid off is larger in cases where the workers wage is considered as "expensive", as measured by the worker's wage relative to the mean wage for the worker's occupation. The coefficients are positive and significant in all regressions, although this measure clearly contains a worker quality component, as can be seen by the strong increase in the coefficient when explicitly controlling for worker quality. Quantitatively, the effect is almost 25 times larger that the effects of skills mismatch in the most complete specification, as a one standard deviation increase in the relative wage leads to a 17[25] percentage point higher probability of displacement.

The effect of worker quality on selective displacement falls between that of skill mismatch and of the direct cost of labor when comparing one standard deviation-sized changes in the underlying variable. In particular, we find that a worker whose relative quality is one standard deviation higher will have an 4[26] percentage point lower chance of being displaced.

The effects of the demographic characteristics on the likelihood of selective displacement are in line with previous literature for France and Germany from almost 20 years ago (Bender et al., 2002). Even though we are considering all separations, and not only economic separations, as our outcome, the effect of age is negative once we control for worker quality, as was found in Sweden by Seim (2019) for Sweden. The estimates are also consistent with those

[22] $\mu^c = 0.009$, $\sigma^c = 0.782$, so the estimated effect is $0.009 * 0.782 = 0.007038$.

[23] $\mu^s = 0.009$, $\sigma^s = 0.754$, so the estimated effect is $0.009 * 0.754 = 0.006786$.

[24] 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. 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.

[25] $\delta = 0.006$, $\sigma^w = 2.92$, so the estimated effect is $0.006 * 2.92 = 0.1752$.

[26] $\xi = -0.129$, $\sigma^Q = 0.31$, so the estimated effect is $-0.129 * 0.31 = -0.03999$.

of Bender et al. (2002) who, although they found negative effects of age on the probability of displacement, did not control for unobserved worker quality. When considering education levels, the likelihood of being displaced decreases with high education levels (although the effect is less prominent for higher tertiary degrees) conditional on the degree of skills mismatch. The effect of seniority is decreasing but convex during over the career, while the coefficient for sex is significant across all specifications, implying that women have a 2.6 percentage point higher risk of being selectively displaced than men during a mass layoff.

When we look at the influence of financial indicators on the likelihood of displacement, only one has a statistically significant impact on the likelihood of separation, conditional on all of the individual variables and the fixed effects. Firm-level value added significantly affects individual displacement probability, in that an individual working in a firm with 1 additional standard deviation of value-added will have a 0.3[27] percentage point lower probability of separating from their employer. None of the measures of profitability (ROA and ROE) have a significant impact, nor does the ratio of purchases to sales in the firm[28]. This lack of a direct effect of the financial indicators is likely due to the presence of firm fixed effects, which absorb much of the cross-firm heterogeneity in profits within our mass layoff sample.

5.3 Heterogeneity analysis and robustness checks

In this section, we propose a series of heterogeneity analyses to gain a richer understanding of our findings, and verify the robustness of our results to an alternative definition of mass layoffs, the one defined in the labor legislation and described in section 3.2.2. For the heterogeneity analysis, we first investigate if the associations between the cost and benefit factors and separation decisions differ by industry or the presence of collective bargaining agreements. This analysis helps us better understand how different market conditions and externally-imposed constraints interact with firm-level dynamics in influencing displacement decisions. Second, we evaluate the differential impact of the cost and benefit factors by gender. Understanding whether and how women are disproportionately affected by selective displacement can allow us to propose better targeted policy interventions.

Sector heterogeneity: We begin our heterogeneity analysis by studying how the effects of our cost and benefit factors vary across broad sectors. To do so, we estimate our model separately by broad sectors and present the results in table A9, noting that there are relatively few observations underlying the commerce sector estimates, leading to lower

[27] $\beta^{VA} = -0.012$, $\sigma^{VA} = 0.27$, so the estimated effect is $-0.012 * 0. = -0.00324$.

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

precision. These sector-specific results show that although the point estimates vary, there is no significant difference between the estimated effects of cognitive or social skills mismatch on separation probability across sector. The effects of relative cost on selective displacement, however, do vary significantly (at the 10% level) across sector, with a higher relative cost mattering more in the construction and commerce sectors than elsewhere in services or in industry. Finally, a higher relative quality measure is associated with a significantly lower separation probability in the industrial sector relative to the services and construction sectors, with the effect in the commerce sector falling in the middle.

The relative importance of the different factors for the different sectors seems consistent with expectations given each sector's productive process. As the industrial sector relies more on technology and innovation than services, construction or commerce, one would expect this sector to most highly value cognitive skills that match the needs of the production process and to be wiling to pay more for quality. On the other hand, the construction and commerce sectors may not require particularly high levels of skills and these skills might be more likely to be in excess supply than the specialized skills needed by other service sector jobs or in industry, leading firms in these sectors to be particularly sensitive to labor costs. The lack of any significant difference in the importance of skills mismatch across sectors may suggest that firms are already managing skills mismatch ahead of mass layoffs such that, conditional on the collective bargaining constraints already in place, there are no other issues related to retaining mismatched workers that more strongly affect certain sectors relative to others.

Collective agreement heterogeneity: Collective agreements can be another source of heterogeneity in the mechanism by which our cost and benefit measures affect the likelihood of targeted displacement. Each collective agreement might have particularities that affect the process and selection into displacement, and if these particularities are directly or indirectly linked to our mismatch, cost and quality measures, one might expect to see different effects of these measures on the risk of selective displacement across different collective agreements. However, not all workers are covered by a collective agreement, so the sector-specific results from above could potentially differ for covered and non-covered individuals, suggesting that it could be useful to compare the risk of selective displacement for workers covered by collective agreements in the sectors studied above with uncovered workers. Accordingly, we grouped the job-specific information on collective agreements, as listed in the DADS-Postes data, into higher-level aggregates by type of job covered by the collective agreement and estimated the model on subsamples defined by these aggregates. We also estimated an additional model pooling all jobs that are not covered by any listed collective agreement in the DADS-Postes data. Table A10 shows these results.

These results show some important differences with the results by sector. Firstly, the services collective agreements seem particularly protective of mismatched workers, as neither type of skills mismatch is a significant determinant of separation for jobs covered by that agreement. On the other hand, workers with high cognitive skills mismatch are particularly at risk in jobs covered by the manufacturing or the agriculture and wood collective agreements. Interestingly, cognitive skills mismatch does not significantly affect separation probability in jobs that are not covered by any agreement. This would be consistent with a union voice model (Freeman and Medoff, 1984; Bryson et al., 2017), in which workers who feel more at risk (due to cognitive skills mismatch) might fight for union representation, while those for whom cognitive skills mismatch does not make them more likely to be laid off will be less likely to feel the need to be covered by an agreement. On the social skills side, it is again workers covered by manufacturing agreements, in addition to those covered by construction and commerce collective agreements, that are most at risk of separation when faced with a high degree of social skills mismatch. The union voice model does not appear to be relevant with respect to social skills mismatch, however, as uncovered workers are the most likely to lose their jobs in a mass layoff for any given degree of social skills mismatch, although the differences are not statistically sigificant with respect any of the sets of collective agreements.

With respect to relative cost, the specificity of services becomes even more apparent when looking at covered workers. In these instances, a higher individual wage relative to the occupation-specific average is no longer associated with a higher risk of selective displacement. As there are many small firms in the commerce sector and the collective agreement disproportionately covers the larger employers, this suggests that these agreements make the risk of separation weigh more heavily on factors other than labor cost. Conversely, the direct cost effect is particularly strong for workers covered by manufacturing collective agreements. Given that the models also control for worker quality, this effect may be indicative of firms using mass layoffs to reduce wage drift among their manufacturing jobs and and bring their salary structures back into line with those set by collective agreement.

The results concerning the impact of relative worker quality suggest that all of the collective agreements provide mode protection against separation in the even of a mass layoff for high quality workers than what they would receive in the absence of a collective agreement (although the difference is only significant relative to jobs covered by the manufacturing collective agreements). The manufacturing collective agreements are the most protective, with a one unit increase in relative quality decreasing the risk of separation by 17.4 percentage points, which is significantly higher than not only uncovered workers, but also those whose jobs in commerce are covered by collective agreements (a 10.1 percentage point lower risk). This could be reflecting the possibility that production processes for manufacturing workers evolve more frequently, in which case employers of those workers would value worker adaptability, as reflected in the worker quality measure, more strongly than for other types of jobs and this would be reflected in a stronger coefficient in our regressions.

Gender heterogeneity: The final dimension of heterogeneity that we explore concerns gender differences in displacement patterns. In order to do so, we estimate three models (presented in table A11): a model estimated only on the sample of women, a model estimated on the sample of men and a model that pools all observations but interacts our cost and benefit measures with an indicator variable for gender. While the first two estimates allow the full set of coefficients to differ by gender, the third set of estimates makes it easier to see the differential effect of our measures on the risk of selective displacement while imposing that all other coefficients are the same for women and men.

Table A11 shows that there are significant gender differences in the determinants of separation risk during a mass layoff with respect to all three of our match value cost measures. Skills mismatch is a stronger determinant of layoff risk for women than for men, regardless of the type of mismatch, although this effect is only significant for social skills mismatch in the specification which imposes common coefficients elsewhere in the model, including in the firm and collective agreement fixed effects. Women are also more susceptible to layoff risk than men when they cost more relative to the market average for their occupation, but higher "quality" women are more protected than men in the event of a mass layoff for an equivalent gain in relative quality. Taken as a whole, these results suggest a sort of duality: women's jobs are more precarious, in that the same size deviation in a "bad" direction comes with a higher layoff risk, but employers also disproportionately want to hold on to their "good" female employees, relative to their male counterparts.

Alternative mass-layoff event definition: As noted above, our analysis is based on a definition of mass layoff that is intended to be compatible with the economics literature (see section 3.2.1) instead of the definition of a mass layoff as it appears in French labor law (see section 3.2.2). In this section we explore the robustness of our results to using the alternative definition of mass layoffs as found in French labor law.

Since the legal definition of mass layoffs relies on worker outflows, we use job flows data spanning the period 2008 - 2018 from the Monthly Workforce Movement Declarations (DMMO - *Déclaration mensuelle des mouvements de main- d'œuvre*)[29] in addition to the data sources mentioned in section 3.1. To these data we apply the French PSE legislation and identify the set of mass layoff firms as in Darcillon et al. (2023). Further details on the PSE legislation are available in Appendix C.

The results from using this alternative definition of mass layoffs are presented in table A12. Relative to table 4, one can see that the model fit is significantly worse despite the fact

[29]The DMMO data collect information on the number of entries and exits into occupations from each establishment in each month, separated by type of entry (new hires, transfers from other establishments of the same firm, promotions, etc.) and exit (economic reasons, worker misbehavior, retirements, promotions, etc.). Unfortunately, the data are exhaustive only for establishments with more than 50 workers (smaller establishments are sampled in a complementary dataset called the EMMO) and some establishments only report flows on a quarterly basis, as opposed to monthly.

that the sample is 71% larger. This difference in samples is largely due to the fact that our main definition requires four consecutive years of data for a firm to apply, whereas the definition of a PSE refers only to economic displacements over a 30-day period for the main criteria, although some extended criteria consider economic displacements over a calendar year.

Despite these differences in sample composition, our main results hold using the alternative definition of mass layoffs. The role of skills mismatch is strikingly stable, with an effect of cognitive skills mismatch that is slightly higher (a 0.8[30] percentage point increase in layoff risk for a one standard deviation higher degree of mismatch, as opposed to the 0.7 percentage point effect in the main specification) and an effect of social skill mismatch which falls from 0.7 percentage points to 0.6[31] percentage points. The effects of the direct cost measure are weakened (from 17.5 percentage points to 12.3[32] percentage points), but remain highly significant. Finally, the effects of the relative quality measure also weaken but remain highly significant, going from a reduction in layoff probability of 4 percentage points for a one standard deviation increase in the worker quality measure in the main specification to an 2.7[33] percentage point reduction when using the PSE-based measure of mass layoffs. Overall, these findings provide strong evidence for the robustness of our conclusions.

6 Conclusion

In this paper, we have used a combination of linked employer-employee administrative data and survey data on skills to explore how firms restructure the composition of their workforces during mass layoffs, and the extent to which heterogeneous skills, and skills mismatch, are important determinants in deciding which workers are laid off. Our results suggest that restructuring occurs in over a relatively short time span (two years) compared to the long-term adjustment suggested by the previous macro literature, although our results are consistent with those findings. The manner in which the skills composition of the workforce evolves during a restructuring 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, relative wages and overall worker "quality" all play important roles in determining who leaves the firm. In particular, 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, collective agreement and

[30] $\mu^c = 0.010$, $\sigma^c = 0.782$, so the estimated effect is $0.010 * 0.782 = 0.00782$.
[31] $\mu^s = 0.008$, $\sigma^s = 0.754$, so the estimated effect is $0.008 * 0.754 = 0.006032$.
[32] $\delta = 0.042$, $\sigma^w = 2.92$, so the estimated effect is $0.006 * 2.92 = 0.12264$.
[33] $\xi = -0.086$, $\sigma^Q = 0.31$, so the estimated effect is $-0.086 * 0.31 = 0.02666$.

year fixed effects. Moreover, our results are robust to an alternative definition of mass layoffs that relies on worker flows (as opposed to changes in stocks) and shortens the time horizon.

Our findings can be useful for designing re-employment initiatives for recent victims of mass layoffs. This group had the greatest degree of skills mismatch in their previous job, implying that programs aiming to help them either need to change the target occupations (since their own skills, which are poorly aligned with the requirements of the job, could make the laid-off workers less attractive to firms hiring those occupations) or fill the skills gaps by providing training in the dimensions where the gaps are largest (if the same types of jobs are targeted).

Our results also suggest women's employment is disproportionately sensitive to skills mismatch, but that lower quality women (as measured by their individual fixed effects in a wage regression) tend to be overrepresented, relative to men, in the set of women who separate during a mass layoff. Insofar as the fixed effects are related to adaptability, these women may have been relatively more constrained earlier in their careers, in which case our results provide further support for initiatives that allow women to be more flexible in their responses to firm demands, such support for publicly-provided or market-based alternatives for the types of non-work activities that women disproportionately undertake.

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A Additional tables and figures

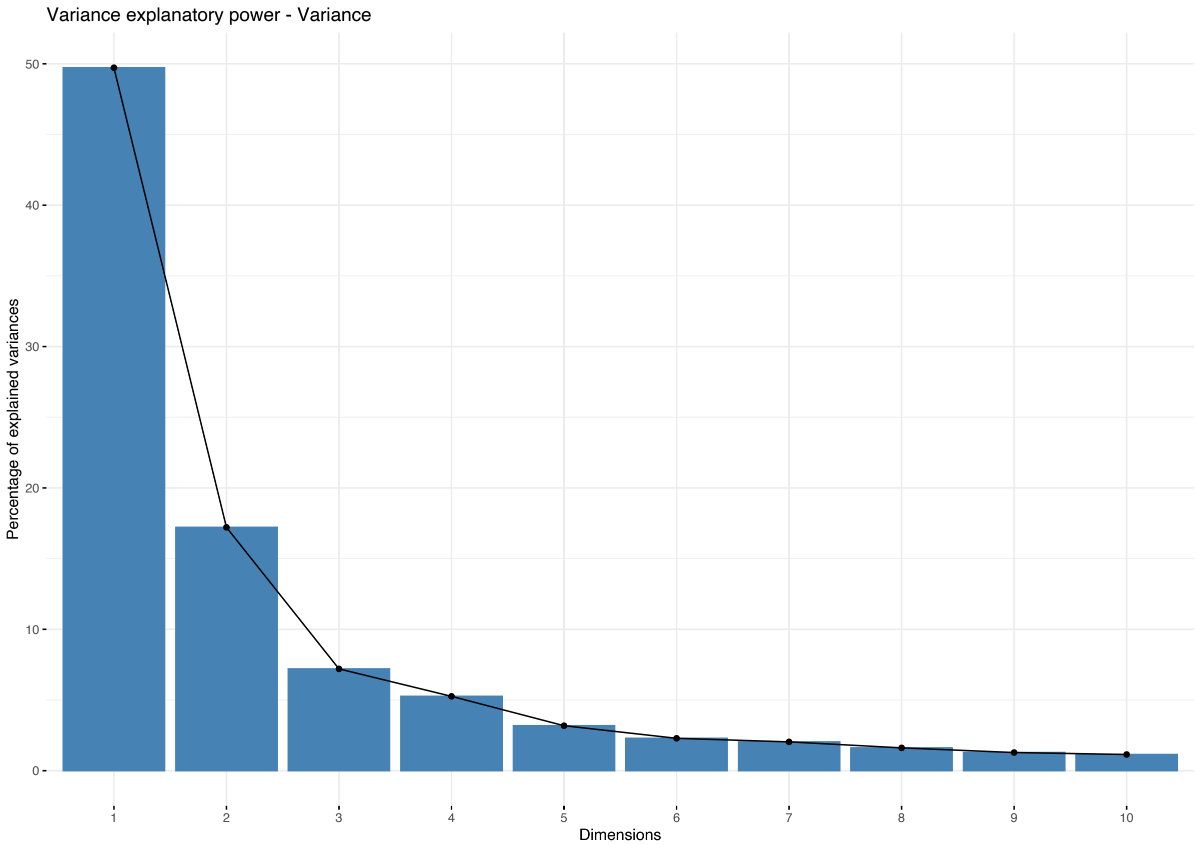
A.1 O*NET - Skills requirements

This section presents the procedure for constructing the skill requirements measures employed in our study. Drawing upon O*NET's comprehensive skill information, we leverage the 35 skill variables and conduct a Principal Component Analysis (PCA) to effectively reduce the dimensionality of the data. This data reduction technique enables us to construct a matrix that effectively maps the principal three vectors onto each of the occupations, being sure to retian the structural variability contained in the data.

One of the challenges of dimension reduction using PCA lies in determining the optimal number of dimensions to retain. Ideally, we aim to retain as many dimensions as necessary to preserve the variability and structure of the data. However, selecting too many dimensions can lead to overfitting and introduce noise, while retaining too few dimensions can result in loss of information and potential bias. Following a rule of thumb for PCA analyses, we retain the number of factors that account for two-thirds of the data variance. To apply this rule, Figure A1 illustrates the contribution of the first 10 factors to explaining the variability in the data. As evident from the figure, the first component alone explains nearly half of the variance. When we combine the second and third components, the first three components collectively account for 75% of the variability in the data. Consequently, we select the first three components for our analysis. Table A1 presents the loadings of each dimension within the resulting three factors used in the study. These loadings indicate the relative importance of each dimension in defining each factor.

To provide further meaning to our analysis, we utilize the factors loadings to group the skills into three distinct clusters. This approach effectively synthesizes the information from the 35 skills in the original dataset into three key dimensions. This allows us to classify each cluster into manual, social, and cognitive skill requirements. As depicted in Figure A2 distinct clusters emerge. The first cluster encompasses skills related to manual requirements (e.g., Installation or Repairing). The second cluster pertains to social skills associated with interpersonal relationships and soft skills. The third cluster comprises technical skills and cognitive tasks. The presented clusters incorporate information on the PCA loadings and the amount of variance they contribute to each dimension. Finally, the vectors are normalized in the interval $[0; 1]$. To validate our analysis, we rank occupations based on their skill requirements. As an illustration, Table A2 presents the top 10 occupations with the highest cognitive, social, and manual skill demands using our skills measures. Overall, the occupations seems to align well with expectations concerning their respective skill requirements.

Figure A1: Explanatory power of variance - PCA



Source: *O*NET.*
Note: The figure presents the explained variance of each of the first 10 factors.

A.2 PIAAC

Cognitive skills To construct our cognitive skills measure, we utilize the information from the two dimensions assessed in the Programme for the International Assessment of Adult Competencies (PIAAC) survey: literacy and numeracy. Due to the adaptive nature of the PIAAC test administration methodology, we employ the PIAAC's constructs, rather than raw responses.

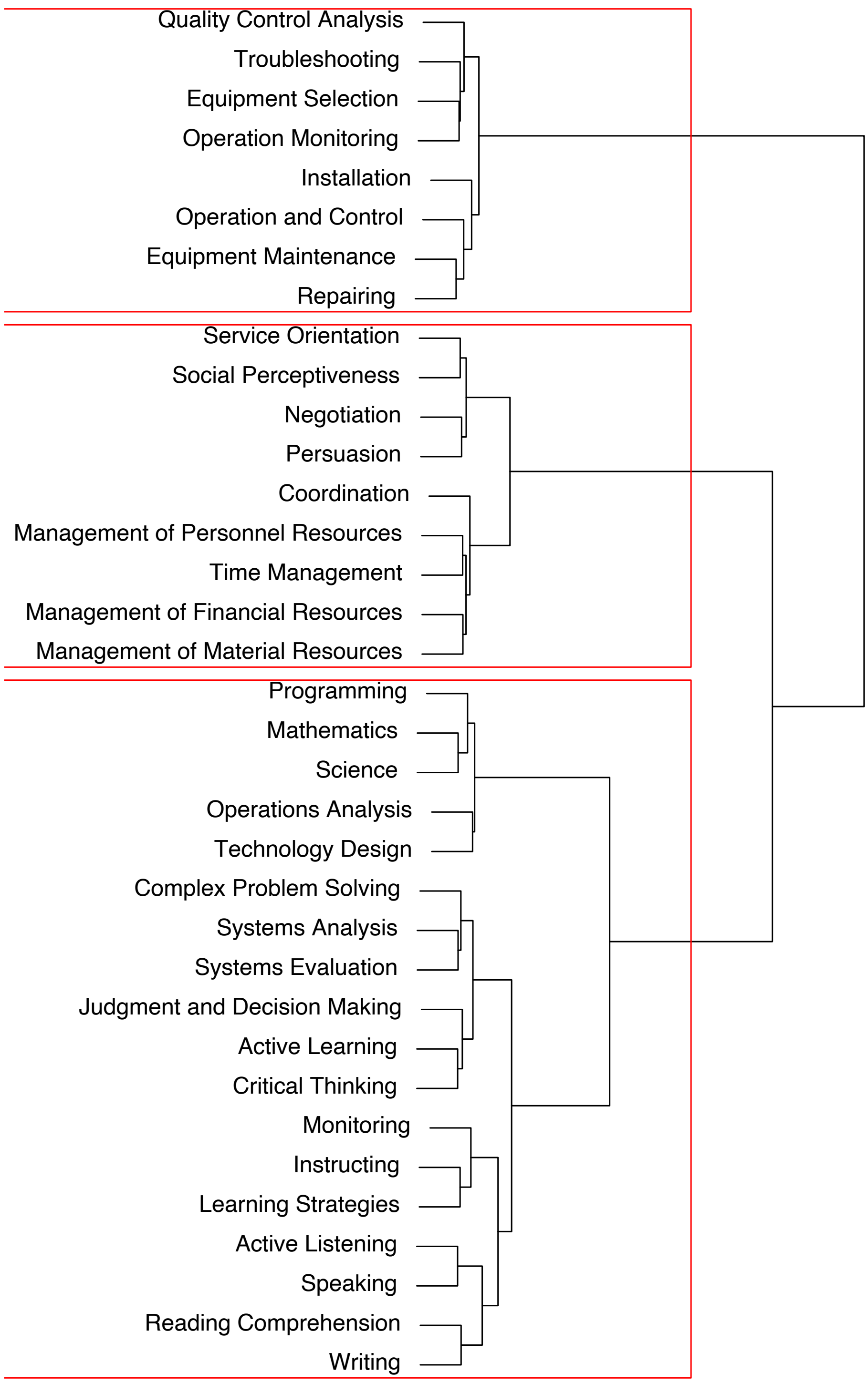
The definition of literacy is broad, encompassing the ability to comprehend texts at varying levels, from the most basic (understanding) to the most complex (applying information from texts to personal development). The design of the literacy assessment questions incorporates the ability to interpret texts within diverse contexts, including personal, health, and occupation-related scenarios, aiming to capture literacy proficiency in job-related activities. Similarly, the definition of numeracy evaluates not only the comprehension of mathematical concepts, but also the ability to locate, interpret, and

Table A1: 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*.
Note: calculations by the authors.

Figure A2: Cluster selection based on PCA and hierarchical clusters based on Ward distance



Source: *O*NET*.
Note: The figure maps the three proposed clusters using the factor loadings of the PCA procedure on the skills.

Table A2: Occupations ranked according to their skill requirements

	SOC6d	title	Manual	Social	Cognitive
1	15-2091	Mathematical Technicians	0.659	0.608	1
2	19-2012	Physicists	0.710	0.954	0.906
3	15-2021	Mathematicians	0.434	0.696	0.884
4	15-2031	Operations Research Analysts	0.457	0.754	0.784
5	17-2011	Aerospace Engineers	0.656	0.806	0.751
6	15-2041	Statisticians	0.437	0.715	0.737
7	19-1021	Biochemists and Biophysicists	0.682	0.856	0.724
8	15-1131	Computer Programmers	0.492	0.503	0.712
9	19-2011	Astronomers	0.408	0.780	0.686
10	19-2099	Remote Sensing Scientists and Technologists	0.471	0.736	0.684

	SOC6d	title	Manual	Social	Cognitive
1	49-3011	Aircraft Mechanics and Service Technicians	1	0.319	0.186
2	49-2094	Electrical and Electronics Repairers	0.950	0.329	0.251
3	17-3024	Electro-Mechanical Technicians	0.947	0.360	0.294
4	15-1142	Network and Computer Systems Admin	0.947	0.566	0.411
5	49-9041	Industrial Machinery Mechanics	0.933	0.188	0.212
6	49-9021	Heating and AC Mechanics and Installers	0.918	0.278	0.134
7	49-9097	Signal and Track Switch Repairers	0.912	0.152	0.154
8	17-2031	Biomedical Engineers	0.905	0.860	0.641
9	49-3042	Mobile Heavy Equipment Mechanics	0.889	0.226	0.148
10	49-2092	Electric Motor, and Related Repairers	0.873	0.226	0.202

	SOC6d	title	Manual	Social	Cognitive
1	11-1011	Chief Executives	0.463	1	0.128
2	11-9151	Social and Community Service Managers	0.418	0.973	0.109
3	11-9032	Education Administrators	0.428	0.969	0.134
4	19-2012	Physicists	0.710	0.954	0.906
5	29-1066	Psychiatrists	0.296	0.952	0.365
6	19-3039	Neuropsychologists	0.340	0.949	0.506
7	11-9161	Emergency Management Directors	0.419	0.941	0.145
8	19-3032	Industrial-Organizational Psychologists	0.461	0.934	0.488
9	27-2022	Coaches and Scouts	0.440	0.934	0.030
10	19-1041	Epidemiologists	0.446	0.928	0.589

Source: *O*NET.*
Note: Calculations by the authors after applying PCA and normalizing the resulting vectors. The table at the top ranks occupations based on cognitive intensity, the middle table ranks occupations based on manual requirements, and the table at the bottom ranks occupations based on social skill demands.

communicate mathematical ideas in real-world contexts, among them work contexts.

Table A3 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[34]. The results indicate that numeracy accounts for a larger share of the total variability, leading to a higher weight for numeracy in the composite cognitive skill measure.

The publicly available PIAAC data presents literacy and numeracy measures as plausible values, with ten values proposed for each dimension. Drawing from the multiple imputation methods described by Little and Rubin (2019), we can utilize these plausible values to derive a set of ten cognitive skills measures for each observation in the sample.

Table A3: Factor loadings for the construction of cognitive skills

Dimension	Variable	Weight
Plausible value - Numeric	PVNUM1	0.763
Plausible Value - Literacy	PVLIT1	0.646

Source: *PIAAC*, 2012.
Note: Authors calculations. The table shows the weights obtained through factor analysis that are used for combining literacy and numeracy measures into a single vector representing cognitive skills.

Social skills As stated earlier, the social skills measures are derived from responses to the Background Questionnaire (BQ) of the survey, specifically six questions pertaining to attitudes and interest towards learning. These measures are associated with personality and interpersonal skill domains. Consistent with the previous approach, we combine the results of these six questions into a single vector using principal component analysis (PCA). While factor analysis (FA) involves rotating the components to aid in interpreting their roles, we directly employ the PCA weights in this instance due to the non-straightforward nature of interpretation. Table A4 presents the estimated loadings for the first factor, indicating the relative importance of each question in our social skill index.

[34] We used the 'varimax' rotation, which is standard in factor analysis.

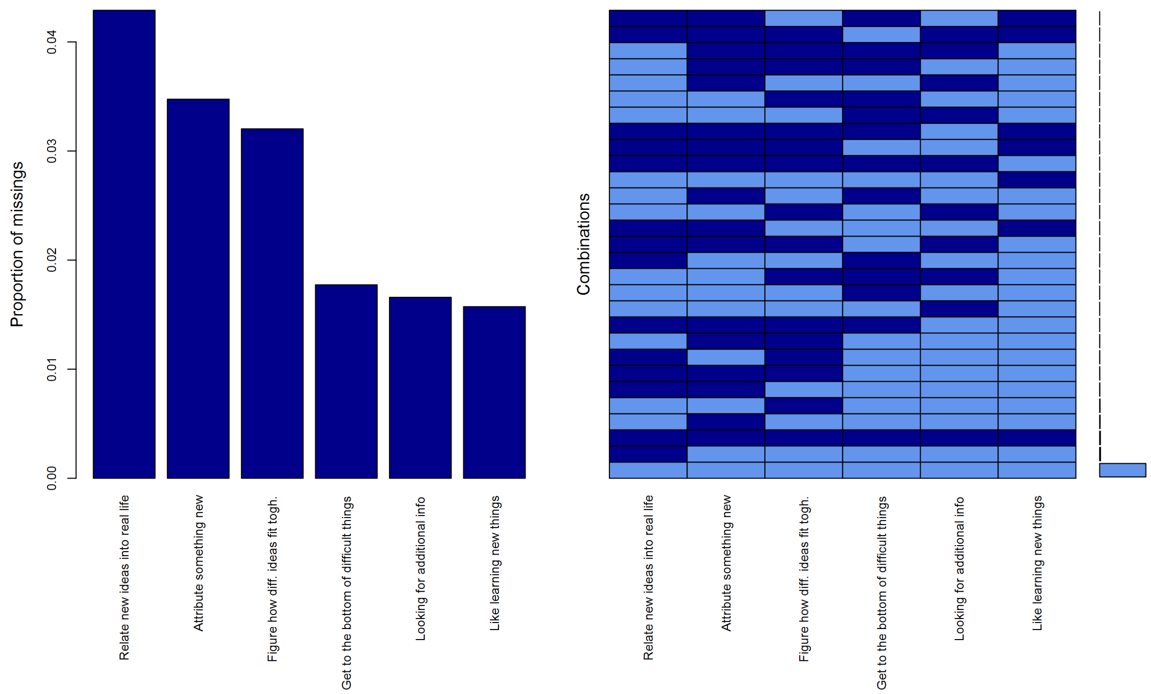
Table A4: Factor loadings for the construction of social skills

	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 how diff. ideas fit together	I_Q04l	0.728
Looking for additional info	I_Q04m	0.612

Source: *PIAAC*, 2012.
Note: Authors calculations. The table shows the weights obtained through principal component analysis (PCA) that are used to construct a single vector representing social skills.

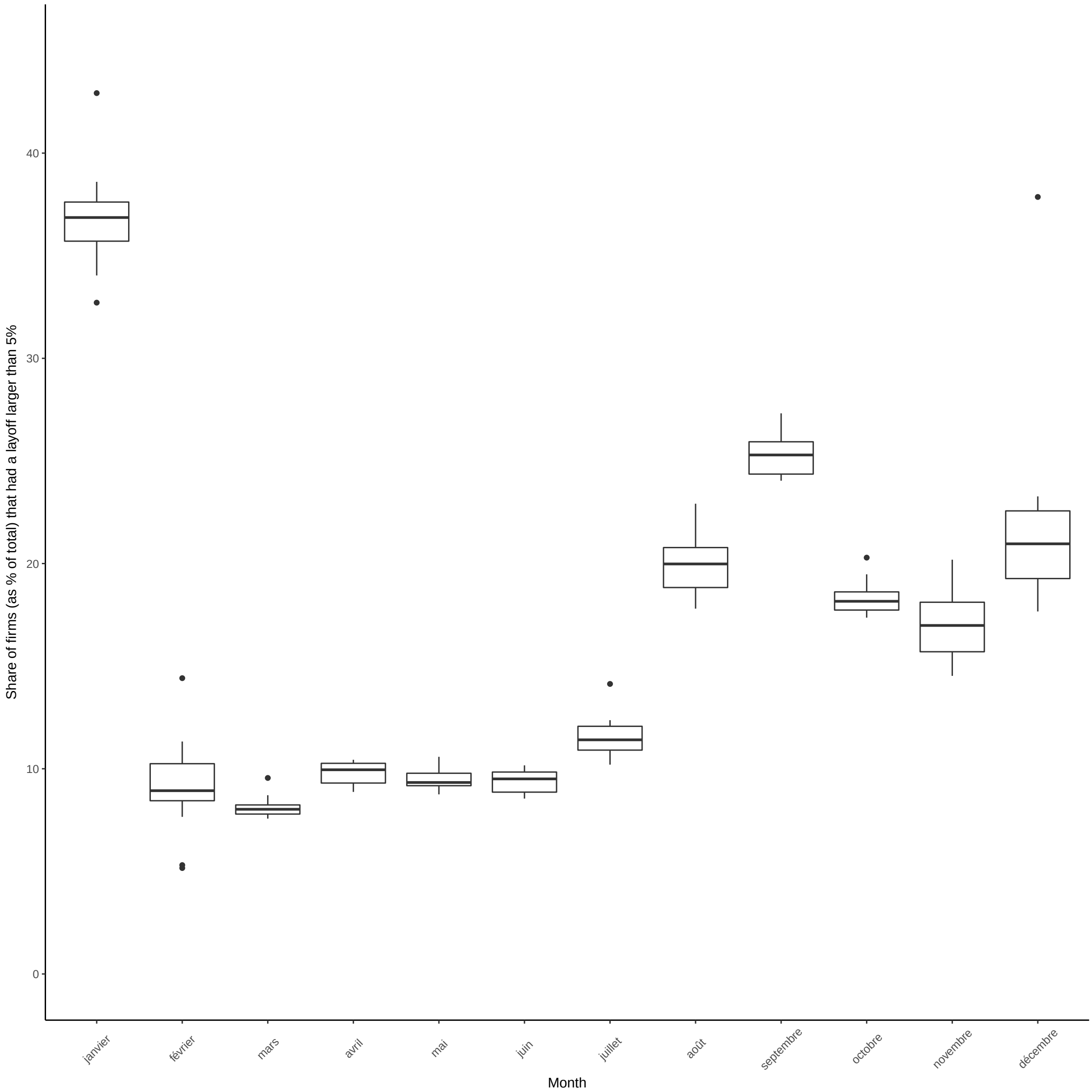
One of the worries in the construction of the social measure is the rate of the missingness for some questions in the background questionnaire. Unlike the numeracy and literacy measures, these are self-reported responses, and a systematic pattern of missing values could be problematic when building a unique measure of social skills. Figure A3 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 A3: Patterns of missingness for Non Cognitive questions



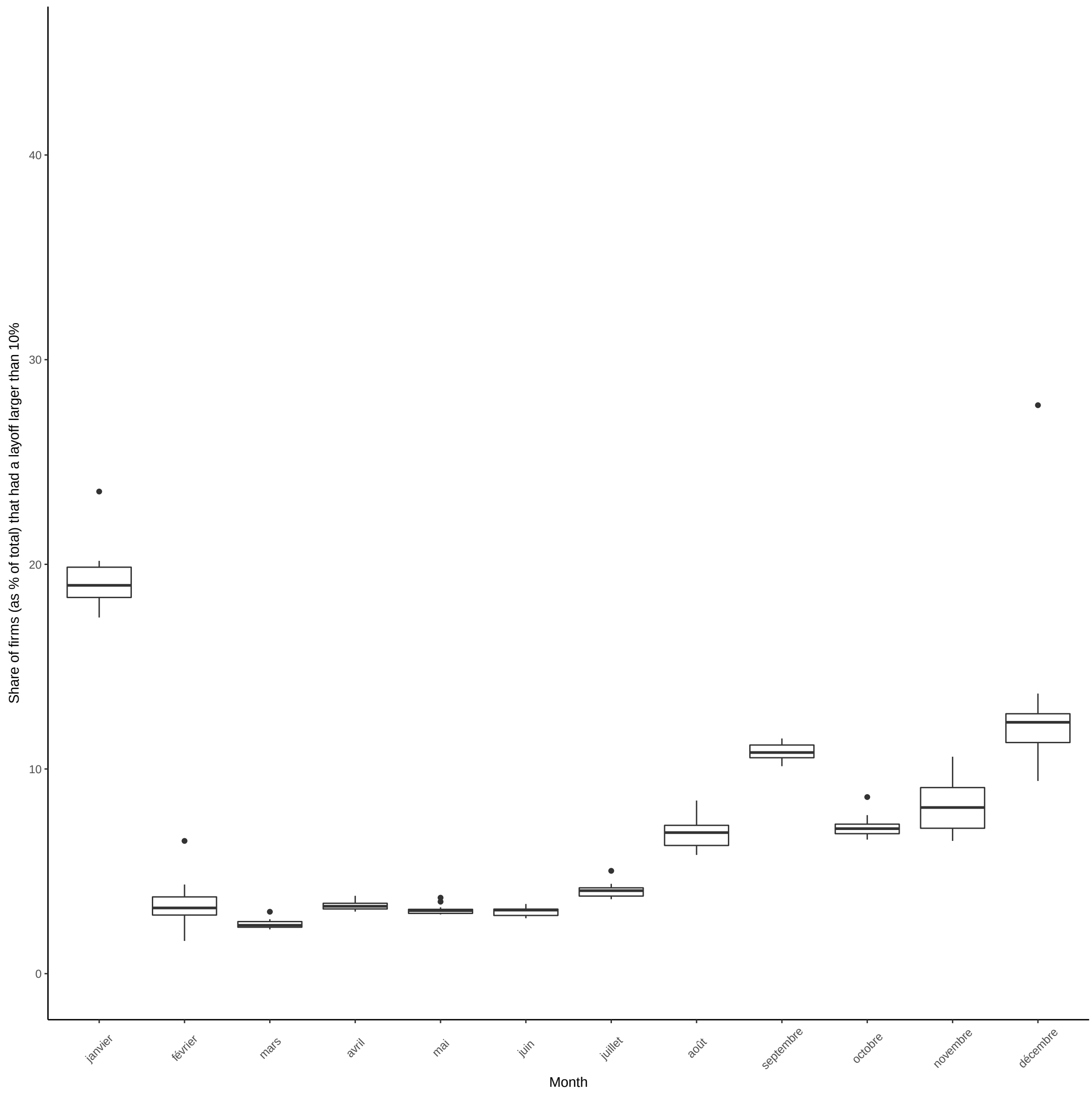
Source: PIAAC France 2012

Figure A4: Firms that downsize - 5% threshold



Source: DADS Postes.

Figure A5: Firms that downsize - 10% threshold



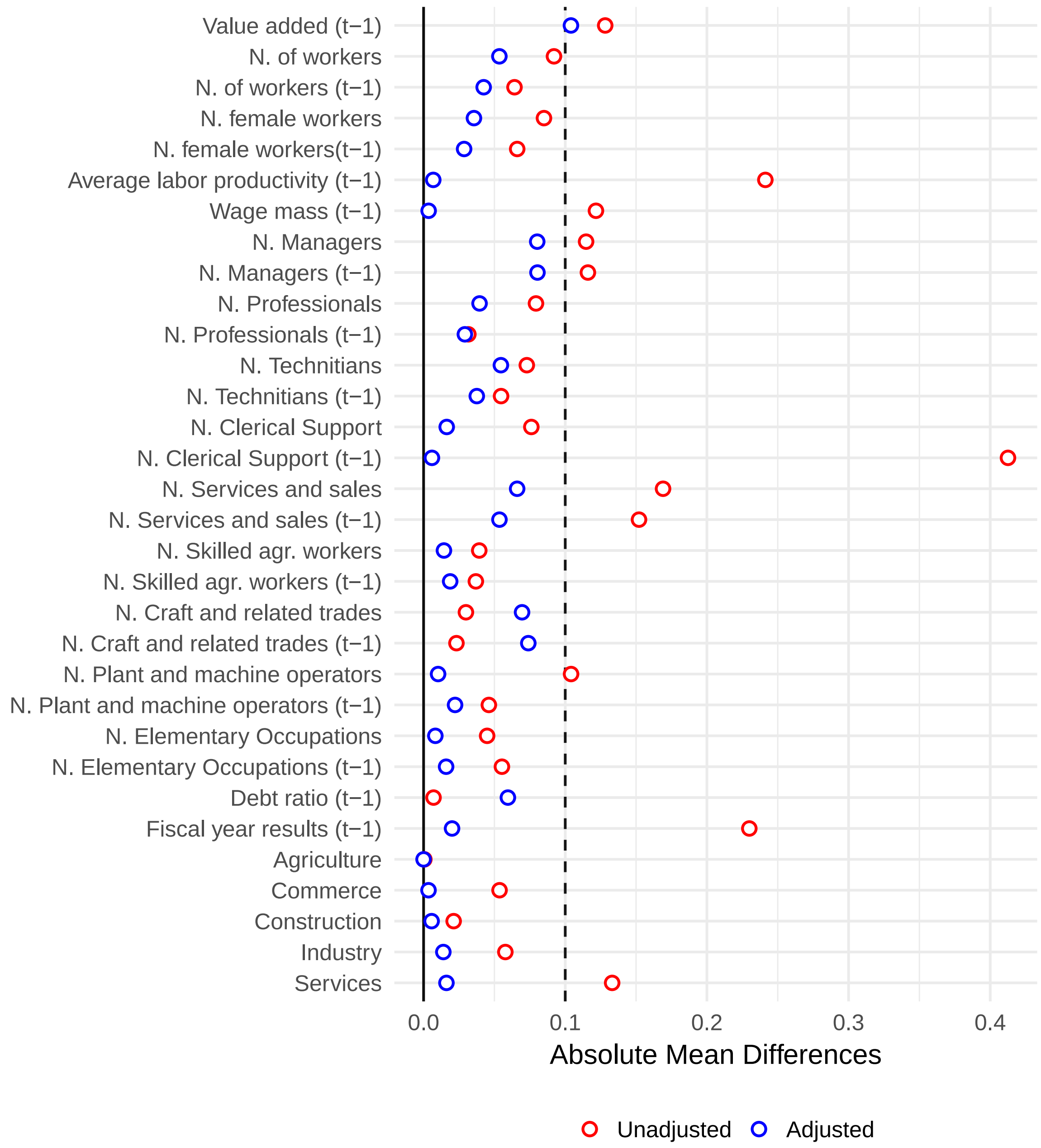
Source: DADS Postes.

Table A5: Balance for selected covariates after matching in 2009

	Unweighted			Weighted		
Variable Name	Mean Control	Mean Treated	Normalized Difference	Mean Control	Mean Treated	Normalized Difference
Distance	0.07	0.09	0.36	0.09	0.09	-0.00
N. of workers	186.28	151.68	-0.09	171.80	151.68	-0.05
N. female workers	73.99	58.12	-0.08	64.75	58.12	-0.04
N. Managers	19.88	13.86	-0.11	18.07	13.86	-0.08
N. Professionals	28.49	21.74	-0.08	25.10	21.74	-0.04
N. Technicians	74.50	61.68	-0.07	71.28	61.68	-0.05
N. Clerical Support	7.31	2.59	-0.08	1.57	2.59	0.02
N. Services and sales	17.16	10.20	-0.17	12.92	10.20	-0.07
N. Skilled agr. workers	0.12	0.18	0.04	0.20	0.18	-0.01
N. Craft and related trades	14.19	12.96	-0.03	15.83	12.96	-0.07
N. Plant and machine operators	12.66	9.39	-0.10	9.07	9.39	0.01
N. Elementary Occupations	11.62	18.96	0.04	17.60	18.96	0.01
Agriculture	0.00	0.00	-0.00	0.00	0.00	0.00
Commerce	0.21	0.16	-0.05	0.16	0.16	-0.00
Construction	0.09	0.07	-0.02	0.07	0.07	0.01
Industry	0.23	0.17	-0.06	0.16	0.17	0.01
Services	0.46	0.59	0.13	0.61	0.59	-0.02
N. of workers (t-1)	183.01	158.57	-0.06	174.73	158.57	-0.04
N. female workers(t-1)	72.08	59.99	-0.07	65.22	59.99	-0.03
N. Managers (t-1)	19.39	14.22	-0.12	17.81	14.22	-0.08
N. Professionals (t-1)	27.43	23.84	-0.03	27.15	23.84	-0.03
N. Technicians (t-1)	76.19	65.97	-0.05	72.98	65.97	-0.04
N. Clerical Support (t-1)	5.50	1.16	-0.41	1.23	1.16	-0.01
N. Services and sales (t-1)	17.99	11.17	-0.15	13.57	11.17	-0.05
N. Skilled agr. workers (t-1)	0.09	0.15	0.04	0.19	0.15	-0.02
N. Craft and related trades (t-1)	14.73	13.74	-0.02	16.90	13.74	-0.07
N. Plant and machine operators (t-1)	12.19	10.28	-0.05	9.36	10.28	0.02
N. Elementary Occupations (t-1)	9.34	17.90	0.06	15.43	17.90	0.02
Value added (t-1)	20183815.73	15076454.75	-0.13	19219910.01	15076454.75	-0.10
Fiscal year results (t-1)	1221970.75	371842.29	-0.23	446163.08	371842.29	-0.02
Average labor productivity (t-1)	153568.57	109908.05	-0.24	111142.95	109908.05	-0.01
Wage mass (t-1)	43796.07	40928.15	-0.12	40844.05	40928.15	0.00
Debt ratio (t-1)	1.15	1.18	0.01	1.45	1.18	-0.06

Source: DADS-EDP panel. The table shows the difference in means for all the treated and matched control units. The treated sample is composed by 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 firms are all firms in the DADS that do not have a mass layoff under the proposed definition. The adjusted control group consist of all the matched firms based on nearest neighbor matching. Columns 3 and 8 compute the standardized 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-values (columns 5 and 10).

Figure A6: Balance for selected covariates after matching in 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 conservative, as Imbens (2015) suggests that a threshold of 0.25 is typically used .

Table A6: Normalized difference in means for matched and layoff units by data year

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 A7: Normalized 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 A8: Selective displacement - Alternative mismatch definition

	(1) Percentile	(2) $\mathbb{1}$-Asymmetric	(3) Quadratic
Skills mismatch			
Over-skilled Cognitive		0.012^{***}	
		(0.003)	
Under-skilled Cognitive		-0.001	
		(0.004)	
Over-skilled Social		0.009^{**}	
		(0.004)	
Under-skilled Social		-0.002	
		(0.005)	
Cognitive	0.024^{***}		0.003
	(0.005)		(0.007)
Cognitive^2			0.001
			(0.003)
Social	0.022^{**}		0.003
	(0.010)		(0.009)
Social^2			0.002
			(0.005)
Perceived cost			
$\frac{w_{it}}{\tilde{w}_{ito}}$	0.061^{***}	0.060^{***}	0.062^{***}
	(0.004)	(0.005)	(0.005)
Realtive quality			
Relative w. quality	-0.130^{***}	-0.128^{***}	-0.130^{***}
	(0.009)	(0.009)	(0.009)
R2	0.329	0.329	0.329
N	171120	171120	171120

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

Source: DADS-EDP panel. The table presents estimates using different definitions of skill mismatch. Column (1) measures the asymmetric skill mismatch measure proposed in the paper by comparing the percentiles of skill k and not the levels. This change considers the relative levels of skills demanded and required. Column (2) uses a discrete measure, classifying an observation as over-skilled if it is more than 1 standard deviation above the mean skill mismatch, and under-skilled if it is more than 1 standard deviation below. Column (3) considers the non-linear effects of skill mismatch and presents the inclusion of quadratic terms. All regressions include firm, region, and collective agreement fixed effects. All regressions include time-varying controls for worker and firm characteristics.

Table A9: Selective displacement by sector

	Industry	Services	Construction	Commerce
Skills mismatch				
Cognitive	0.011***	0.008***	0.010**	0.004
	(0.002)	(0.002)	(0.004)	(0.005)
Social	0.008**	0.009***	0.013**	0.000
	(0.003)	(0.003)	(0.006)	(0.009)
Perceived cost				
$\frac{w_{it}}{\tilde{w}_{ito}}$	0.057***	0.056***	0.077***	0.072***
	(0.007)	(0.007)	(0.010)	(0.018)
Relative quality				
Relative w. quality	−0.162***	−0.117***	−0.115***	−0.145***
	(0.014)	(0.013)	(0.020)	(0.036)
R2	0.326	0.335	0.344	0.434
N	45964	95660	21927	7569

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

Source: DADS-EDP panel. The table presents the average coefficient and multiple imputation-corrected standard errors estimated from the $k-$regressions presented in equation 6. All regressions include firm, region, and collective agreement fixed effects.

Table A10: Selective displacement by collective agreement

	Agric. & wood	Commerce	Construction	Manufacturing	Services	No Coll. Agr.
Skills mismatch						
Cognitive	0.012**	0.005	0.009***	0.019***	0.003	0.006
	(0.005)	(0.004)	(0.002)	(0.004)	(0.004)	(0.006)
Social	0.001	0.009**	0.011***	0.010*	0.002	0.018*
	(0.008)	(0.004)	(0.004)	(0.005)	(0.006)	(0.010)
Perceived cost						
$\frac{w_{it}}{\tilde{w}_{ito}}$	0.040**	0.013	0.059***	0.108***	0.042***	0.054***
	(0.018)	(0.012)	(0.006)	(0.008)	(0.014)	(0.015)
Relative quality						
Relative w. quality	−0.102***	−0.101***	−0.135***	−0.174***	−0.139***	−0.087***
	(0.038)	(0.022)	(0.013)	(0.015)	(0.027)	(0.031)
R2	0.402	0.318	0.314	0.384	0.387	0.339
N	7797	45478	47800	48432	11728	9885

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

Source: DADS-EDP panel. The table presents the average coefficient and multiple imputation-corrected standard errors estimated from the $k-$regressions presented in equation 6. All regressions include firm, and region fixed effects.

Table A11: Selective displacement by gender

	Female	Male	Interacted
Skills mismatch			
Cognitive	0.012^{***}	0.007^{***}	0.011^{***}
	(0.003)	(0.002)	(0.003)
Social	0.016^{***}	0.006^{**}	0.016^{***}
	(0.005)	(0.003)	(0.004)
Cognitive $\times D_M$			-0.003
			(0.003)
Social $\times D_M$			-0.010^{**}
			(0.005)
Gender			
Male			-0.003
			(0.005)
Perceived cost			
$\frac{w_{it}}{\tilde{w}_{ito}}$	0.065^{***}	0.047^{***}	0.042^{***}
	(0.008)	(0.005)	(0.006)
$\frac{w_{it}}{\tilde{w}_{ito}} \times D_M$			0.028^{***}
			(0.006)
Relative quality			
Relative w. quality	-0.170^{***}	-0.106^{***}	-0.111^{***}
	(0.017)	(0.010)	(0.010)
Relative w. quality $\times D_M$			-0.030^{***}
			(0.007)
R2	0.408	0.359	0.329
N	62188	108932	171120

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

Source: DADS-EDP panel. The table presents the average coefficient and multiple imputation-corrected standard errors estimated from the $k-$regressions presented in equation 6. All regressions include firm, region, and collective agreement fixed effects.

Table A12: Selective displacement - Alternative definition of mass layoff event

	(1)	(2)	(3)	(4)	(5)
Skills mismatch					
Cognitive	0.006^{***}	0.008^{***}	0.008^{***}	0.008^{***}	0.010^{***}
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Social	0.011^{*}	0.010^{***}	0.009^{**}	0.009^{**}	0.008^{**}
	(0.006)	(0.004)	(0.004)	(0.004)	(0.003)
Worker characteristics					
Male		-0.030^{***}	-0.031^{***}	-0.031^{***}	-0.027^{***}
		(0.001)	(0.001)	(0.001)	(0.001)
Age		-0.000	-0.000	-0.000	-0.004^{***}
		(0.001)	(0.001)	(0.001)	(0.001)
Age^2		-0.000	-0.000	-0.000	0.000^{***}
		(0.000)	(0.000)	(0.000)	(0.000)
Seniority		-0.006^{***}	-0.006^{***}	-0.006^{***}	-0.006^{***}
		(0.000)	(0.000)	(0.000)	(0.000)
Seniority^2		0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}
		(0.000)	(0.000)	(0.000)	(0.000)
Upper and Post Secondary		-0.006^{***}	-0.007^{***}	-0.007^{***}	-0.007^{***}
		(0.002)	(0.002)	(0.002)	(0.002)
Bachelor		-0.019^{***}	-0.020^{***}	-0.020^{***}	-0.019^{***}
		(0.002)	(0.002)	(0.002)	(0.002)
Higher Tertiary		-0.009^{***}	-0.011^{***}	-0.011^{***}	-0.004
		(0.002)	(0.002)	(0.002)	(0.002)
Perceived cost					
$\frac{w_{it}}{\tilde{w}_{ito}}$			0.013^{***}	0.013^{***}	0.042^{***}
			(0.002)	(0.002)	(0.003)
Firm characteristics					
Value added				-0.011^{***}	-0.011^{***}
				(0.003)	(0.003)
ROA				0.001	0.001
				(0.001)	(0.001)
ROE				0.003^{***}	0.003^{***}
				(0.001)	(0.001)
Purchases/Sales				-0.000	-0.000
				(0.004)	(0.004)
Relative quality					
Relative w. quality					-0.086^{***}
					(0.005)
R2	0.173	0.180	0.180	0.181	0.181
N	292613	292613	292613	292613	292613

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

Source: DADS-EDP panel. The table presents the average coefficient and multiple imputation-corrected standard errors estimated from the $k-$regressions presented in equation 6. All regressions include firm, region, and collective agreement fixed effects. All regressions include time-varying controls for worker and firm characteristics.

B Combining survey information into administrative data

B.1 Data combination

In order to undertake our econometric analyses, we must combine a variety of datasets, each of which contains different variables of interest with some common identifying variables and drawn from a common population. Combining data from diverse sources to respond to an economic question has a long history in economic research (Arellano and Meghir, 1992; Angrist and Krueger, 1992; Meyer and Mittag, 2019). More recently, with the accumulation, organization, and accessibility of large datasets, there has been a growing emphasis on integrating *administrative* and *survey* data (Ridder and Moffitt, 2007; Athey et al., 2020; Colnet et al., 2023).[35] This section serves two primary objectives. First, it underscores the importance and challenges associated with linking survey and administrative data. Second, it delves into the detailed methodology employed to integrate these distinct data sources. Specifically, we present the methodology employed to combine survey data from the PIAAC with French administrative employment records.

The growing availability of administrative datasets and their accessibility to researchers have fueled the use of administrative data in economic studies. From a statistical perspective, this increased reliance on administrative data has been accompanied by a belief in the reliability of the estimates generated, primarily due to the assumption that the sole source of error lies in the linkage of records to produce the databases (Kapteyn and Ypma, 2007). However, this view has recently been challenged, with the argument that if the data quality falls below a certain threshold, estimates from big data could be significantly biased (Meng, 2018).

Moreover, the availability of administrative data sources relevant to specific economic questions can be limited, and it is often the case that the variables of interest to researchers are not available in these sources. As a result, researchers typically rely on surveys specifically designed to capture the desired information about the population. But designing and administering surveys is a complex and expensive process. As Kapteyn and Ypma (2007) note, surveys are known to be subject to three specific issues: measurement error, item non-response, and unit non-response. While economists primarily focus on measurement error and representativeness, non-response can lead to biased population estimates if it is strongly correlated with the variables of interest. This problem becomes even more challenging in more complex designs involving longitudinal data collection.

[35] Athey et al. (2020) and Colnet et al. (2023) are specifically concerned with combining observational and experimental data, but the principle remains similar to our approach.

By integrating information from survey and administrative data, one can hope to overcome the limitations of each source and provide a more comprehensive understanding of real-world phenomena relevant to public policy. In our particular case, where administrative data lacks information on the skills of the working population, combining these two data sources becomes the only viable approach to the quantification of skills mismatch and the analysis of its role in the selection into labor displacement.

B.2 Combining skills into DADS-EDP Panel

Due to the lack of skills measures in the French administrative data, direct measurement of the size of mismatch is practically impossible. To address this limitation, we must combine several data sources, either directly or indirectly. The direct method, involving record linkage, requires participant consent and access to uncensored, common identifiers across data sets. These criteria are rarely met (and are not met in our case), making it an unfeasible approach to data combination. Moreover, even when direct matching is possible, the consent requirement often leads to reduced survey response rates due to privacy concerns, potentially compromising the resulting sample's representativeness and robustness. For example, Daikeler et al. (2020) linked survey response to administrative data and have shown that consent to linkage can correlate with observed characteristics, potentially biasing estimates.[36] To overcome such shortcomings, we utilize the shared observable individual and firm characteristics in the DADS-EDP and PIAAC datasets to indirectly estimate skill endowments for individuals in the DADS-EDP panel. This approach aligns with the methodologies proposed by Ridder and Moffitt (2007), and Little and Rubin (2019).

One key assumption of our approach is that the joint distribution of skills and observable variables is equivalent in the DADS-EDP and PIAAC samples. Several reasons support this assumption: Firstly, both datasets are designed to be representative the French working population. The PIAAC survey (donor data) employs a sampling and weighting design aiming for worker population representativeness, with sample size influenced by registry quality to ensure accurate identification of the worker skill distribution. Conversely, the administrative data (recipient data) draws observed characteristics from a random $1/12^{\text{th}}$ sample of the entire working population, ensuring sufficient size for representativeness. As both data sources are representative of the same underlying population, the joint distribution of observable characteristics is likely to be common across both samples.

[36] In Daikeler et al. (2020) work, for the case of Germany, in 2015, only two thirds of the individuals consent survey response to administrative record linkage. This figure diminishes to half if we consider it with respect to the respondents in 2012.

An additional specificity of the donor data is the presence of plausible values. The PIAAC dataset includes 10 sets of skill measure values and associated weights, representing multiple plausible draws from the *conditional* skill distribution, in order to account for the unfolding nature of the questionnaire used for skills measurement (not all individuals answered the same questions) and to increase the accuracy of the joint distribution of skills measures for the overall population and various subpopulations (Yamamoto et al., 2013).

This enriched representation of the skills information provides a more complete characterization of the skill distribution and its direct link to observable characteristics, which will be exploited in the data combination. Moreover, this multiple plausible value structure helps mitigate the risk of underestimating imputed data variance. Intuitively, the OECD uses a model used to estimate skill measures in the PIAAC data, and given that the parameters of this model are estimated (and model fit is not perfect), simply using the expected skill measures conditional on the observables in the model would remove uncertainty due to sample variation. By providing multiple imputations based on the posterior distribution of the model's estimated parameters, the PIAAC data allows subsequent estimations to correctly accommodate this model uncertainty. We account for this variation in our data combination process, as described below.

Finally, our approach takes advantage of the high degree of comparability between the DADS-EDP and PIAAC datasets. Beyond being representative of a common population, both data sources share a set of common variables that can be readily harmonized across the samples. In particular, we can arrive to identical category definitions and groupings in both data sets, and both data sets use the same classification system with consistent levels of granularity.

B.3 Imputation algorithm

We impute the joint skills distribution into the DADS-EDP panel using double multiple imputation and stochastic regression imputation methods. Our method relies on projecting the 10 plausible values of the skills measures onto a set of explanatory variables in the PIAAC data to robustly characterize the joint distribution of the skills and other observables. We then use these common covariates between the PIAAC and the DADS-EDP data to ultiply impute the skills into the DADS-EDP data using the observation-specific estimated conditional distribution of skills (conditional on observables), where the imputation involves a deterministic and a stochastic component. The deterministic part uses k-draws from distribution of the estimator, while the stochastic part comes from the unexplained components of the first set of projections. The procedure is divided into the following steps:

B.3.1 Characterization of the distribution of the vector of parameters

The first step of our method consist in projecting, for each set of plausible values, each skills measure onto the set of covariates, using the survey weights. Following Lumley and Scott (2017), we use a weighted general linear model estimator for complex survey design, to account for the PIAAC sampling design.

$$\arg\min_{\boldsymbol{\beta}^m} \|\boldsymbol{W}^{\frac{1}{2}}(\boldsymbol{S}^m - \boldsymbol{X}_{\text{PIAAC}}\boldsymbol{\beta}^m)\|^2 \tag{B1}$$

where m is the number of plausible values in the PIAAC survey, $\boldsymbol{S}^m$ is the $(n \times 1)$ vector of skills measures for plausible value set m, $\boldsymbol{X}$ is the $(n \times k)$ matrix of covariates, $\boldsymbol{\beta}^m$ is the $(k \times 1)$ vector of parameters for plausible value set m, and $\boldsymbol{W}$ is an $(n \times 1)$ vector of weights. The set of covariates shared between the samples include worker, job and firm characteristics. Worker characteristics include gender, a sixth degree polynomial on age, a third degree polynomial on seniority, and the educational level of the worker (5 categories). Job characteristics include the logarithm of monthly earnings and the occupation (2-digit ISCO-08 level). Firm characteristics 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. For each set of plausible values, we obtain a vector of residuals and a posterior (asymptotically normal) distribution of the estimator $\hat{\boldsymbol{\beta}}^m$. The residuals correspond to the non explained part of the model, and can be used to impute the stochastic component of the skills measure.

Combining the information from the m-projections, the posterior distribution of estimator $\tilde{\boldsymbol{\beta}}$ that uses all of the information from the plausible values has a normal distribution in which the first moment is the average of the m-projections, and the variance is the combination of the within and between variance. Formally,

$$\tilde{\boldsymbol{\beta}} \sim \boldsymbol{\mathcal{N}}\left(\tilde{\boldsymbol{\beta}}, \tilde{\sigma}^2(\boldsymbol{X}_{\text{PIAAC}}^T \boldsymbol{X}_{\text{PIAAC}})^{-1}\right) \tag{B2}$$

In this equation, $\tilde{\boldsymbol{\beta}} = \frac{1}{m}\sum \hat{\boldsymbol{\beta}}^m$, and $\tilde{\sigma}^2 = (\frac{1}{m} + \frac{1}{10m})\sum \hat{\sigma}_m^2 + \frac{\sum(\hat{\sigma}_m^2 - \bar{\hat{\sigma}}_m^2)^2}{m-1}$, where $\bar{\hat{\sigma}}_m^2$ is the average of the plausible value-specific estimated variances. This calculation provides us with a complete characterization of the distribution of the estimator that uses the information of the observables, but adjusts for the complex design of the survey.

B.3.2 Random draws from the posterior distribution of coefficients

Given our estimate of the posterior distribution of $\tilde{\boldsymbol{\beta}}$, we take k random draws from this distribution where $\boldsymbol{\beta}^{(k)}$ indicates the k^{th} draw. In this paper we sample 10 times ($k = 10$). Drawing from such a distribution incorporates the information embedded within the plausible values and their weights. This step ensures consistency between the imputed values and the observed characteristics of the individuals.

B.3.3 Calculating the multiple imputation

We then combine the samples as in the two sample instrumental variable approach described in Ridder and Moffitt (2007). We therefore obtain k skill vectors:

$$\boldsymbol{S}^{(k)} = \boldsymbol{\beta}^{(k)} \times \boldsymbol{X}_{\text{DADS}} \tag{B3}$$

Note that although $\boldsymbol{S}^{(k)}$ depends on $\boldsymbol{X}_{\text{DADS}}$ in a deterministic manner, it already incorporates the uncertainty of the plausible values and their weights due to the construction of $\boldsymbol{\beta}^{(k)}$.

Table B1: Projection of Cognitive PV on covariates

	No seniority	No firm size	No occupation	No education	No wage	Complete
(Intercept)	−1.755	−1.956	−2.649	−1.023	−0.902	−1.771
	(0.286)	(0.281)	(0.212)	(0.340)	(0.188)	(0.282)
Female	−0.085	−0.090	−0.058	−0.031	−0.109	−0.085
	(0.027)	(0.027)	(0.024)	(0.027)	(0.027)	(0.027)
Real Monthly Wage	0.132	0.136	0.227	0.247		0.127
	(0.030)	(0.029)	(0.028)	(0.038)		(0.030)
Age - Between 25-34	0.017	0.018	0.001	0.029	0.050	0.013
	(0.045)	(0.046)	(0.046)	(0.049)	(0.047)	(0.046)
Age - Between 35-44	−0.141	−0.141	−0.174	−0.177	−0.107	−0.150
	(0.047)	(0.052)	(0.052)	(0.052)	(0.052)	(0.050)
Age - Between 45-54	−0.306	−0.305	−0.348	−0.438	−0.276	−0.323
	(0.048)	(0.052)	(0.055)	(0.053)	(0.052)	(0.052)
Age - More then 55	−0.373	−0.377	−0.441	−0.585	−0.352	−0.405
	(0.056)	(0.063)	(0.063)	(0.063)	(0.060)	(0.062)
Lower secondary	0.536	0.606	0.588		0.571	0.541
	(0.075)	(0.079)	(0.079)		(0.072)	(0.076)
Upper and Post Secondary	0.911	0.995	1.046		0.952	0.917
	(0.068)	(0.071)	(0.071)		(0.063)	(0.068)
Bachelor	1.352	1.448	1.672		1.418	1.362
	(0.073)	(0.077)	(0.072)		(0.068)	(0.074)
Higher Tertiary	1.481	1.591	1.871		1.574	1.498
	(0.079)	(0.088)	(0.080)		(0.078)	(0.083)
11 to 50 workers	−0.024		−0.003	0.004	−0.020	−0.026
	(0.032)		(0.034)	(0.033)	(0.032)	(0.033)
51 to 250 workers	0.030		0.040	0.068	0.034	0.026
	(0.036)		(0.037)	(0.039)	(0.036)	(0.037)
250 to 1000 workers	0.037		0.053	0.089	0.037	0.030
	(0.039)		(0.040)	(0.042)	(0.039)	(0.041)
More than 1000 people	0.125		0.162	0.144	0.138	0.116
	(0.046)		(0.050)	(0.050)	(0.046)	(0.048)
Seniority		0.006	0.005	−0.006	0.005	0.003
		(0.010)	(0.010)	(0.010)	(0.009)	(0.009)
Seniority^2		−0.000	−0.000	0.000	−0.000	−0.000
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Seniority^3		0.000	0.000	−0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R2	0.453	0.459	0.411	0.371	0.442	0.453
N	3702	3773	3701	3699	3876	3698

Source: *PIAAC*, 2012.
Note: Authors calculations. The table shows the estimated coefficients obtained when projecting the plausible values of cognitive skills into the covariates. The resulting coefficients and standard deviation corrects for the variation between and across the estimated values. All the columns (excluding column 4, in the table) include occupation dummies (ISCO-08, 2-digits).

Table B2: Projection of Social PV on covariates

	No seniority	No firm size	No occupation	No education	No wage	Complete
(Intercept)	−0.318	−0.382	−1.328	−0.204	14.827	−0.314
	(0.390)	(0.391)	(0.215)	(0.414)	(0.832)	(0.398)
Female	0.015	0.023	0.045	0.042	0.001	0.021
	(0.036)	(0.035)	(0.031)	(0.036)	(0.088)	(0.036)
Real Monthly Wage	0.060	0.104	0.140	0.130		0.089
	(0.032)	(0.030)	(0.028)	(0.032)		(0.031)
Age - Between 25-34	0.038	0.061	0.063	0.075	0.233	0.065
	(0.066)	(0.072)	(0.067)	(0.070)	(0.165)	(0.071)
Age - Between 35-44	−0.001	0.057	0.063	0.061	0.266	0.066
	(0.067)	(0.077)	(0.074)	(0.074)	(0.168)	(0.075)
Age - Between 45-54	−0.018	0.089	0.091	0.049	0.314	0.089
	(0.066)	(0.078)	(0.073)	(0.072)	(0.175)	(0.075)
Age - More then 55	−0.145	0.011	0.008	−0.032	0.126	0.010
	(0.066)	(0.081)	(0.078)	(0.077)	(0.187)	(0.080)
Lower secondary	−0.009	−0.040	−0.014		−0.018	−0.026
	(0.086)	(0.083)	(0.085)		(0.210)	(0.084)
Upper and Post Secondary	0.206	0.177	0.233		0.570	0.183
	(0.084)	(0.080)	(0.081)		(0.202)	(0.082)
Bachelor	0.388	0.347	0.530		1.031	0.347
	(0.089)	(0.085)	(0.082)		(0.208)	(0.085)
Higher Tertiary	0.455	0.390	0.628		1.175	0.377
	(0.094)	(0.090)	(0.083)		(0.222)	(0.092)
11 to 50 workers	0.078		0.084	0.103	0.204	0.088
	(0.038)		(0.037)	(0.037)	(0.086)	(0.038)
51 to 250 workers	0.072		0.069	0.108	0.214	0.093
	(0.049)		(0.049)	(0.048)	(0.114)	(0.049)
250 to 1000 workers	0.053		0.056	0.103	0.203	0.083
	(0.048)		(0.047)	(0.047)	(0.106)	(0.048)
More than 1000 people	0.048		0.073	0.103	0.226	0.090
	(0.064)		(0.063)	(0.065)	(0.154)	(0.065)
Seniority		−0.018	−0.017	−0.024	−0.056	−0.021
		(0.012)	(0.012)	(0.012)	(0.028)	(0.012)
Seniority^2		0.001	0.001	0.001	0.002	0.001
		(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Seniority^3		−0.000	−0.000	−0.000	−0.000	−0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R2	0.112	0.115	0.093	0.105	0.977	0.117
N	3542	3595	3541	3539	3700	3538

Source: *PIAAC*, 2012.
Note: Authors calculations. The table shows the estimated coefficients obtained when projecting the plausible values of non cognitive skills into the covariates. The resulting coefficients and standard deviation corrects for the variation between and across the estimated values. All the columns (excluding column 4, in the table) include occupation dummies (ISCO-08, 2-digits).

C Institutional framework of mass layoffs in France

This section examines with more detail the institutional framework governing the regulatory process of layoffs for economic reasons in France (ED). It outlines the legal framework for economic displacement, the procedural timeline, and the implications for identifying mass layoffs from a data perspective.

The layoff process for economic reasons is characterized by its heterogeneity, with several thresholds that influence its execution. First, a firm's size determines the extent of its obligations, with larger organizations facing more stringent requirements. Second, the scale of the layoff can impact the timing of various procedures. 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 splitting large layoffs into smaller pieces. 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."[37]

We begin by examining the concept of economic displacement, followed by an investigation of the definition of a mass layoff.

C.1 Economic displacement

Under French labor law, economic displacement is a specific type of separation characterized by distinct features in terms of its nature and underlying reasons.

- It is an *involuntary* separation (the decision follows the employer's will and not the employee).

[37] "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)

- 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.[38]

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 section 2, we examined how changes in productivity could cause the value of production from a match to change. From the legal standpoint, such change could arise from:

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

ii The firm's technology having changed;

iii The firm having made a strategic decision to reorganize to improve its competitiveness[39]. According to the jurisprudence, it may not be used to improve it but only to maintain it;

iv The firm needing to shut down operations and 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, 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)[40]. The definition of the reach (perimeter) of the group in this sense is far from the context of the firm, which could make the

[38]" 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"]

[39]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 jurisprudence states that firms cannot lay off workers to improve productivity, but only to keep it from falling. Still, the *maintenance* of productivity is very difficult to prove and is conditional on the judge's interpretation.

[40]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*].

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.

C.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 being fired. Below a summary of the process as a function of the number of layoffs by the firm.

C.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 or he 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[41].

Ind.3 In this meeting, the employee is told the decision and the causes. The firm offers her or 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[42]. 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 her or him the "contrat de sécurisation professionnelle (CSP)" if the firm has less than 1000 employees or a retraining

[41] Article L1233-11 - Code du travail. https://www.legifrance.gouv.fr/codes/article_lc/LEGIARTI000006901023/
[42] Article L1233-5 - Code du travail https://www.legifrance.gouv.fr/codes/article_lc/LEGIARTI000036261856/.

period if the firm (or economic group) has more than 1000 employees[43]. If the employee accepts the option of retraining, it can last from 4 to 12 months .

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

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[44].

C.2.2 Layoff of two or more employees (below nine)

A similar procedure as the one stated before should be implemented. However, 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 furthermore notify the Ministry of Labor.

The information provided 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.

C.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).

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 C1 presents the number of PSE for the period 2006 to 2015. As we can see, the number of events is low relative to the calculated number of events per year using our definition based on the size of the firm, suggesting

[43] 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.

[44] 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.

that the the economic displacement accompanied by a PSE is not the principal channel by which a firm reduces its workforce. As suggested by our review of the legislation and jurisprudence, one cause for this is likely to be the barriers associated with using the mechanism and its high cost (which includes the cost in time).

Table C1: Number of firms that start a mass layoff period

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	$1,690$

Source: *French Ministry of Labor*, $2006-2015$.
Note: The table presents the number of PSE approved by the French Ministry of Labor in the period 2006-2015.