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A firm-level analysis of hiring credits

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A firm-level analysis of hiring credits

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Abstract

In the aftermath of the Great Recession, hiring credits have become popular worldwide. The empirical literature shows positive but moderate effects of such interventions on employment. However, an in-depth analysis of the characteristics of the beneficiary firms and their wage-setting policies is still lacking. By using a linked employer-employee dataset, this paper presents a firm-level analysis of a three-year employer-borne payroll tax cut for permanent hirings introduced in Italy in 2015. After estimating firm and worker fixed effects through the standard AKM model, we show that the hiring credits' take-up is significantly higher for firms that pay lower wages, are less productive, employ workers with lower mean abilities and have a lower retention rate. This result is robust to several specifications and stratifications of the sample and provides a further and different perspective from which to question the use of active labour market policies based on employer-borne payroll tax cuts.

Keywords: active labor market policies, hiring credits, firm premium, AKM, labor market.

JEL: D22, J08, J21.

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Un’analisi a livello d’impresa degli incentivi all’occupazione

Sommario

A seguito della Grande Recessione, gli incentivi all’occupazione sono diventati popolari a livello globale. La letteratura empirica mostra effetti positivi ma moderati di tali interventi sull’occupazione. Tuttavia, manca ancora un’analisi approfondita delle caratteristiche delle imprese beneficiarie e delle loro politiche retributive. Utilizzando i dati INPS, questo studio presenta un’analisi a livello di impresa di una riduzione triennale dei contributi previdenziali a carico del datore di lavoro per le assunzioni a tempo indeterminato (L. 190/2014), introdotta in Italia nel 2015. Dopo aver stimato gli effetti fissi delle imprese e dei lavoratori attraverso il modello standard AKM, mostriamo che l’adozione dei crediti per l’assunzione è significativamente più elevata per le imprese che pagano salari più bassi, sono meno produttive, impiegano lavoratori con abilità medie inferiori e presentano un tasso di ritenzione più basso. Questo risultato è robusto rispetto a diverse specifiche e stratificazioni del campione e offre una prospettiva ulteriore e differente per mettere in discussione l’uso di politiche attive del mercato del lavoro basate sulla riduzione dei contributi previdenziali a carico dei datori di lavoro.
Parole chiave: politiche attive del lavoro, incentivi all’occupazione, premi d’impresa, AKM, mercato del lavoro.
JEL: D22, J08, J21.

1 Introduction

Hiring credits to employers are widely used across Europe and beyond (Cahuc et al., 2019; Kluve, 2010) and they have become increasingly important since the Great Recession. Even if the effectiveness of these measures in creating new jobs depends on a number of contingent factors (McKenzie, 2017; Neumark, 2016; Vooren et al., 2019), the empirical literature has shown that private sector hiring credits are moderately successful at increasing employment, even if there is concern about subsidised jobs duration (Card et al., 2010; Cahuc et al., 2019; Crépon and Van Den Berg, 2016). However, while raising a weak employer demand is crucial to the success of these programs, empirical studies related to the characteristics of firms accessing hiring credits to explain their participation are still scarce. In addition, the literature focuses on analysing hiring credits targeted at specific types of workers or high-unemployment areas, but there is a lack of knowledge on how hiring credits that apply to the universe of the worker population may affect firm incentives and hiring strategies.

This paper aims to fill this gap and is motivated by several research questions. First, a well-known fact is that not all firms appear to be in need of these programs thus it is interesting to investigate the characteristics of the firms participating in them to account for the heterogeneity of the use of hiring credits across firms (Couch et al., 2013; Elvery et al., 2023). Second, this analysis may help to explain the decision to take up the scheme and provide insights into the relationship between the economic situation of firms and their participation in hiring credit programs. Third, evidence on firms' characteristics allows us to speculate on the nature of the jobs that are activated and the consequences for workers who are involved in subsidised hirings. These issues have valuable policy implications related to the design of hiring credit measures (i.e. if these interventions should be implemented with or without specific targets and requirements), the timing of their implementation and their nature of counter-cyclical interventions, and their effectiveness compared to other active labour market policies (ALMPs) when considering the heterogeneous productivity of firms and workers participating in these schemes. This analysis is particularly important in the case of untargeted hiring credits whose policy goal is not specifically oriented toward workers with a weak attachment to the labour market. Thus, a change in the workforce composition and job quality induced by the type of firms stimulated by the policy may lead to different policy implications.

In this paper, we contribute to the literature by providing evidence on the difference in the characteristics of subsidised firms and other recruiting firms and on the allocation of workers with different mean abilities across firms. To capture these differences, we empirically analyse the relationship between the firms' pay-setting practices, as proxied by firm fixed effects, and their decision to take up an untargeted employer-borne payroll tax cut for permanent hirings. Our analysis uses linked employer-employee data provided by the Italian National Institute for Social Security (INPS) to assess the relationship between firm wage premiums, estimated in a two-way fixed effects wage equation *à la* Abowd et al. (1999, AKM henceforth), and firms' usage of an economy-wide employer-borne payroll tax cut introduced in Italy in 2015. It allowed a three-year total social security contribution cut that could reach a yearly cap of 8060 euros, which was meant for permanent hirings. The Italian case is interesting because in this country hiring credits have been implemented for a long time and represent the major component of ALMPs.

As well-established in the literature (Abowd et al., 1999; Card et al., 2013, 2016; Song et al., 2019; Casarico and Lattanzio, 2019), firm fixed effects are employer-specific wage premiums that may reflect compensation policies based on rent sharing or efficiency wages motivations. Firm-specific wage premiums may also be related to the workplace environment and non-monetary benefits that firms offer to workers or may represent compensation for unfavourable amenities (Card et al., 2018; Sorkin, 2018; Bana et al., 2023). Hence, firm fixed effects are a proxy for variables reflecting the employer's ability to pay (e.g., market power, productivity, profits, turnover costs), the firm culture and the workplace environment.

We believe that firm-specific wage premiums are an important dimension for understanding, on the one hand, the characteristics of the firms involved in these policies and, on the other hand, the reasons why firms exploit such tax cuts. It could be that high-wage premium firms, which are likely to be the more productive ones (Card et al., 2018), may intensively rely on tax rebates in order to further expand their businesses and consolidate their market power. Alternatively, firms paying lower wage premiums might resort to hiring credits because they are in dire need of cheap labour to survive.

In carrying out the empirical analysis, we draw from two strands of literature. The first one analyses the effect of a payroll tax cut on firms' outcomes and behaviour. Saez et al. (2019) study an automatic payroll tax cut in favour of young workers in Sweden. Using administrative data and implementing a difference-in-differences strategy, they find positive effects of the policy for subsidised firms in terms of both value-added per worker, profits, sales and capital assets. Benzarti and Harju (2021a) use a quasi-experimental approach and show that payroll tax cuts make firms more resilient during recessions by relaxing liquidity constraints. A related study is the one proposed by Benzarti and Harju (2021b) who exploits discontinuities in the employer-borne payroll tax rate in Finland to assess how payroll taxes affect firms' choice of input factors.

The second branch of literature provides evidence on how firm characteristics affect workers' participation in labour market policies which allows them certain benefits. These studies use the AKM framework to estimate firm effects while controlling for unobserved worker heterogeneity. Specifically, Lachowska et al. (2022) show the substantial role of firm fixed effects in explaining the claim rates of unemployment insurance in the U.S. Bana et al. (2023) provide robust evidence of the positive association between higher wage premiums paid by firms and the parental leave take-up rate in California. Our empirical strategy follows this approach but, differently from the existing literature, we focus on a labour market policy that directly benefits employers, via tax cuts.

Empirical research on hiring credits implemented in Italy shows positive effects of targeted employer-borne payroll tax cuts for young workers (Brunetti and Ricci, 2021; INPS, 2022) and long-term unemployed individuals (Pasquini et al., 2018). Rubolino (2022) provides a firm-level analysis of an employer-borne payroll tax cut for new female hires implemented since 2013. The study shows that this measure has positive effects not only on employment but also on revenues for the subsidised firms, suggesting that the incentive targeted toward women has broken down gender stereotypes and, in this way, improved business performance.

Differently from this literature, we consider an economy-wide incentive that reduced labour costs for employers who permanently hired workers in 2015. The existing literature shows that these economy-wide tax rebates produced an increase in employment (Sestito and Viviano, 2018) also with respect to specific groups of workers, such as the young people (Deidda et al., 2021). However, studies at the firm level of this policy are missing. Hence, our contribution broadens the knowledge on this economy-wide hiring credit along a different perspective by providing novel evidence on how the characteristics of firms, which are reflected in their wage premiums, may drive the firm's decision to take up.

Matching social security records with firm-level financial data, we follow the framework proposed by Bana et al. (2023) and adopt a two-step empirical strategy. We first estimate firm wage premiums in a two-way fixed effects wage regression *à la* AKM where we control for worker fixed effects, time-varying characteristics such as age and (potential) labour market experience of the worker, occupation dummies (i.e. for the worker being an apprentice, blue collar, white collar, middle manager or executive) and year fixed effects. We then estimate an equation at the firm level for the years when the tax cuts worked, that is between 2015 and 2018, that allows us to gather evidence on the association between firm-specific wage premiums and the employers' usage of hiring credits. Firms' access to the subsidy is measured by the incidence rate, which is the share of permanent subsidised contracts relative to total permanent contracts at the firm-year level.

Our estimates report strong evidence of a negative correlation between firm-specific wage premiums and the usage of hiring credits. A doubling of the wage premium is associated, on average, with a 7-10% decrease in the incidence rate depending on the estimating equation. This result is robust to several specifications and stratifications of our sample. Interestingly, we find that the association is robust across firm sizes and stronger for firms that employ workers with lower abilities. The role of the firm-specific wage premium is slightly stronger in the Service sector and is equivalently important for shrinking and growing firms in terms of size. In addition, we estimate the firm-level model controlling for the retention rate, which is a proxy of the firm's non-wage characteristics that workers value (Sorkin, 2018). Even if the results are somehow attenuated, the negative association between the firm wage premium and the take-up of hiring credits is confirmed.

Overall, our findings show that firms that are less productive and pay lower wages have been the main beneficiaries of the untargeted hiring credit measure. Given that, as Benzarti and Harju (2021b) and Saez et al. (2019) show, payroll taxes tend to significantly affect firm behaviour through the liquidity constraints channel, our findings suggest that the main motivation of the firm decision to take up the scheme is to exploit the alleviation of liquidity constraints, while firms with better investment and growth opportunities are likely to be less sensitive to the payroll tax cut. Hence, the rebate in employer-borne payroll taxes offered by the program seems to represent a de facto indirect financial support for firms with financial constraints, questioning the effectiveness of the policy in promoting the engagement of employers who might be able to activate stable and well-paid jobs. Another interpretation of our results is that, given the cap of the subsidy, lower-paying firms have a greater incentive (ceteris paribus) to take up the policy and to hire lower-ability workers (Elvery et al., 2023).

The paper is organised as follows. Section 2 discusses the institutional background of our study. Section 3 describes the dataset and the methodology. Section 4 presents summary statistics. Section 5 reports our result whereas Section 6 concludes.

2 Institutional background

Hiring credits are quite common in Italy (Vergari, 2016) and typically they are represented by employer-borne tax cuts targeted at new hires of disadvantaged workers (e.g. young people, women or long-term unemployed people), or to hirings in less developed Southern regions.[1]

[1] In the last 30 years, hiring credits were targeted to several and specific groups of workers spanning from sailors (DL. 457/1997) to inmates (Law 381/91).

The targets reflect the well-known Italian disparities across regions and demographic groups (Boeri and Garibaldi, 2007; Fernández-Villaverde et al., 2023).

A legislative novelty took place between 2015 and 2016 when the government introduced two measures of unconditional hiring incentives (Law 190/2014 and Law 208/2015), available to all workers and firms in the private sector. Both measures incentivised permanent hirings or conversions from fixed-term contracts that occurred in 2015 and 2016, respectively. The main eligibility criterion was that the worker had not had a permanent contract in the last six months prior to the new (subsidised) contract. In 2015, there was a three-year total exemption of social contribution costs charged to the employer (up to a threshold of €8,060 per year) whereas, for permanent contracts activated in 2016, its duration was reduced to two years and the amount was reduced to 40% of employer-borne contributions (with a cap of €3,250 per year).[2] These interventions were unprecedented for the Italian context as they introduced for the first time unconditional and untargeted hiring credits for permanent jobs.

Between 2015 and 2016, the two measures involved 1.5 million and 600,000 permanent contracts, respectively (INPS, 2017), which are 57% and 35%, respectively, of total permanent hirings/conversions that occurred in 2015 and 2016, respectively.

The rationale for the introduction of these measures may be found considering that a wave of two-tier reforms, which occurred from the late 1990s onwards, created a dual structure with a stock of open-ended contracts unaffected by the reforms, coexisting with a growing part of flexible contracts (Boeri and Garibaldi, 2019).

As a result, fixed-term contracts activated over time amounted to approximately 60% of new hires in the '00s (Daruich et al., 2023). A second wave of interventions was carried out between 2012 and 2015 with the aim of reducing the dual structure of the labour market. More closely related to our analysis is the structural reform introduced with Law 183/2014 (the so-called Jobs Act, which became active from March 2015 onwards) which, on the one hand, introduced a new labour contract for all the new open-ended jobs and, on the other hand, reformed the employment protection legislation (EPL) reducing firing costs for firms with more than 15 employees by removing the possibility of judicial reinstatement after "unfair dismissal" for workers permanently employed. Instead of getting back their jobs, workers will be paid with a reimbursement by employers depending on their tenure in the firm.

The hiring subsidies analysed in this paper were introduced to support employment levels and to promote the widespread use of open-ended contracts (Ardito et al., 2023).

In the empirical analysis, we will mainly focus on the measure introduced in 2015. As a robustness check, we will extend the analysis to the hirings that have benefited from the incentive in 2016.

3 Data and methodology

In this section, we present the data that we used to perform our analysis. In subsection 3.1, we provide information on employee-level data and in subsection 3.2 on firm-level data. We use anonymous tax identifiers to merge data from several data sources; in subsection 3.3 we describe our two-step strategy; and in subsection 3.4, we describe the sample on which we focus our analysis on.

[2]In Italy, payroll taxes borne by employers amount to slightly more than 23% of wages and they mainly refer mainly to social security contributions paid to INPS.

3.1 Matched employer-employee data

Our main data source for the analysis is provided by INPS, which records the work history for the universe of all employees in the private non-agricultural sector. INPS gathers information primarily through a form that employers have to periodically submit to pay social contributions to their employees. The information referred by the firm allows to retrieve details about both the job and the individual who holds it. For instance, the data include information on annual gross earnings, number of weeks worked in a given year, occupation (blue collar, white collar, middle manager, executive), gender, year of birth and first year as an employee. There is no information on hours worked, but INPS provides a full-time equivalent (FTE) weeks measure, which allows us to make weekly wages comparable for both full-time workers and part-time workers.

Furthermore, we also have a firm identifier for each job position registered in our dataset. This proves fundamental for matching job-related data with balance sheet data which we describe in the next section. Finally, INPS gathers information on the set of policies and subsidies attached to each employee that is registered in his archives and we will use this information to identify the hiring credit introduced with Law 190/2014.

3.2 Firm data

We focus on the "firm side" of the policy introduced in 2015. First of all, we have access to the following firm "demographics": firm identifier, birth date, closing date, industry, province and legal status. Thanks to a unique tax firm identifier, we are able to merge data collected by INPS with CERVED data which collects information on firms' balance sheets, such as sales, value added (VA), labour costs, and profits, for the universe of Italian limited liability companies. The data come from standardized reports the employers have to file annually and private partnerships and sole proprietorships are not included.

3.3 Estimation strategy

Since our idea is to link firms' characteristics and the firm take-up of hiring subsidies, we follow a similar strategy to that followed by Bana et al. (2023) in the case of maternal leaves, and rely on the estimation of firm-specific wage premiums using the AKM method Abowd et al. (1999). We have information on the composition of the firms in terms of part-time contracts, workers' gender and occupation (apprentice, blue collar, white collar, middle manager and executive). Owing to the richness of these data, we go beyond the specification introduced by Bana et al. (2023) by using a larger set of controls. To characterize our specification in this first step, we rely on well-defined evidence of the fact that firms pay similar workers differently (Card et al., 2013, 2016, 2018; Macis and Schivardi, 2016; Song et al., 2019; Casarico and Lattanzio, 2019).

Using yearly data from 2005-2018, we estimate firm wage premiums from the following equation:

$$w_{ijt} = \theta_i + \psi_{j(it)} + X_{it}\beta + \epsilon_{ijt} \tag{1}$$

The dependent variable represents log real weekly wages for individual i at firm j at time t;[3] θ_i is the individual fixed effects; $\psi_{j(it)}$ represents the wage premium being paid by firm j with respect to a randomly chosen firm in the sample. X_{it} contains a cubic polynomial for age (normalized at 40), a set of dummies for occupations interacted with a cubic polynomial in experience (current year minus year of the first job as an employee) and a full set of time dummies. We exclude the linear term in age and in experience to avoid collinearity with time and ϵ_{ijt} represents an error term.

To estimate equation (1), we use a panel at the worker level that spans from 2005 to 2018. Then, we dropped observations related to contracts that lasted less than 4 weeks in a year and workers who had less than two years of (potential) labour market experience. Since workers' mobility is crucial for identifying firm fixed effects, we restrict to the largest firms-workers connected set in order to estimate the firm fixed effects (Abowd et al., 2002). Restricting the analysis to this set means that we focus on 99% of the observations in our panel. Furthermore, given that workers may have more than one job in a year, we select the main job based on the type of contract and on the wage. Therefore, if a worker has two jobs in the same year and only one is permanent, we select this last one, and if the worker has two jobs of the same type we select the highest paying. We proceed with the estimation of equation (1) as in Abowd et al. (2002).

Once estimated equation (1), we end up with the so-called firm-specific wage premiums which is our main variable of interest. The literature interprets the firm wage premium as representative of firms' wage-setting policies (Card et al., 2013) practised by firms to all employees. Such premiums may be interpreted as time-invariant factors that may reflect the surplus produced by the firm and rent-sharing wage-setting policies (Card et al., 2016).

To have unbiased estimates, the main assumption behind AKM models is the so-called exogenous mobility assumption. Specifically, workers may move between firms in accordance with a pattern but what is important is that mobility is not related to components of the error term of the equation (1). For example, if there was an idiosyncratic "match effect" to drive mobility, and a worker-specific surplus may occur from the match with a certain firm, we would be mistakenly attributing this effect to a firm-specific wage premium common to all workers employed at that firm.

To test this assumption, we follow a routine developed by Card et al. (2013, 2016). First, we calculate the mean wages of coworkers for individuals who change jobs in a certain year. Then, we define the average wages of movers up to two years prior to and after a move and we rank these averages based on the quartile of origin and destination of one's coworker wages. Thus, we end up with 16 cells formed as a combination of each quartile of mean coworkers' wages in the old and new firms. For clarity, we report in Figure 1 the mean wage from those who start from the first or the last quartile of the distribution of coworker wages.

Looking at Figure 1, it is reasonable to state that the exogenous mobility assumption may be accepted. In fact, if there were match effects such as those defined, for instance, by dynamic match models (Eeckhout and Kircher, 2011), the difference in firm wage premiums before and after a firm switch (here proxied by coworker wages) would not represent firm wage premiums only. If this were the case, the estimates would be biased and the additive specification strongly disputable. However, looking at the symmetry of wage trajectories before and after a move, there is no evidence of a general premium to move. Furthermore, we do not see sudden drops in wages before the switch and a rise afterwards: this means that

[3] We have winsorised values of log wages that are above(below) 99th(1st) percentile of the log wage distribution over the period.

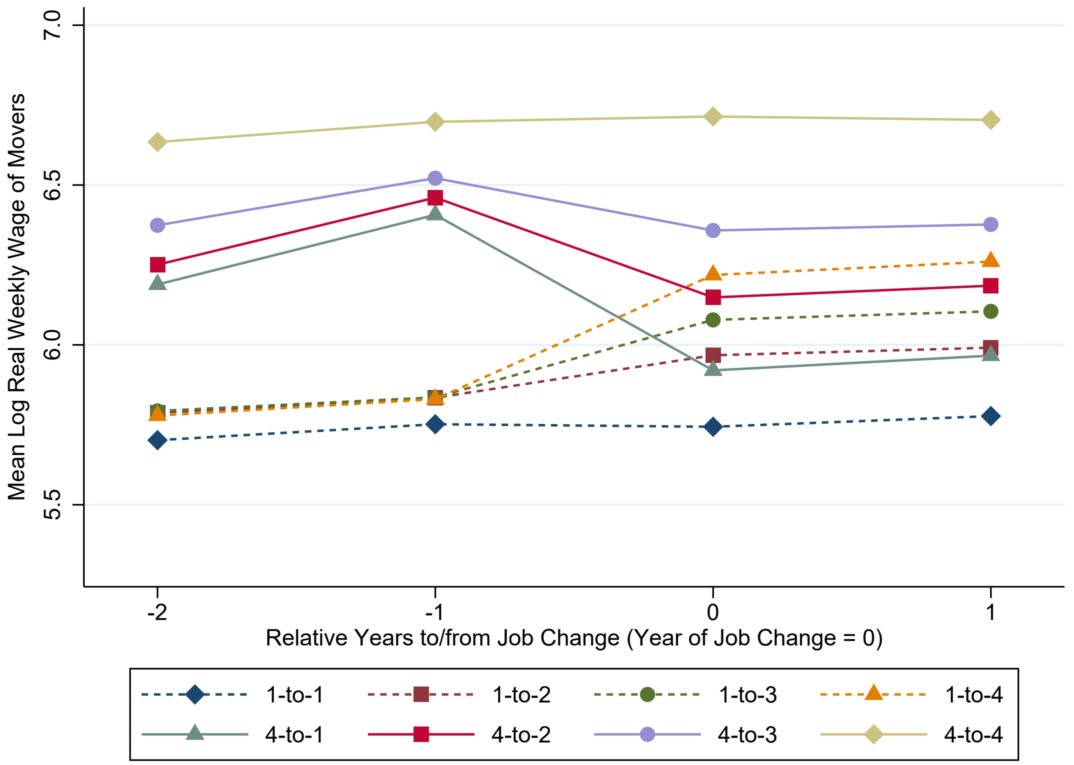


Figure 1: Mean weekly wage of movers across quartiles of average coworker weekly wages. Data relate to the period 2005-2018.

we do not have unobservable negative shocks to firms that could lead workers to move to better firms. The same reasoning could apply to shocks in individuals' productivity, which could be correlated with mobility and wages.

After estimating the model (1), we proceed to the firm-level analysis to assess the relationship between firms' wage premiums and hiring credits usage. For summary statistics about equation (1) estimates see Table A.1 in Appendix A.

We include $\hat{\psi}_j$ obtained in the estimation of (1) in the following equation:

$$Incidencerate_{jt} = \hat{\psi}_j \beta + X_{jt}\delta + \eta_s + \pi_r + \lambda_t + \xi_{jt} \tag{2}$$

The dependent variable is the *incidence rate* in firm j at time t, that is, the ratio of subsidised permanent contracts on total permanent contracts at the firm-year level. We refer to firms that exhibit a positive *incidence rate* as subsidised firms.[4] The benchmark specification for X_{jt} in equation (2) consists of: the share of apprentices, the share of females, the share of part-time workers and average tenure (in terms of workers' years of experience in the labour market) and (log) firm size.[5] In further specifications we add (log) VA per worker and we include the average θ_i's estimated in (1) as a proxy for the ability of workers

[4]We define a firm as subsidised if it has used the payroll tax cut introduced by Law 190/2014 at least once in a given year.

[5]Apprentice contracts are under a special and facilitated tax regime for the employer, and they also represent an ALMP too (D'Agostino and Vaccaro, 2021). Therefore, we decided to insert the share of apprentices in equation (2) to account for the participation in ALMPs by firms and to investigate possible complementarities between this policy and hiring credits.

in the firm. This set of controls expands upon the ones that are used by Bana et al. (2023). Furthermore, we add regional, time and industry-fixed effects.[6]

Our focus is on the coefficient β, which measures the relationship between firm wage premiums and the incidence rate hiring credits. This relationship could be interpreted as causal if no source of endogeneity is present in equation (2). Even if this cannot be tested, we will show that the effects of firm wage-setting policies on the incidence rate are robust across several samples and specifications. There remain some concerns that unobservable variables may be correlated with firm premiums and incidence rates, but thanks to the richness and vastness of our data, we will show that this is unlikely. Furthermore, we use clustered standard errors at the firm level because the outcome variable is likely to be correlated within the firm.

Finally, to account for the biasedness and inconsistency of AKM variance components due to sampling error in the estimated firm and individual effects (Andrews et al., 2008; Kline et al., 2020), we proceed with a split-sample approach (more on this topic is provided in Subsection 5.3).[7] Therefore, we randomly split the main sample that we use to estimate equation (1) and we use half of the sample to estimate wage premiums and the other half to estimate firm-level controls in equation (2). By doing so, we avoid that workers included in the estimation sample of equation (1) to be also considered for the estimation of equation (2). Artificially reducing mobility in our sample (since we estimate firm effect with half the sample) helps us to establish the direction in which measurement error drives our estimates. Due to reduced worker mobility in our split samples and given that AKM estimates are carried out considering firms connected by worker mobility, we will focus on firms with at least 10 employees on average (sample restrictions are described in the next section).

3.4 Sample restrictions

We exclude firms that were born in 2015 or later to avoid endogeneity issues. Indeed, if an individual decided to start a business in 2015 because of the hiring credits, and if this decision was somehow linked to firm premiums, then an endogenous correlation between firm premiums and the incidence rate may emerge. For model (2) we mainly use firms that have on average at least 10 employees. Averages are calculated in the AKM estimation time span 2005-2018. Even if this choice reduces the number of firms in our sample, this may not be an issue. Indeed, by considering these types of firms we avoid extreme values of the incidence rate in the lower tail of the firm size distribution (in a firm with one employee, the incidence rate is more likely to reach a value of 0.5 or even 1 than in firms with 10 employees), and in this way we provide more stable results. In addition to this, given that we are producing firm-level estimates, we focus on the CERVED sample of firms which are a subsample of companies that are on average larger than the average in the universe of Italian firms. After

[6]The estimates we show in the main text are calculated using a dummy variable to discriminate firms operating in the Industry sector with respect to the Service sector, according to ATECO classification fixed effects (Italian counterpart of NACE). The results are robust to industry fixed effects calculated at the 2-digit ATECO classification. The industry is composed of mining, water and waste management, energy, manufacturing and construction industry.

[7]Sampling error in estimated firm and individual fixed effects was originally noted by Krueger and Summers (1988) and Abowd et al. (2004). Andrews et al. (2008) noted that the bias induced by measurement error was an increasing function of workers' mobility between firms. This phenomenon has therefore been labelled as "mobility bias". For instance, we estimated equation (1) on two independent random samples defined in the years 2005-2018, and for those firms with at least 10 employees on average between 2005 and 2018 the correlation between estimated firm premiums on the separate samples is 0.84.

all this, we end up with our main sample which is composed of 134,692 firms, of which 91,020 of which are subsidised firms. Some numbers related to the subsidies introduced in 2015 in our sample are presented in Table A.2 in Appendix A.

4 Descriptive statistics

In this section, we present summary statistics for firms recorded in the CERVED archives, described in Subsection 3.2 in Table 1. The first and second columns of the table report summary statistics for firms that remain in our panel once we draw information on CERVED balance-sheet reports and drop firms born in 2015 or later. We end up with almost 442,000 firms with more than 11 million employees. The last two columns refer to our main sample, which restricts the previous sample to firms with at least 10 employees on average in the period 2005-2018. Table 1 reports the mean incidence rate by within-firm wage and firm premium quartiles and by economic activity (Industry and Service) and macro-region (South, Centre and North) in each sample we selected. The table also shows the number of employees, treated employees and firms for each selected sample.

First of all, we can see that the mean incidence rate declines when considering the sample of firms with at least 10 employees. This happens either if we consider all the firms in each sample or only subsidised firms. The table also shows a clear negative relationship between the incidence rate and both within-firm wages and firm wage premiums in each sample we consider. The negative correlation is somewhat more pronounced with respect to within-firm wages than with respect to firm premiums. Furthermore, we report the mean incidence rate by economic activity and we see that the mean incidence rate is higher in the Service sector than in Industry. In Appendix A, we provide a more granular description of the distribution of the incidence rate across sectors (see Figure A.1). Last, when looking at the mean incidence rate by macro-regions, we find that the usage of hiring credits is more pronounced in the less-developed areas of the South and Islands with respect to other macro-regions.

In Figure 2a-2d, we further investigate the relationship between firm and worker characteristics and the incidence rate for the main sample defined in Subsection 3.4. We first consider within-firm wages, firm premiums and firm productivity, here proxied by log VA per worker, which are the variables in the bulk of our analysis since they describe two important and related firm characteristics: wage-setting policies and productivity. We then take into account worker mean ability at the firm level, corresponding to the mean of workers' fixed effects estimated in equation (1), since this may give us more insights on the allocation of workers and composition effects related to the policy. Each graph reports the average incidence rate calculated for each percentile of each variable.

The relationship that is depicted in the aforementioned figures is unambiguous: it is negative in terms of within-firm wages, firm premiums and value-added, and the evidence is confirmed along the distribution of each variable. The relationship also remains negative also when we look at worker mean ability at the firm level.

The descriptive statistics we provide in this section make the case for an in-depth analysis of firms' characteristics to understand the role of firm wage premiums on the usage of hiring credits such as those introduced by Law 190/2014 in 2015. In addition, the graphs show a rather linear relationship between the wage premium and the incidence rate, which corroborates the methodology we described in Subsection 3.3.

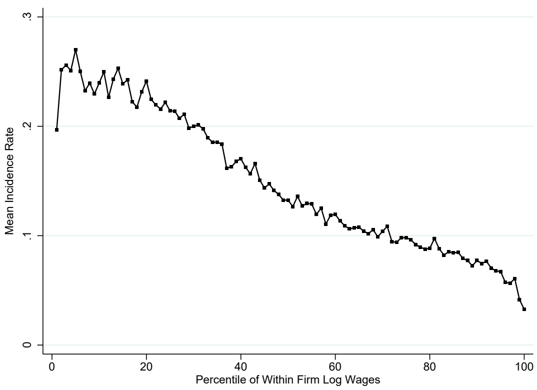
The evidence is confirmed when restricting the sample to subsidised firms only (see Ap-

Table 1: Summary statistics for the incidence rate

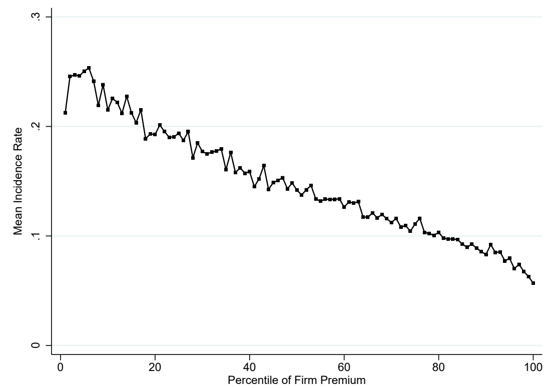
	Cerved Sample	Cerved Sample - Subsidised Firms	Cerved Sample - 10 Employees	Cerved Sample - 10 Employees Subsidised
Mean incidence rate	.153	.322	.120	.183
Mean incidence rate by:				
1st Quartile of within-firm wage	.221	.435	.186	.276
2nd Quartile of within-firm wage	.184	.386	.137	.211
3rd Quartile of within-firm wage	.128	.281	.094	.146
4th Quartile of within-firm wage	.085	.186	.065	.104
Mean incidence rate by:				
1st Quartile of firm premium	.197	.416	.171	.259
2nd Quartile of firm premium	.174	.353	.131	.201
3rd Quartile of firm premium	.142	.291	.103	.158
4th Quartile of firm premium	.106	.240	.075	.118
Mean incidence rate by:				
Industry sector	.132	.271	.097	.153
Services sector	.167	.357	.142	.212
Mean incidence rate by:				
South and Islands	.183	.272	.103	.246
Centre	.178	.368	.138	.155
North	.129	.272	.103	.246
Employees	11,117,608	8,974,137	9,482,918	8,125,877
Treated employees	769,745	769,745	560,715	560,715
Firms	442,304	215,265	134,692	91,020

Notes: Columns (1) and (2) represent statistics for firms in the CERVED sample born before 2015. Columns (3) and (4) restrict the CERVED sample to firms born before 2015 and with at least 10 employees on average in the period 2005-2018. We exclude agriculture, the public sector and the activities of extra-territorial bodies. Industry is composed of mining, water and waste management, energy, manufacturing and construction industry. Size is calculated as an average in the years 2005-2018. The within-firm wage is the average of within-firm log wages calculated for the period 2015-2018.

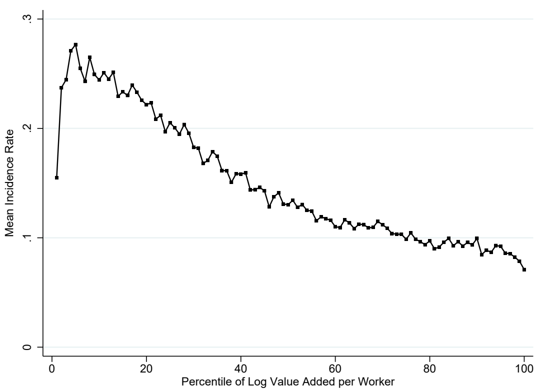
pendix A, Figures A.2a-A.2d).



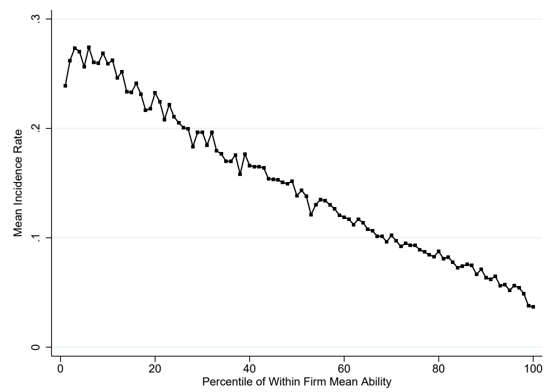
(a) Incidence rate by percentile of within-firm log wage



(b) Incidence rate by percentile of firm premium



(c) Incidence rate by percentile of log VA per worker



(d) Incidence rate by percentile of worker mean ability

Figure 2: Graphs are based on firm-level data in the period 2015-2018. We restrict the analysis to firms born before 2015, with at least 10 employees and registered in CERVED records.

5 Results

In Subsection 5.1 we present our benchmark estimates; Subsection 5.2 reports additional results and specifications for equation (2); Subsection 5.3 discusses the importance of measurement error in our estimates; Subsection 5.4 presents the results obtained from two robustness checks.

5.1 Firm premiums and incidence rate

In this section, we present our benchmark estimates for equation (2) for the main sample (firms with at least 10 employees on average between 2005-2018). Table 2 reports four specifications for equation (2). In the first column, we control for the firm wage premium, estimated in equation (1), and for variables describing the composition of the workforce of the firm, that is, the share of female, part-time workers and apprentices employed by firm j in year t. Furthermore, we insert worker within-firm tenure, i.e., the average tenure of workers employed by the firm, and the log of firm size. In the second column, we add firm employees' mean ability, as defined in Subsection 3.3 whereas the third and fourth columns add log

Table 2: OLS estimates for the entire sample

	(1)	(2)	(3)	(4)
Firm premium	-0.1051***	-0.0985***	-0.0728***	-0.0775***
	(0.0031)	(0.0031)	(0.0034)	(0.0033)
Log VA per worker			-0.0190***	-0.0129***
			(0.0007)	(0.0007)
Worker mean ability		-0.1109***		-0.0900***
		(0.0034)		(0.0037)
Part-time workers share	0.0300***	0.0201***	0.0141***	0.0110***
	(0.0022)	(0.0022)	(0.0023)	(0.0023)
Female workers share	-0.0257***	-0.0342***	-0.0245***	-0.0316***
	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Apprentices share	0.0315***	0.0281***	0.0222***	0.0213***
	(0.0066)	(0.0066)	(0.0066)	(0.0066)
Within-firm worker tenure	-0.0072***	-0.0057***	-0.0072***	-0.0060***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Firm size	-0.0043***	-0.0048***	-0.0064***	-0.0062***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Mean incidence rate	0.120	0.120	0.120	0.120
Observations	468,884	468,884	457,850	457,850

Notes: Data include both subsidised and not subsidised firms with at least 10 employees on average in the period 2005-2018. The dependent variable is the subsidy incidence rate. The first column controls for the share of women, part-time workers, apprentices, and worker mean tenure at the firm-year level and log firm size. The second column adds as a control "worker mean ability" as the average of individual effects at the firm-year level estimated in (1). Column (3) repeats Column (1) but adds log VA per worker. Column (4) repeats Column (2) but log VA per worker is added. Standard errors are clustered at the firm level. CERVED sample is used. Year, regional and industry fixed effects are included. ***p<0.01.

value added per worker to the first and second columns, respectively. In each specification, we include time, regional and industry-fixed effects. Concerning this, in our benchmark results represented in Table 2, we include a dummy equal to 1 if the firm is in the Service sector as opposed to the Industry sector. When including finer industry controls (roughly 90 industry fixed effects), the results for equation (2) are highly comparable (see Appendix A, Table A.3).

As stated above, we are primarily interested in the relationship between firm wage premiums and the incidence rate of hiring subsidies. This relationship is summarized by β in equation (2) and is reported in the first row of Table 2. Concerning this, Table 2 shows a clear negative and significant relationship between our variables of interest and the incidence rate in each specification. Moving to the specifications where we control for log VA per worker, we see that the value of the coefficient of $\hat{\psi}_j$ decreases. This result is consistent with the interpretation of the firm wage premium as the surplus that firms share with their workforce, a phenomenon that may be partly captured by the VA per worker.

To interpret the coefficients related to firm wage premiums, it might be useful to provide further insights into the estimates obtained with (1): for the firms we consider in Table 2, our estimates of $\hat{\psi}_j$ span from 1.5 to 4.7 log-points. Therefore, given that our estimated coefficients for firm premiums in (2) span from -0.07 to -0.1, we can state that a 100% increase in wage premiums is associated with a reduction, on average, of the incidence rate by a value which is approximately equal to the mean of the incidence rate (which is reported at the bottom of Table 2). In other words, if we started from the minimum of the $\hat{\psi}_j$ distribution and added 1 log point to it (which roughly means moving from the first quartile to the second quartile), we would see an average reduction of the incidence rate roughly equal to 7-10 percentage points. This magnitude of the estimated β mimics the descriptive statistics reported in Table 1, where moving from one quartile of firm wage premiums to the next is associated with an average reduction of the incidence rate of approximately 25%.

Delving deeper into Table 2, other interesting features of our estimates appear. We find that firms that used more intensively hiring credits have a lower VA per worker on average and that worker mean ability is negatively related to the incidence rate. This result is unsurprising given the positive assortative matching between workers and firms reported in the existing literature.

Furthermore, the firms that have used the hiring credits more intensively are also those that have a lower share of women employed in their workforce and that lean on part-time contracts relatively more. On average, the firms that exploited the subsidy more are smaller, and have a less experienced workforce. The apprentices' share is positively related to the incidence rate, which could point to some sort of complementarity between the usage of this economy-wide hiring incentive and other forms of contractual relationships that exhibit more favourable fiscal conditions (D'Agostino and Vaccaro, 2021). In Appendix A, Table A.4, we show that the results are robust even when we consider all firms with no size restriction. We also provide estimates restricting the main sample to those firms that had access to hiring credits (see Appendix A, Table A.5) for the same specifications of Table 2. The relationship between the incidence rate and the variables of interest remains virtually unchanged in terms of the sign of the relationship. What is different is the magnitude of β that in Table A.5 spans from -0.1 to -0.15, coherently with the fact that the mean incidence rate is now higher given that we restrict the sample to subsidised firms only.

To sum up, according to our estimates, we can state that those firms paying lower wages, are less productive and employ lower-skilled workers and resorted more, on average, to the untargeted hiring incentives.[8]

5.2 Additional results

To investigate the extent to which the results above are robust to different specifications and subsamples, we proceed with a deep stratification of our sample. This allows us to exclude the possibility that the coefficients of firm wage premiums shown in Table 2 are not driven by the choice of particular subsamples and are instead representative of the more structural behaviour of firms concerning the untargeted hiring credits.

We present the heterogeneity analysis in Figure 3 where we report estimated βs for several subsamples.[9] We have stratified for average firm size (the mean is calculated between 2005-

[8] These results are confirmed even when we repeat the equations in Table 2 but we use as controls the pre-policy values of the control variables and we estimate firm wage premiums for the period 2005-2014. The magnitude of β is still between 7-10%.

[9] The coefficients represent β from equation (2) and are estimated using as controls the share of women, the share of part-time workers, the share of apprentices, worker mean tenure at the firm-year level, log firm size and log VA per worker. The black dots represent the coefficients for the full sample, whereas the blue diamonds represent the estimates for the sample that includes only subsidised firms. We exclude agriculture,

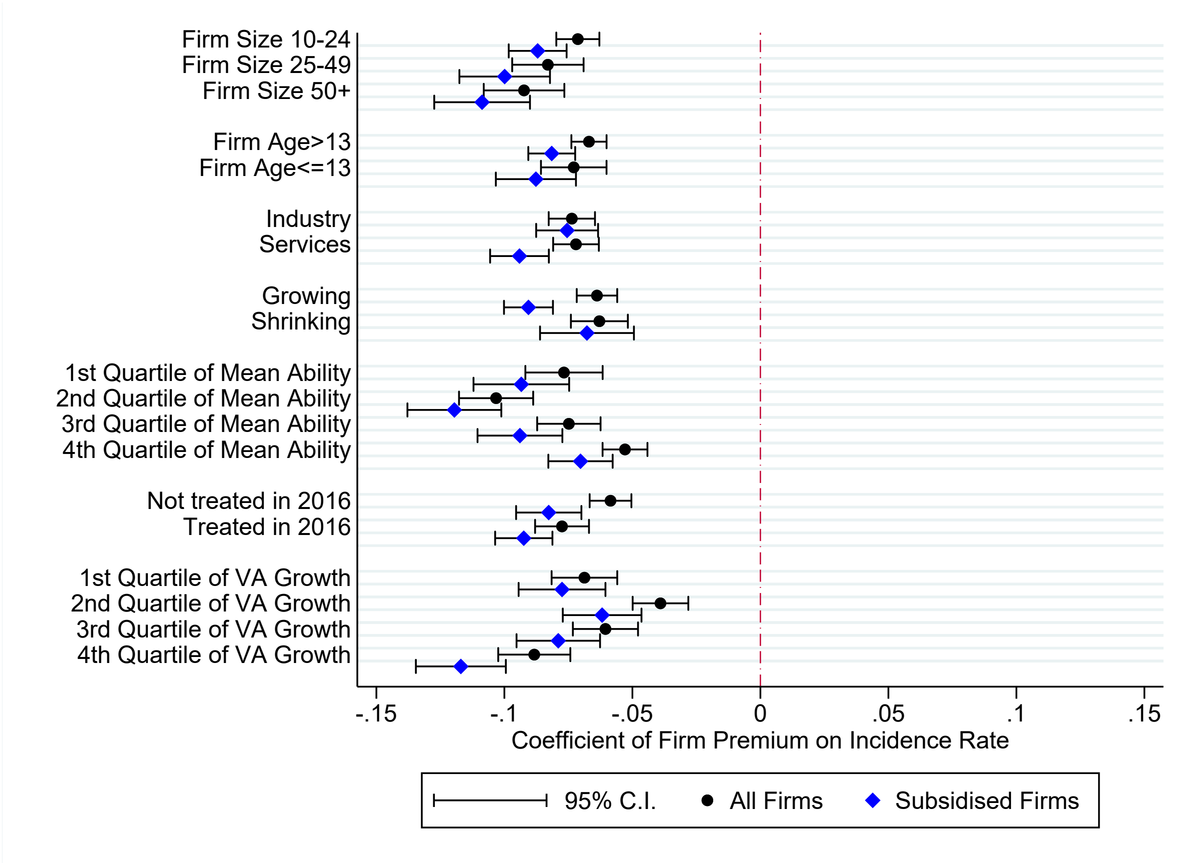


Figure 3: Coefficients of firm wage premiums for stratified subsamples estimates.

2018) and for Industry and Service sector. We have also differentiated for firm age, i.e., the number of years we observe firm j in our panel for the AKM model estimation, therefore between 2005-2018, whose mean value is 13. We have included a time-invariant measure of worker's average ability at the firm level and estimated equation (2) in each quartile of the distribution of this variable.[10] Following Bana et al. (2023), we have further stratified firms according to their average workforce growth rate calculated as an average between 2005-2018.[11] Lastly, we have averaged the VA growth over 2005-2018 and stratified on this to assess how productivity dynamics affect the relationship between the incidence of hiring credits and firm wage premiums. [12] In Figure 3, we report estimates for the full sample (black dots) and for subsidised firms only (blue diamonds). For more details on the regressions we estimated for Figure 3, see Table A.6 in section A of the Appendix.

Figure 3 shows that the relationship of interest is always negative and the magnitude is relevant. The accuracy of the estimates slightly decreases when we restrict to subsidised firms

the public sector and activities in extra-territorial bodies. Industry is composed of mining, water and waste management, energy, manufacturing and construction industry. Industry, regional and time-fixed effects are included. We restrict the sample to firms with at least 10 employees on average in the period 2005-2018. The confidence intervals are at 95% level and standard errors are clustered at the firm level.

[10] We have averaged over 2005-2018 the mean ability estimated with θ_is in equation (1) at the firm level.

[11] Therefore, we classify firms as growing when the average growth rate is positive and as shrinking when the average growth rate is 0 or negative.

[12] We have winsorised values of the VA growth rate that are above/below the first/last percentile of the distribution of such variable.

because the dimension of the sample shrinks. However, the estimates are always significant at the 95% level. Furthermore, the coefficients estimated in all of the stratifications do not take unusual values reinforcing the evidence in Table 2.

Moving to the single pieces of evidence in Figure 3, we start by considering how the distribution of firm size affects the coefficients of the firm wage premium. Even if the estimated coefficients are highly comparable, they increase (in absolute value) with firm size, which means that firm wage premiums are more important predictors of the use of the incentives for larger firms than for smaller ones and this could reflect different determinants in firms' take-up of subsidised hirings or simply measurement error in firm fixed effects estimated in equation (1). Indeed, attenuation bias may affect the estimated coefficients since, as it is well known, wage premiums are poorly estimated for smaller firms. Hence, it is likely that after correcting for the estimation error, the estimates would increase, at least for firms with 10-24 employees. Therefore, we could infer that if the size of firms in the full sample were upscaled, an invariant coefficient across firm size would emerge even in this case.

Stratifying for firm age gives further insights since younger firms may be more in need of using the subsidy and saving on labour costs to survive. However, for both firms with an age greater and smaller than 13 (that is the average firm age in our sample), firm premiums are negatively related to the incidence rate.[13] Furthermore, both for firms in the full sample and for the restricted sample of subsidised firms, the estimated coefficients are always comparable, even if there is slight variability between the two samples. Indeed, the behaviour of the estimates with respect to firm age could be somehow related to an estimation issue affecting firm premiums in equation (1). For these firms $\psi_{j(it)}$ is estimated with a slightly reduced number of observations and this could be reflected in how estimates move between the two groups. However, testing such a hypothesis is beyond the scope of our analysis[14].

Considering the heterogeneous effects of economic activity, the importance of firm premiums for predicting the incidence rate is slightly stronger in the sample restricted to subsidised firms, otherwise, the estimates are virtually the same in both Industry and Service activities.

Furthermore, we stratified for firms growing or shrinking in terms of size since firm premiums could be different in these two groups, as could the incentives to take up the policy. For instance, if growing firms are also those with higher firm wage premiums, their attitude in hiring using subsidies might affect β from equation (2). The values of β are highly comparable across the two groups for both samples. Confidence intervals for the coefficients related to shrinking firms are somewhat larger than those related to growing firms because we consider firms with at least 10 employees on average between 2005-2018 and it is straightforward that firms of this size, that are hiring on a permanent basis and that are also shrinking in terms of size, are less likely to be found in the data.

In addition, it is interesting to see that estimates vary when we move across different quartiles of within-firm workers' mean ability. The coefficient related to the firm wage premium follows the same pattern for the full and subsidised firms' samples. In addition, the coefficient is smaller in the first quartile of the mean ability distribution than the coefficient in the second quartile. Then, from the second quartile onwards, the coefficient decreases but

[13]Firms exhibit such average age for two main reasons. First because, firms in our panel are larger than the average firm in the population of Italian firms, and second because we exclude firms born after 2015. Furthermore, firms with an age greater than 13 are part of the balanced panel case for the years 2005-2018. Therefore, this stratification may be seen as confirming our main results even when restricting to the balanced panel.

[14]For a discussion on how time is related to the AKM model estimation, refer to Lachowska et al. (2023).

remains negative and significant. This might again be attributable to measurement error that stems from the estimation of equation (1). Indeed, given that the measurement error in fixed effects estimates from equation (1) decreases with firm size, the behaviour of the estimates related to the first quartile could reflect some attenuation bias. However, the fact that the higher the level of mean ability of a firm is, the weaker (but still negative) the relationship of firm wage premiums with the take-up of hiring subsidies, is coherent with the estimates reported in Table 2, and reinforces the hypothesis of a positive assortative matching between workers and firms. Indeed, it seems that firms that intensively use hiring credits are those with lower wage premiums and are therefore to some extent less productive (Card et al., 2018), and those with a lower-ability workforce. This evidence is reinforced considering that the probability of being hired with a subsidised contract is negatively correlated with both worker ability and wage premiums (see Figure A.3 and Figure A.4 in Appendix A). Overall, these findings show that negative selection is at play, in terms of both workers and firms, when considering the participation in the hiring credits program introduced in Italy in 2015.

Finally, we consider firms' productivity dynamics in terms of average VA growth in the period 2005-2018 and subsample firms with respect to quartiles of VA growth.[15] Indeed, the estimates reported in Table 2 may be biased if firms with a worse productivity dynamic are also those with lower wage premiums and if VA growth is related to the subsidy take-up. However, Figure 3 shows that the coefficients across the quartile of VA growth move around the range of variation expressed by Table 2.

5.3 Measurement errors, firm wage premiums and incidence rate

Notwithstanding the robustness of the estimates shown in the previous sections, a concern that one may have is whether possible measurement errors might affect the results. As noted in Section 3, when estimating equations like (1), it is important to be aware of the so-called "mobility bias". In our case, we have tried to contain this type of bias by focusing on firms that have at least 10 employees.

To further address this issue, we proceed with a split sample approach similar to that described in Bana et al. (2023). To be more specific, we randomly split in two the original panel defined at the worker level. We cut half of the observations of the sample such that workers recorded on one side of the sample (sample A) will not be on the other (sample B). Therefore, we estimate equation (1) with sample A and equation (2) with the other. In this context, $\hat{\psi}_j$ in equation (2) will be estimated on sample A and used to estimate equation (2) whose controls will be calculated using observations coming from sample B.

The main limitation of this procedure is that in each split sample, we will have a reduced connected set in terms of both workers (we split the sample on workers specifically) and firms. For instance, the largest connected set where we estimate equation (1) in the main sample is composed of more than 3 million firms while in each subsample the estimate will be carried out on 2.4 million firms. The number of firms is not cut in half as the number of workers because, apart from very small firms, we are simply distributing firms' workforce in each subsample. However, the number of firms we have for equation (2) is reduced with respect to the original sample once we merge each of the largest connected sets, as we do when we use firm premiums estimated in sample A to calculate how firm premiums relate to

[15] Mean VA growth rate is -2.2% at the first quartile and 1.7% at the fourth quartile in the estimation sample.

Table 3: OLS estimates for the split sample

	(1)	(2)	(3)	(4)
Firm premium	-0.103***	-0.0875***	-0.0765***	-0.0699***
	(0.0044)	(0.0045)	(0.0047)	(0.0048)
Log VA per Worker			-0.0154***	-0.0114***
			(0.0009)	(0.0009)
Worker mean ability		-0.0893***		-0.0738***
		(0.0046)		(0.0048)
Part-time workers share	0.0216***	0.0130***	0.0078**	0.0040
	(0.0032)	(0.0033)	(0.0034)	(0.0034)
Female workers share	-0.0317***	-0.0390***	-0.0316***	-0.0377***
	(0.0026)	(0.0027)	(0.0026)	(0.0027)
Apprentices share	0.0402***	-0.0367***	-0.0346***	-0.0326***
	(0.0113)	(0.0113)	(0.0114)	(0.0114)
Within-firm worker tenure	-0.0073***	-0.0060***	-0.0072***	-0.0063***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Firm size	-0.0029***	-0.0036***	-0.0043***	-0.0045***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Mean incidence rate	0.105	0.105	0.105	0.105
Observations	219,004	219,004	214,207	214,207

Notes: Data include both subsidised and not subsidised firms with at least 10 employees on average in the period 2005-2018. The dependent variable is the subsidy incidence rate. The first Column controls for the share of women, the share of part-time workers, the share of apprentices, worker mean tenure at the firm-year level and log firm size. The second Column adds as a control "worker mean ability" as the average of individual effects at the firm-year level estimated in equation (1). Column (3) repeats Column (1) but includes log VA per worker. Column (4) does the same with respect to Column (2). Standard errors are clustered at the firm level. CERVED sample is used. Year, regional and industry fixed effects are included. These estimates are obtained using a split sample approach so that firm effects are estimated with workers that are not part of the sample used to estimate the equation at the firm level. ***p<0.01.

the incidence rate at the firm level through equation (2).[16]

This procedure may be helpful in our case for two main reasons: reducing mobility in our estimates mechanically increases the mobility bias in variance components of $\hat{\psi}_j$ and this allows us to uncover how the mobility bias affects our estimates. Furthermore, using independent samples to estimate ψ_j and worker mean ability, which we use as a control in equation (2), may restore the correct degree of correlation between these two variables.

We present the estimates related to the split-sample approach in Table 3. As expected, the relationship is somehow attenuated due to increased mobility bias, but it is confirmed that this attenuation is not driven by measurement errors in firms' wage premiums. Furthermore, the behaviour of β shown in Table 3 is more coherent with the fact that we found a positive correlation between individual effects and firm premiums.[17] Indeed, when we control for

[16]For instance, we move from 134,692 firms in the main sample for the years 2015-2018 to 61,742 firms when we estimate equation 2 on the dual connected set of firms with at least 10 employees on average in years 2005-2018 and which are recorded in CERVED data.

[17]See Table A.1 in the Appendix.

workers' mean ability, the coefficient related to the wage premium is reduced due to the positive correlation between the two variables.

5.4 Partial payroll tax cut and amenities

In this subsection, we run a robustness analysis on the relationship of interest, the link between firm premiums and the incidence rate. For this purpose, we estimate equation (2) on the hiring credit policy introduced in 2016 by Law 208/2015 described in Section 2 which provided a partial payroll tax cut. We carry out the same analysis as in the previous case, but we focus on the years 2016-2018. We present the estimates the estimates in Table 4.

Table 4: OLS estimates for all sample - Law 208/2015

	(1)	(2)	(3)	(4)
Firm premium	-0.0288***	-0.0263***	-0.0199***	-0.0217***
	(0.0015)	(0.0015)	(0.0016)	(0.0016)
Log VA per worker			-0.0054***	-0.0030***
			(0.0004)	(0.0004)
Worker mean ability		-0.0405***		-0.0357***
		(0.0018)		(0.0019)
Part-time workers share	0.0131***	0.0095***	0.0092***	0.0080***
	(0.0011)	(0.0011)	(0.0012)	(0.0012)
Female workers share	-0.0151***	-0.0182***	-0.0152***	-0.0179***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Apprentices share	-0.0102***	-0.0118***	-0.0124***	-0.0130***
	(0.0036)	(0.0036)	(0.0036)	(0.0036)
Within-firm worker tenure	-0.0026***	-0.0020***	-0.0025***	-0.0020***
	(0.0000)	(0.0001)	(0.0000)	(0.0001)
Firm size	-0.0001	-0.0001	-0.0005**	-0.0004***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Mean incidence rate	0.0400	0.0400	0.0400	0.0400
Observations	338,758	338,758	331,445	331,445

Notes: Data include both subsidised and not subsidised firms with at least 10 employees on average in the period 2005-2018. The dependent variable is the subsidy incidence rate. The first Column controls for the share of women, part-time workers, apprentices, and worker mean tenure at the firm-year level and log firm size. The second Column adds as a control "worker mean ability" as an average of individual AKM effects at the firm-year level. Column (3) repeats Column (1) but adds log VA per worker. Column (4) repeats Column (2) but log VA per worker is added. Standard errors are clustered at the firm level. CERVED sample is used. Year, regional and industry fixed effects are included. ***p<0.01.

The coefficients estimated are still negative, and again, the firms that used hiring credits more intensively, exhibit lower firm wage premiums. Furthermore, comparing Table 2 and the ones in Table 4, is remarkable how they follow exactly the same pattern, apart from the magnitude. The only difference is the negative sign related to the coefficient of the share of apprentices, which could indicate that in the case of a partial tax cut, no complementarity can be found between the two fiscal regimes. With respect to the interpretation of the magnitude of the coefficients, which turn out to be approximately 3 times smaller than those of the previous case, it is necessary to consider that the 2016 incentive was less generous in that it covered 40% of employer contributions and for a two-year period for a total value of approximately 2.5 times lower than that of the previous incentive, and accordingly, the number of hirings that benefited from this incentive was proportionally lower as can be seen from the mean incidence rate reported in Table 4. Thus, the different magnitudes are proportional to the difference in the scale of the average of the dependent variable. These findings not only confirm the robustness of the previous results but also point to the fact that the negative relationship between firm premiums and firm take-up of economy-wide hiring credits may be a structural feature of this specific kind of ALMP.

A final concern regarding the interpretation of the estimates is that firm-specific wage premiums might be a compensating wage differential for less desirable working conditions rather than a true rent component related to firm productivity(Sorkin, 2018; Bana et al., 2023). Since we are analysing a subsidy that was given to firms conditioned on permanent hirings, it could be argued that contractual stability is compensated for by lower wages. At the same time, one may easily argue the opposite. Indeed, a firm more committed to stabilising its workers could also be a firm paying higher wages because of a more inclusive management culture or a strategy to attract workers with higher abilities. This issue is assessed in Bana et al. (2023) and Lachowska et al. (2022), who provide evidence of the fact that the within-firm wage level and non-monetary dimensions of worker compensation are positively related.

We follow this literature by using the retention rate, which may be considered as a proxy of the desirability of the workplace (Sorkin, 2018). This variable is calculated as the share of workers who stay at firm j between t-1 and t. If it is a measure of desirability and if it is negatively (positively) correlated with wage premiums, we expect that our estimates understate (overstate) the true link between wage premiums and the incidence rate. Since, the retention rate is also representative of worker turnover at the firm level and therefore negatively (and mechanically) related to our dependent variable, to avoid endogeneity issues, we consider the one-year lag of this variable. Table 5 reports the results of these further estimates. Since β is lower than the one presented in Table 2, it seems more likely the case that wage premiums and retention rate are positively related, confirming the findings in the cited literature. At the same time, even if the results are somehow attenuated, firm wage premiums still have a significant relationship with the incidence rate, which means that they are capturing some unobserved dimension of firms' behaviour that exerts an influence on the incidence rate.

In summary, the estimates reported throughout the paper robustly demonstrate that firms paying lower wage premiums, which are less productive and that offer to the workforce a less attractive work environment resort more intensively to untargeted hiring credits of the kind analysed in this paper.

6 Conclusion

Hiring credits have been widely used across Europe and the United States since the Great Recession (Cahuc et al., 2019) although the empirical literature has provided evidence of their moderate effectiveness in terms of the employment outcomes of targeted individuals. We fill a gap in the literature by focusing on the selection mechanisms behind firms' take-up of such policies.

By using rich and vast administrative data for Italy and an estimation strategy based on

Table 5: OLS estimates with lagged retention rate

	(1)	(2)	(3)	(4)
Firm premium	-0.0597***	-0.0566***	-0.0427***	-0.0461***
	(0.0029)	(0.0029)	(0.0032)	(0.0032)
Log VA per worker			-0.0099***	-0.0061***
			(0.0006)	(0.0006)
Worker mean ability		-0.0671***		-0.0568***
		(0.0031)		(0.0034)
Lagged retention Rate	-0.2228***	-0.2184***	-0.2203***	-0.2178***
	(0.0023)	(0.0022)	(0.0023)	(0.0023)
Part-time workers share	0.0133***	0.0076***	0.0047***	0.0029
	(0.0021)	(0.0021)	(0.0022)	(0.0022)
Female workers share	-0.0089***	-0.0144***	-0.0077***	-0.0123***
	(0.0017)	(0.0018)	(0.0018)	(0.0018)
Apprentices share	-0.0140**	-0.0123**	-0.0075	-0.0071
	(0.0062)	(0.0062)	(0.0062)	(0.0062)
Within-firm worker tenure	-0.0049***	-0.0040***	-0.0049***	-0.0042***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Firm size	-0.0056***	-0.0058***	-0.0071***	-0.0070***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Mean incidence rate	0.120	0.120	0.120	0.0450
Observations	467,110	467,110	456,212	456,212

Notes: Data include both subsidised and not subsidised firms with at least 10 employees on average in 2005-2018. The dependent variable is the subsidy incidence rate. The first Column controls for the share of women, part-time workers, apprentices, and worker mean tenure at the firm-year level and log firm size. The second Column adds as a control "worker mean ability" as an average of individual AKM effects at the firm-year level. Column (3) repeats (1) but adds log VA per worker. Column (4) repeats (2) but log VA per worker is added. Standard errors are clustered at the firm level. CERVED sample is used. Year, regional and industry fixed effects are included. The lagged retention rate is included in each column. ***p<0.01.

the standard AKM model, we have shown the specific features of the firm benefiting from untargeted hiring credits as the ones introduced by Law 190/2014. The take-up is higher when firms do have low-wage setting policies, employ workers with low ability, or have low productivity. The results are robust to several specifications and sample stratifications. We have also assessed possible measurement error biases and provided results to support the hypothesis that mobility bias is not driving the negative composition that we find. We have provided estimates on the interplay between amenities, firm premiums and the firm-level take-up of the policy. By using the firm-level retention rate to proxy such desirability (Sorkin, 2018), our main results are confirmed when we insert this variable into the estimating equation.

In conclusion, in addition to the literature on the employment impact of hiring incentives, which has pointed to the low effectiveness of these instruments from a cost-benefit perspective, our analysis casts further and reasonable doubts stemming from the type of firms that have benefitted from these policies. Setting low-wage premiums may indicate that the firms have a poor market positioning, poor ability to put workers' skills to good use, and managerial attitudes prioritizing short-term cost cuts over strategic investments in the pursuit of product and process competitiveness.

Jobs created with these hiring subsidies also deserve some thought. Even if the employment status of workers hired with the subsidy has improved (Sestito and Viviano, 2018), policy-induced jobs seem concentrated in worst-paying firms, and this questions the quality of the employment promoted by this type of policy.

We are aware that our results do not take into account the causal impacts of hiring credits on the performance of recruiting firms, and we leave this analysis to future research. Further research is also needed to assess whether different designs, such as specific targets or conditionalities, may have different composition effects and impacts at the firm level. Since such kinds of labour market policies are and will continue to be widely diffused, this evidence may prove fundamental for future policy-making.

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Appendix

A Additional tables and figures

Table A.1: Summary statistics for AKM model estimates

	All sample	Largest Connected set
Sample size		
Workers	21.917.040	21.403.520
Firms	3.516.066	3.116.526
Summary Statistics		
Observations	178.696.272	175.452.849
Mean log wages	6.140	6.143
Standard deviation of log wage	.455	.456
Summary of estimates		
Standard deviation of firm effect		.226
Standard deviation of worker effect		.312
Correlation of worker/firm effects		.195
RMSE of AKM residuals		.172
Adjusted R^2		.834
Model with time dummies only		
Standard deviation of firm effect		.274
Standard deviation of worker effect		.327
Correlation of worker/firm effects		.156
RMSE of AKM residuals		.196
Adjusted R^2		.819

Notes: Table reports summary statistics for model (1); "Model with time dummies only" refers to a specification for (1) that excludes all controls except time dummies.

Table A.2: Summary statistics, hiring credits introduced by Law 190/2014

	Cerved sample	Cerved sample – 10 employees on average
Treated workers:		
Female	279,301	93,938
Male	490,944	358,030
Under 30	230,150	175,781
30-49	434,578	313,596
50+	105,517	71,338
Total	769,745	560,715
Firms	442,304	134,692
Treated firms	215,265	91,020

Notes: Table reports the number of workers involved in the policy by gender and age. At the bottom, we report the number of firms involved in each sample. We exclude firms born after 2015. The last column reports statistics referring to the sample of the benchmark analysis.

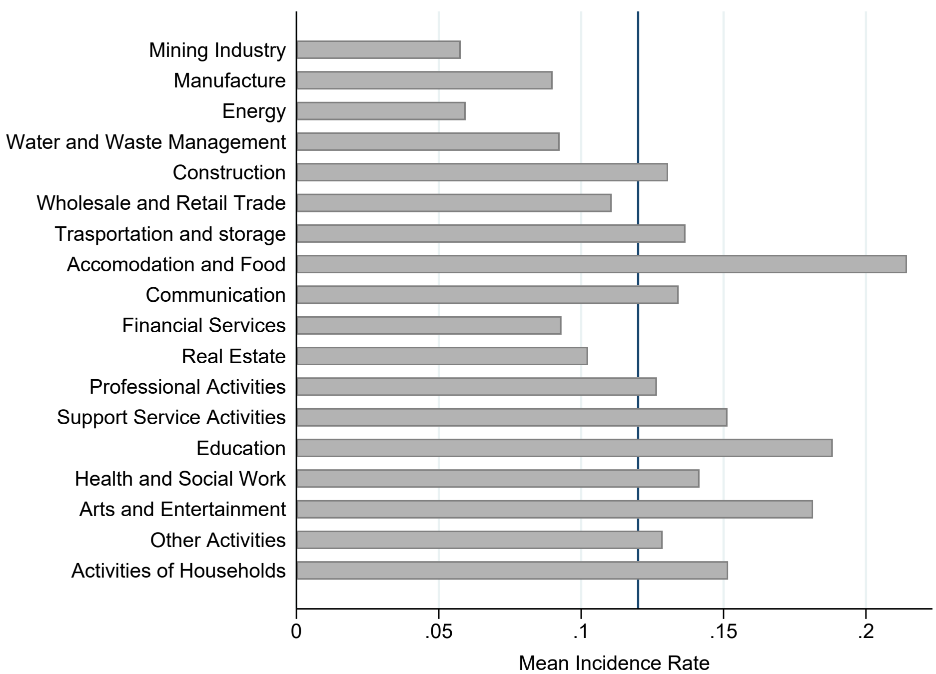
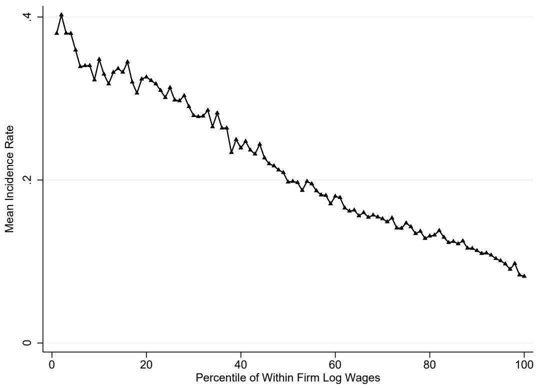


Figure A.1: Incidence rate by 1 digit Ateco sector in the sample of the benchmark analysis

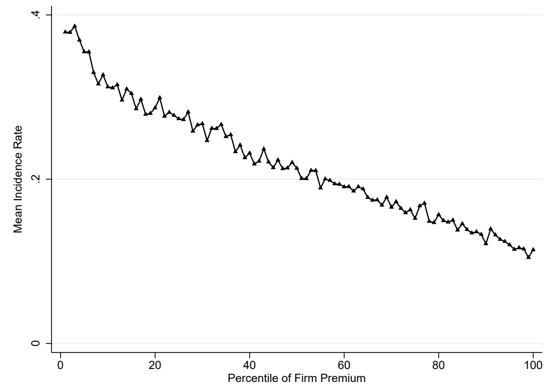
Table A.3: OLS estimates for all samples with finer industry controls

	(1)	(2)	(3)	(4)
Firm premium	-0.0907***	-0.0893***	-0.0651***	-0.0711***
	(0.0033)	(0.0033)	(0.0033)	(0.0033)
Log VA per worker			-0.0173***	-0.0123***
			(0.0007)	(0.0007)
Worker mean ability		-0.0997***		-0.0792***
		(0.0035)		(0.0038)
Part-time workers share	0.0322***	0.0259***	0.0195***	0.0181***
	(0.0024)	(0.0024)	(0.0025)	(0.0025)
Female workers share	-0.0214***	-0.0291***	-0.0195***	-0.0257***
	(0.0022)	(0.0022)	(0.0022)	(0.0023)
Apprentices share	0.0364***	0.0333***	0.0276***	0.0265***
	(0.0066)	(0.0066)	(0.0066)	(0.0066)
Within-firm worker tenure	-0.0072***	-0.0057***	-0.0072***	-0.0060***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Firm size	-0.0037***	-0.0040***	-0.0056***	-0.0054***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Mean incidence rate	0.120	0.120	0.120	0.120
Observations	468,884	468,884	457,850	457,850

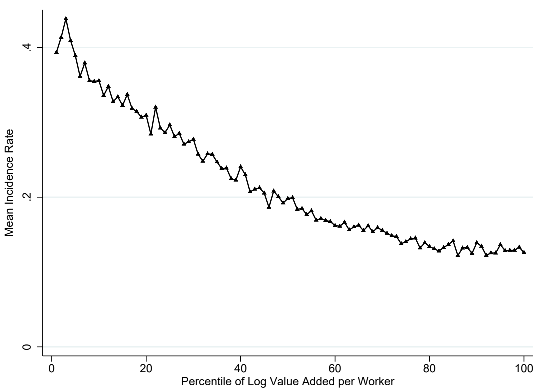
Notes: Data include both subsidised and not subsidised firms with at least 10 employees on average in the period 2005-2018. The dependent variable is the subsidy incidence rate. The first Column controls for the share of women, part-time workers, apprentices, and worker mean tenure at the firm-year level and log firm size. The second Column adds as a control "worker mean ability" as an average of individual AKM effects at the firm-year level. Column (3) repeats (1) but adds log VA per worker. Column (4) repeats (2) but log VA per worker is added. Standard errors are clustered at the firm level. CERVED sample is used. Year, regional and two ATECO digit fixed effects are included. ***p<0.01.



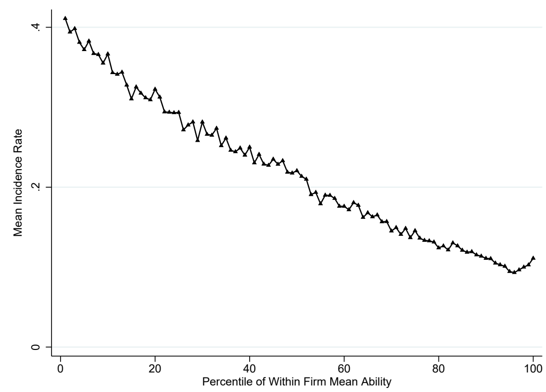
(a) Incidence rate by percentile of within firm log wages



(b) Incidence rate by percentile of firm premiums



(c) Incidence rate by percentile of log VA per worker



(d) Incidence rate by percentile of worker mean ability

Figure A.2: Graphs are based on firm-level data in the period 2015-2018. We restrict the analysis to subsidised firms born before 2015, with at least 10 employees in the period 2005-2018 and registered in CERVED records. Worker mean ability is the firm-level average θ_is calculated from (1).

Table A.4: OLS estimates for all firms in the sample

	(1)	(2)	(3)	(4)
Firm premium	-0.105***	-0.133***	-0.0672***	-0.103***
	(0.0020)	(0.0020)	(0.0021)	(0.0022)
Log VA per worker			-0.0268***	-0.0194***
			(0.0005)	(0.0005)
Worker mean ability		-0.131***		-0.103***
		(0.0022)		(0.0025)
Part-time workers share	0.0341***	0.0182***	0.0108***	0.0078***
	(0.0012)	(0.0013)	(0.0013)	(0.0013)
Female workers share	-0.0237***	-0.0266***	-0.0178***	-0.0242***
	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Apprentices share	0.0351***	0.0355***	0.0277***	0.0270***
	(0.0037)	(0.0037)	(0.0037)	(0.0037)
Within-firm worker tenure	-0.0056***	-0.0036***	-0.0052***	-0.0038***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Firm size	-0.0081***	-0.0068***	-0.0099***	-0.0087***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Mean incidence rate	0.153	0.153	0.153	0.153
Observations	1,381,371	1,381,371	1,328,042	1,328,042

Notes: Data include both subsidised and not subsidised firms. The dependent variable is the subsidy incidence rate. The sample includes the years 2015–2018. The first Column controls for the share of women, part-time workers, apprentices, and worker mean tenure at the firm-year level and log firm size. The second Column adds as a control "worker mean ability" as an average of individual AKM effects at the firm-year level. Column (3) repeats (1) but adds log VA per worker. Column (4) repeats (2) but log VA per worker is added. Standard errors are clustered at the firm level. CERVED sample is used and we exclude firms born in 2015. Year, regional and industry fixed effects are included. ***p<0.01.

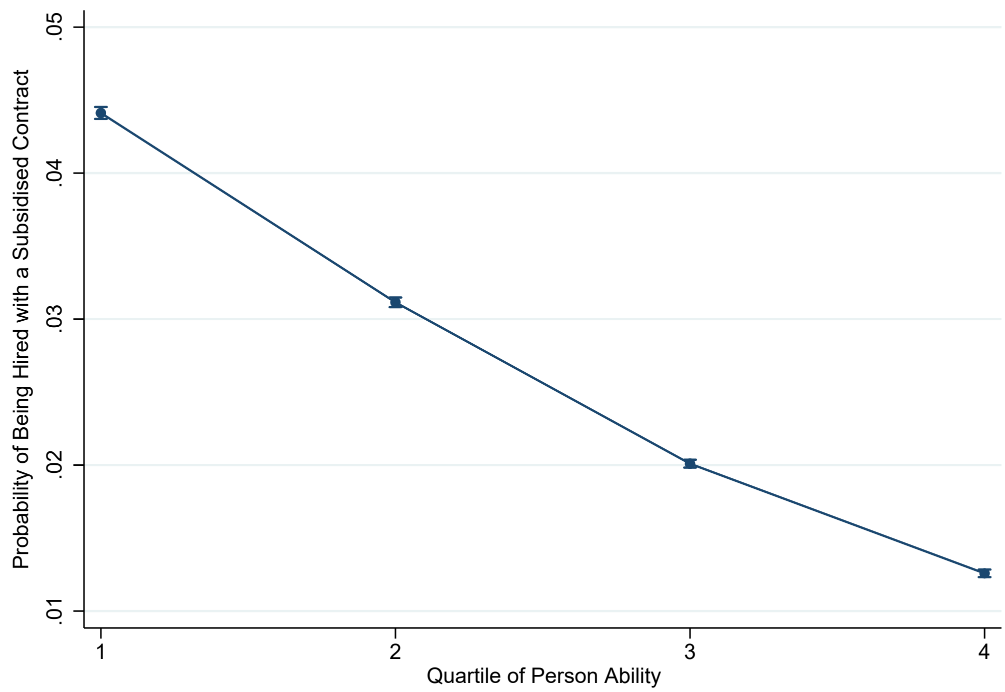


Figure A.3: Figure reports the estimated probability of being hired with a subsidised contract in 2015 calculated with a linear probability model with robust standard errors. 99% confidence intervals are reported; 7,115,726 individuals are in the estimation sample as described in Section 3.4.

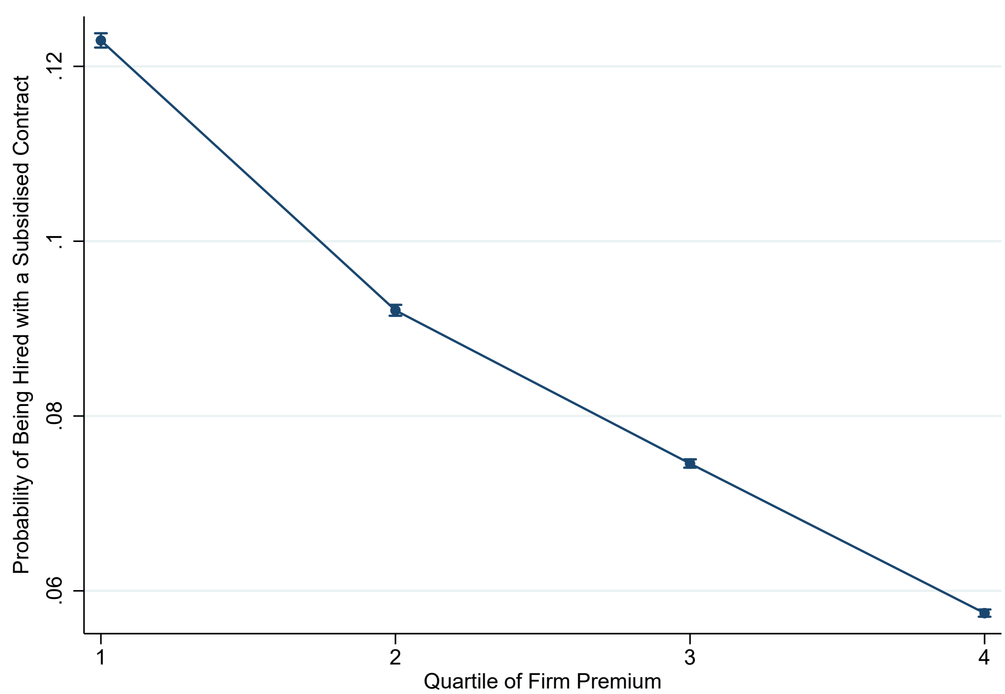


Figure A.4: Estimated probability of being hired with a subsidised contract in 2015 calculated with a linear probability model with robust standard errors. 99% confidence intervals are reported; 7,115,726 individuals are in the estimation sample as described in Section 3.4.

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Table A.5: OLS estimates for subsidised firms

	(1)	(2)	(3)	(4)
Firm premium	-0.1511***	-0.1368***	-0.0898***	-0.0954***
	(0.0040)	(0.0040)	(0.0043)	(0.0043)
Log VA per worker			-0.0378***	-0.0282***
			(0.0010)	(0.0010)
Worker mean ability		-0.1932***		-0.1411***
		(0.0050)		(0.0052)
Part-time workers share	0.0374***	0.0193***	0.0044	-0.0006
	(0.0028)	(0.0028)	(0.0029)	(0.0029)
Female workers share	-0.0279***	-0.0422***	-0.0284***	-0.0389***
	(0.0024)	(0.0024)	(0.0023)	(0.0024)
Apprentices share	0.0344***	0.0288***	0.0236***	-0.0229***
	(0.0077)	(0.0077)	(0.0077)	(0.0077)
Within-firm worker tenure	-0.0076***	-0.0050***	-0.0073***	-0.0055***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Firm size	-0.0389***	-0.0389***	-0.0386***	-0.0383***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Mean incidence rate	0.183	0.183	0.183	0.183
Observations	305,546	305,546	301,417	301,417

Notes: Sample restricted to subsidised firms with at least 10 employees on average in the period 2005-2018. The dependent variable is the subsidy incidence rate. The first Column controls for the share of women, part-time workers, apprentices, and worker mean tenure at the firm-year level and log firm size. The second Column adds as a control "worker mean ability" as an average of individual AKM effects at the firm-year level. Column (3) repeats (1) but adds log value added per worker. Column (4) repeats (2) but the value added per worker (in logarithm) is added. Standard errors are clustered at the firm level. CERVED sample is used. Year, regional and industry fixed effects are included. ***p<0.01.

Table A.6: Coefficient of firm effect on the subsidy incidence rate

	All Sample	Subsidised Firms
Firm size 10-24	-0.0713***	-0.0870**
Observations	280,907	166,402
Firm size 25-49	-0.0830***	-0.100***
Observations	101,073	72,542
Firm size +50	-0.0923***	-0.109***
Observations	75,870	62,473
Firm age >13	-0.0669***	-0.0815***
Observations	337,204	218,166
Firm age <=13	-0.0730***	-0.0877***
Observations	120,646	83,251
Industry	-0.0736***	-0.0754***
Observations	225,527	144,160
Services	-0.0720***	-0.0941***
Observations	232,323	157,257
Growing	-0.0638***	-0.0906***
Observations	346,512	244,884
Shrinking	-0.0628***	-0.0677***
Observations	111,317	56,522
1st Quartile of mean ability	-0.0767***	-0.0934***
Observations	104,646	69,869
2nd Quartile of mean ability	-0.103***	-0.119***
Observations	114,081	74,290
3rd Quartile of mean ability	-0.0748***	-0.0939***
Observations	119,100	76,767
4th Quartile of mean ability	-0.0528***	-0.0702***
Observations	120,023	77,138
Not Treated in 2016	-0.585***	-0.0827***
Observations	252,443	134,365
Treated in 2016	-0.0775***	-0.0924***
Observations	205,407	167,052
1st Quartile of VA growth	-0.0687***	-0.0775***
Observations	100,915	69,166
2nd Quartile of VA growth	-0.0390***	-0.0618***
Observations	124,253	79,166
3rd Quartile of VA growth	-0.0605***	-0.0789***
Observations	122,459	77,936
4th Quartile of VA growth	-0.0883***	-0.117***
Observations	109,021	71,130
Mean incidence rate	0.120	0.183

Notes: Coefficients represent β from Column (2) and are estimated using as controls the share of women, part-time workers, apprentices, worker mean tenure at the firm-year level, log firm size and log VA per worker. We exclude agriculture, the public sector and activities in extra-territorial bodies. Industry is composed of mining, water and waste management, energy, manufacturing and construction industry. Industry, regional and time-fixed effects are included. We restrict to firms with at least 10 employees on average in the period 2005-2018. The confidence intervals are at 95% level and standard errors are clustered at the firm level. ***p<0.01.

Table A.7: Summary statistics (2005-2018)

	All sample	Largest connected set
Age	39.21	39.17
Tenure	18.41	18.39
FTE Weeks	35.75	36.80
Weekly wages	516.01	517.96
Firm size	8.29	9.16
Part-time workers share	24.03	23.55
Permanent workers share	85.38	85.18
Blue-collar workers share	55.35	55.47
White-collar workers share	38.02	35.85
Executives share	0.68	0.69
Middle managers share	3.20	3.25
Apprentices share	4.76	4.75
Female workers share	40.91	40.62
Workers	21.917.040	21.403.520
Firms	3.516.066	3.116.526
Observations	178.696.272	175.452.849

Notes: Table reports summary statistics for the panel we use to estimate the AKM model; the main job is selected. The main criterion for defining the main job is the type of contract (permanent is preferred to fixed term contract) and highest wage job in a given year. Tenure is defined as the current year minus the first year as an employee. The FTE weeks are full-time equivalent weeks. Weekly wages are FTE adjusted wages.

Table A.8: Summary statistics for firm variables in the period 2015-2018

	Not Subsidised	Subsidised	All Sample
Incidence rate	0.00	0.183	0.120
Firm premium	2.98	2.98	2.98
Within-firm tenure	22.52	20.31	21.04
FTE weeks	39.58	39.47	39.28
Within firm mean age	42.89	41.02	41.64
Firm size	26.63	73.70	56.87
Within-firm wages	551.59	531.33	536.98
Within-firm log wages	6.20	6.18	6.19
VA per worker	64.95	57.26	59.72
Female workers share	0.34	0.35	0.35
Permanent workers share	0.84	0.84	0.83
Part-time workers share	0.20	0.21	0.21
Blue-collar workers share	0.58	0.57	0.58
White-collar workers share	0.36	0.37	0.36
Middle managers share	0.018	0.016	0.017
Executives share	0.006	0.005	0.005
Apprentices share	0.033	0.039	0.037
Within-firm worker age	42.38	40.83	41.76
Observations	468,884		

Notes: Table reports summary statistics for variables at the firm level in the main estimation sample as described in 3.4, in the period 2015-2018.