Who Profits from General Training Subsidies? Evidence from a French Individual Learning Account

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Abstract

Workers could under-invest in general training, hence governments often subsidize lifelong learning. Yet, how effective are subsidies to general training? This paper studies the effect of the French Individual Learning Account (CPF), a scheme endowing all workers with generous training credits to be spent on the training market. We show that the total amount of training undertaken is not significantly affected by the subsidy. This happens because, in equilibrium, more than half of the benefit of the subsidy is captured by training producers through a significant change in prices. Moreover, for every 1% change in the subsidy, producers profits react by 0.17%, but no significant effect on the entry/exit of firms in the training market is observed. Our results can be rationalized with an inelastic demand for training and imperfectly competitive training markets. Under such conditions, subsidies to lifelong learning end up being a simple transfer to training producers and consumers, with no effect on aggregate welfare.

Keywords: training, subsidies incidence, imperfect competition

JEL Codes: M53, H22, J24, J28, L13

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1 Introduction

Governments often engage in various forms of subsidization of professional training (OECD, 2020). In fact, since Becker (1964) famously distinguished between training in general or firm-specific skills, it is generally thought that investment in general skills training will be financed mostly by the worker himself.[1] Yet, training was shown to have high non-monetary costs for workers, widely uncertain private returns, and potential externalities, so that workers might under-invest in general training, especially if they are credit-constrained (Bassanini et al., 2005).

There is mixed evidence on the capability of governments to stimulate investment in general skills. A stream of litrature has studied the effect of small training voucher programs (Hidalgo et al., 2014; Van den Berg et al., 2020; Görlitz, 2016; Schwerdt et al., 2012), finding very small and often insignificant effects on training participation. However, experimental studies of training vouchers are typically small, and concentrated on a small and disadvantaged population, so that might not be informative of equilibrium effects of training subsidies. Another stream of the literature focused on tax deduction of firms' training costs, which are found to be more effective in stimulating training participation, for example in the Netherlands (Leuven and Oosterbeek, 2004). Yet, deductions to firms are more likely to foster investment in firm-specific skills, not general ones. When tax deductions were instead granted to workers, they were more likely to end up financing general training, but had a much more limited effect on overall training participation (van den Berge et al., 2022).

In this paper we study what is the equilibrium effect of a large national training subsidy guaranteed to workers, the French *Compte Personnel de Formation* (CPF). The CPF is an "Individual Learning Account" in which each worker accumulates training credits proportionally to its years of social security contributions, and can then spend them freely on a market of certified training courses. This kind of scheme is increasingly popular in Europe[2]. We find that a change of the value of CPF is unrelated to training participation, suggesting no effect of training subsidies on training participation. To explain this result, we take a new perspective based on incidence theory: because CPF credits are spent by trainees on a training market, where workers buy courses offered by profit-maximizing training producers, part of the subsidy might be captured by producers. In fact, we show that a €1 change in the subsidy triggers a €0.53 change in prices, so that more than half of the subsidy is captured by producers. Consistently with this, producers' revenues change by 1.3% for every euro change in the average hourly subsidy used by consumers, concentrated in training producers more heavily relying on CPF-subsidized training. Instead, no effect is detected on total costs, labor costs and on the number of trainees, so that profits also change by 0,8% for every euro change in the average hourly subsidy used by consumers.

What do these results suggest about the training market? Microeconomic theory dating back to Harberger (1962) points out that if a per-unit subsidy in a perfectly competitive market generates a) an insignificant increase in quantity, and b) a significant, but less than 1-to-1, increase in prices, then both supply and demand for training should be quite inelastic (Fullerton and Metcalf, 2002). However, researchers recently highlighted that low elasticity of quantity consumed to subsidy changes can derive not only from inelastic supply and demand but also from imperfect competition (Weyl and Fabinger, 2013). In fact, we show that

[1] Nonetheless, it was also shown that general training might in part be financed by firms (Acemoglu and Pischke, 1999, 2000).

[2] Examples include the *Opleidingscheques* in Flanders (Belgium), the *Bildungsprämie* in Germany, the Cheque formação in Portugal, the *Individual Training Accounts* in Scotland, the *Chèque annuel de formation* in Geneva Canton (Switzerland), and the Individual Training Accounts in the United States. Other examples, with some slight deviation from the standard case, are The *Bildungskonto* in Upper Austria, the *SkillsFuture* Credit in Singapore, and *Carta ILA* in Tuscany (Italy).

our results can be rationalized either by inelastic demand for training and perfectly inelastic supply under perfect competition, or by imperfectly competitive training markets. We argue that the latter mechanism is more plausible, as the training market is likely less than perfectly competitive. For example, asymmetric information on training quality risks making the market for training courses a market for “lemons”, with low-quality training providers pushing high-quality ones out of the market. Hence, reputation, repeated interaction, as well as policies such as mandatory certifications, used to mitigate asymmetric information in the training market, could in turn build entry barriers and jeopardize competition.

Our results contribute to the literature studying on-the-job training by studying the effect of training subsidies when training is acquired in a training market. We are the first, to our knowledge, to consider the general equilibrium effect of training subsidies on both training participation and prices. A large literature has focused on the question of whether or not human capital accumulation is under-financed (Bassanini et al., 2005; Acemoglu and Pischke, 1999, 2000), so as to justify (or not) subsidization policies. Yet, scholars under-considered the fact that subsidies to general training risk failing to increase training participation in general equilibrium. Impact evaluations of training vouchers (Hidalgo et al., 2014; Van den Berg et al., 2020; Görlitz, 2016; Schwerdt et al., 2012) were unfit to study potential effects of subsidies on prices, as vouchers are typically concentrated on a small target population. In turn, tax deductions studied by Leuven and Oosterbeek (2004) are more likely to benefit firm-specific skills, rather than general training. A study which is more in line with our focus on general skills is instead van den Berge et al. (2022), which considers tax deductions for workers lifelong learning expenditures. While they also find a null effect of deductions on training participation, consistently with our results, their setting doesn’t allow them to study the effect of deductions on training prices.

Second, our study enriches the literature on the effect of subsidies in Industrial Organization and Public Economics by studying subsidies incidence in the case of training subsidies. Classical incidence studies found that, consistently with models which assume perfect competition, subsidies mostly generate an increase in prices where marginal costs are high and supply elasticities low (e.g. in the housing market, Gibbons and Manning, 2006; Fack, 2006). Instead, when markets are imperfectly competitive, pass-through of subsidies to consumers depends on how market power interacts with the shape of the demand function (Weyl and Fabinger, 2013). Exploiting quasi-experimental variation in subsidies, studies such as Kirwan (2009); Cabral et al. (2018); Pless and van Benthem (2019) test the degree of imperfect competition in the market for agricultural land, health insurance, and solar energy systems. In this paper, we study a market for investment in skills which is characterized by high asymmetric information and regulation, similarly to Turner (2012). We find that the incidence of training subsidies partially falls on suppliers, and that the subsidy is directly related to suppliers’ profits. We argue that the most plausible mechanism behind our findings is the presence of market power by suppliers in the training market.

In terms of policy implications, we offer an evaluation of an important Active Labor Market Policy in France. The policy was costly, financed through a contribution by firms of 0.2% of the wage bill, and was relatively welcomed by social parties. Nonetheless, some scholars had voiced concerns about effectiveness and equity of this kind of subsidies (Cahuc and Zylberberg, 2006). We show that CPF failed to increase training, ending up being a transfer, mostly to producers. The silver lining is that, studied through the lenses of a sufficient statistics framework, the dead weight loss arising from CPF is also close to zero. As a general implication, the paper offers insights on the effectiveness of subsidization strategies relying on a secondary market for the subsidized good, which often occurs whenever consumer choice is considered more efficient than central planning e.g. in building subsidies, in upper education, in health insurance. In case of inelastic supply/demand or imperfect competition in the market for the subsidized good, a subsidy could fail to increase the consumed quantity. In our example example, policy makers who want to support human capital investment should – before subsidizing it – take measures to ensure that supply is sufficiently elastic and the market competitive, for example easing market entry. Interestingly, in a market with large asymmetric information, such as the one for training, regulators might face a tradeoff between the need to guarantee training quality and the risk of reducing competition.

The rest of the article is structured as follows. Section 2 presents our empirical setting: the institutional context, the data, and some descriptives of the policy shock. Section 3 explains our identification strategy. Section 4 presents the results. Section 5 discusses the mechanisms. Section 6 draws implications in terms of welfare and policy. Section 7 summarizes and concludes.

2 Empirical setting

2.1 The French CPF

Introduced in 2015, the *Compte Personnel de Formation* (CPF) provides workers with credits to be spent for training, guaranteeing a fixed amount of additional credits for every year of social security contributions, depending on personal characteristics. Credits are accumulated in a "personal" account, in the sense that only workers can access it and decide how to use it, which is also "portable", in the sense that workers maintain the credits even when changing employer[3]. Initially, the scheme covered only employees of the private sector, while workers of the public sector were added to the program from 2017, and self-employed workers from 2019 (in this study, we are anyway going to focus on private sector workers). Importantly, CPF credits can be used to finance only training courses from a list of eligible providers. As of 2018, the annual cost of CPF was estimated at about €650 Millions, roughly 10% of French public expenditures in professional training as calculated by the OECD.

CPF underwent a significant reform in January 2019. Before the reform, between 2015 and 2018, CPF credits were accounted in hours. Workers gained 24 hours of training each year up to 120 (then 12 per year up to 150) if working full time, with the exception of low qualified workers, who obtained 48 hours yearly up to 400. To use their credits, workers had to select any training among the ones available on an online internet platform (*"Mon Compte Formation"*). Then, they had to submit a request to industry-specific training agencies to approve the financing of the training with their CPF credits. Finally, the training agency would pay the training provider and reduce the amount of hours credits in the worker CPF account of an amount equal to the duration of the training. This pre-reform institutional context is summarized in Panel A of Figure 1.

Importantly, industry-specific training agencies would not be willing to finance a CPF-subsidized hour of training at any rate, but they were fixing different caps to per-hour subsidy payable for each hour of training. These caps were reported in official tables communicated to the government (an example of these table is reported in Figure 9 in the Appendix). For instance, suppose that in 2018 a worker has 120 CPF hours in his account, and wanted to undertake a training which costs €80 per-hour for 50 hours of training duration,

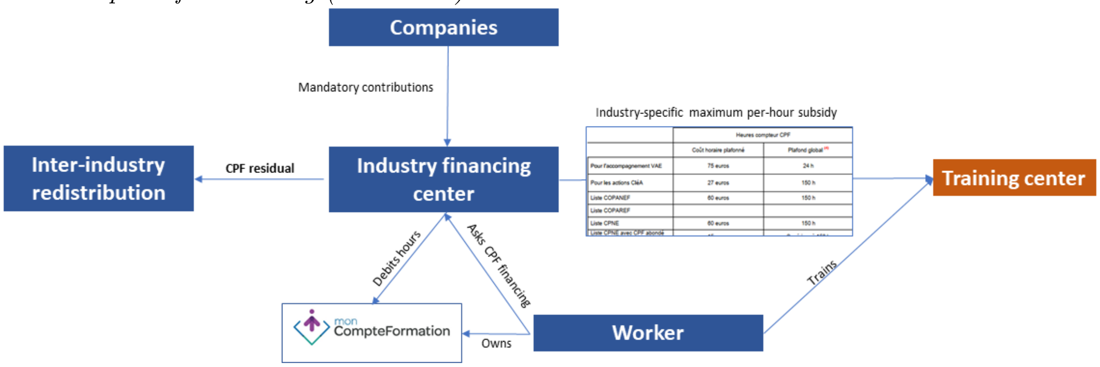
[3]By contrast, the previous device (*Droit Individuel de Formation – DIF*) replaced by CPF, was instead attached to each working contract: the employer could see the amount of training guaranteed to each employee on the payslip, the credits disappeared if the contract terminated, and the worker could not transfer training credits from one employer to the other.

so €4,000 of total cost of the training. Assume that for that specific kind of training his training agency fixed a maximum subsidy up to €60 per hour. Hence, €3,000 of the training cost will be covered by 50 hours of CPF credits, 70 hours will remain available on the worker CPF account, while €1000 of training costs will remain uncovered. For covering these costs uncovered by CPF credits, discretionary additions (*Abondements complémentaires*) could be offered by the training agency, consisting in an extra lump-sum amount of financing. These additions have to be actively requested by workers, have very complex rules that depend on workers' characteristics, and are often assigned with a degree of discretion by industry financing centers. In case there would still be leftover costs to pay, the worker would finance them by himself.

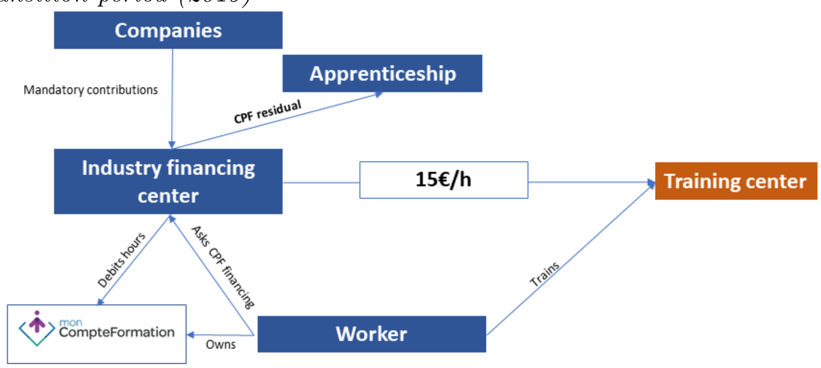
Before 2019, industry-specific training agencies had strong incentives to be generous in financing CPF. In fact, the CPF subsidy was financed through large mandatory contributions by companies, 0,2% of the wage bill. Contributions by companies were collected by industry training financing centers to be used only for CPF training within the industry. If contributions exceeded the cost of all CPF used by workers in the industry during the year, leftover resources would be redistributed across industries. Industry training agencies had thus incentives to avoid leaving money from CPF contributions "on the table", allowing high caps to per-hour subsidy, in order to keep the money within the industry. Several French regulators confirmed this mechanism. We quote a regulator from the Minister of Labor in charge of supervision of CPF: "The system pushed industry training financing agencies to fix whatever high per-hour subsidy cap, just to consume the CPF financing line, and avoid giving up the money". Finally, it is worth noting that despite its generosity CPF was underused in 2018: individuals tended to accumulate credits without using them (Figure 10 in the Appendix), so that most individuals actually reached the maximum amount of hours which could be accumulated in the account.

Figure 1: Pre and post-reform organisationof the CPF

Panel A: the pre-reform setting (2015-2018)



Panel B: the post-reform transition period (2019)



Notes. Panel A reports the functioning of CPF before the reform of 2019. Workers own an amount of CPF credits, which can be used to pay for training up to industry-specific caps to the per-hour subsidy. Industry financing centers collect mandatory contributions from companies, decide per-hour subsidy caps, and are forced to give the unused funds to inter-industry redistribution. Panel B reports the functioning of CPF in 2019 (transition year after the reform). Workers own an amount of CPF credits, which can be used to pay for training up to €15 per-hour subsidy. Industry financing centers collect mandatory contributions from companies, finance training at uniform €15 per-hour subsidy, and can use the unused funds for subsidizing apprenticeship within the industry.

The CPF was reformed in January 2019[4], and the main change was the so-called "monetization" of the credits: for all private workers, the account would be denominated in Euros rather than hours. As a consequence, industry-specific per-hour subsidy caps were abolished: an hour of CPF, once having different values in different industries according to per-hour subsidy caps defined by training agencies, became after 2019 uniformly worth 15 Euros[5]. Although the final goal of the reform was to allow workers to use CPF directly in euros, directly paying training providers through a mobile app and bypassing industry financing centers, between January and November 2019 a transition period was enacted, which in practice affected almost all trainings of 2019[6]. Our analysis will focus on this transition period, during which CPF worked in an

[4] *Loi pour la liberté de choisir son avenir professionnel* of September the 5th 2018.

[5] Although the reform was expected, the exact magnitude of the uniform rate was not clear until the very end. The discussions about the CPF reform started in January 2018, but a reform of the CPF system in the sense of a monetization was already in the electoral program of the Macron government, elected in 2017. After a year of discussion and several changes due to harsh bargaining between the government and industry training agencies, the 15 Euros uniform rate was decided by Decree in December 2018, after the approval of the law, to be applied from January 2019. Consequently, large anticipation was not likely. Figure 11 in the Appendix suggests only a small bunching of CPF-subsidized trainings at the end of 2018.

[6] As Figure 11 in the Appendix shows, the value of trainings undertaken through the unique mobile up in December 2019

extremely similar way to the pre-reform years, but the per-hour subsidy was harmonized at 15 Euros per hour across industries (Panel B of Figure 1). Specifically, workers still submitted requests to the training agency of their industry to pay training providers and debit their CPF account, but the value of the CPF subsidy was determined as the amount of hours available on the CPF account multiplied by the uniform 15 Euros rate. Because industry-specific caps were mostly higher than €15 before the reform, the reform determined a huge drop in the CPF subsidy. Discretionary additions were still possible from the training agency, if the CPF subsidy was not enough to cover the cost of training. In fact, some industry financing centers started using discretionary additions to increase the total value of their workers' CPF in 2019, attenuating the reform. Training agencies were nonetheless not incentivized to do so, since the reform allowed training agencies to keep the unused CPF contributions for financing apprenticeship in their industry. We can thus expect that the cut in CPF will not be fully compensated by an increase in discretionary additions.

2.2 Data sources, sample selection, and cleaning

For the purpose of this study, our main source of data is the SI-CPF (*Système d'information du CPF*). This database is an unexploited administrative source, which registers all CPF training episodes since 2015. It is built by the French public investment bank in charge of monitoring the CPF and it's used by French authorities to build official statistics on the device. Between 2015 and 2019, the SI-CPF recorded information sent by employers on employment of workers, to calculate CPF credits, and from financing centers to calculate CPF consumption, determine redistribution requirements and from 2019 to actually reimburse training agencies. The dataset contains: personal characteristics of beneficiaries (identifier, sex, age, working status, diploma, CPF stock, etc.); data on the training (duration, title of the training, name, training provider, etc.); and financial data (cost, financing center, amount financed through CPF, amount financed through discretionary additions,...). Training provider is reported basing on the firm fiscal identifier, and local labor markets where the training occurs are defined basing on reported municipality and postal code of the training establishment. SI-CPF was never used for academic purposes before, and a selected sub-sample was extracted in collaboration with the French Ministry of Labor for the purpose of this study. We selected private sector workers, excluding training episodes concerning other training devices, draft training episodes, and CPF trainings by unemployed workers, as described in Table 6 in the Appendix. After the first selection, outliers were eliminated[7]. Finally, we drop CPF training episodes financed by other institutions than industry-specific financing centers (1.2% of the observations)[8].

Our second data source is the official documentation on the caps to the per-hour value of the CPF subsidy allowed by training agencies. We construct a small database digitalizing publicly available documentation from the inter-industry training organization, the national training council, and from the training agencies themselves[9]. Through the French Labor Ministry, we also sent requests of additional information to training agencies to complete the dataset and ensure a better understanding of the process. The final dataset records 224 different per-hour subsidy caps according to the industry financing agency and the year (2017 to 2019),

is negligible, and most trainings are still the result of previous validation by industry financing centers. The December 2019 period is also a particular one in France, due to historically harsh strikes of public transportation.

[7]In the pre-2019 period, the Ministry suggested that some operators inserted the total cost for the whole session instead of that for the individual: we drop all training episodes with average training cost both above Q3+3 IQR and above 95% for each training kind (1.4% of the observations are dropped). This selection is consistent with practices adopted by the French administration when using SI-CPF. Extreme values (inferior to 1% or superior to 99%) for program duration or prices were replaced as missing (3.1% of observations).

[8]These are exceptional cases financed by employers, regions, and by the unemployment agency *Pôle emploi*

[9]Named FPSPP, CNEFOP and OPCA respectively

and for different kinds of training[10]. We merge this new dataset with SI-CPF, sucessfully assigning a subsidy cap to more than 90% of the training episodes[11].

Our final source is called BPF (*bilans pédagogiques et financiers*), which reports balance-sheet information for training providers, e.g. public and private firms such as language schools, vocational schools, driving licence agencies, chambers of commerce... . This source is an administrative dataset coming from mandatory declarations by any training provider which uses public subsidies (not only CPF). It's collected by the Ministry of Labor, and it's used for official statistics as well as supervision by the French government. The advantage of these data is that they are more quickly updated than balance-sheet administrative data from tax declarations, and include more detailed information. BPF provides financial data (revenues, costs, subsidies received), breakdown of costs paid by the training providers (employees wages, teacher wages, external consultant wages) and information on the staff (number of teachers, external consultants). This information doesn't only concern CPF-subsidized trainings but all trainings undertaken at the training provider, including unsubsidized trainings or trainings subsidized by other devices. We use a version of BPF as of the beginning of 2021, which reliably covers training providers activities until fiscal year 2019. The data report outliers, so that we trim our variables of interest – revenues, costs, profits, and revenues from CPF – to the 1-99th percentile. We merge BPF with SI-CPF basing on firm fiscal identifier. The merge is quite satisfying: 93,3% in 2018 and 95,1% in 2019 of SI-CPF training episodes found a match in the BPF dataset.

2.3 Descriptives of the shock

Before digging into identification, we present 3 descriptives of the shock to per-hour subsidies generated by the reform of January 2019. First, Figure 2 displays the maximum cap to the per-hour subsidy applied in 2018 as reported in official documentation and from interviews with industry financing centers, for the 9 most common groups of training kind. The graph also reports mean, mode and IQR of the average actual amount of CPF subsidy used to cover the training, in per hour terms, observed in the data. This set of figures points out two considerations. First, our data gathering of the different per-hour subsidy caps across industry looks accurate: with few exceptions, the per-hour value of the CPF subsidy actually seen in the data is never above the per-hour subsidy cap. Interestingly, although the per-hour value of the CPF subsidy is often bunched at the value of the cap, suggesting that the per-hour subsidy cap is binding, the subsidy used by consumers is sometimes below the cap, possibly as prices themself are lower than the total subsidy[12]. This happens

[10]In practice, the subsidy cap is the same for groups of training kinds. We identify 10 of them: Skills balance (*Bilan de compétences*), certification for conduction of industrial machines (*CACES*), Certification of professional general and specific skills (*VAE, CléA, CQP*), certification of enterpreneurial skills (*Création d'entreprise*), IT and accounting certificates (*Informatique et bureautique*), language certificates (*Langues*), base vehicle driving licence (Permis B), others (Autres). They have been constituted according to the classifications by training agencies.

[11]In some cases (4.1% training episodes in 2018 and 10.1% training episodes in 2019) the financing center does not fix a cap to per-hour value of the subsidy, but a cap to the total subsidy for the training episode. This happens almost always when the training is aimed at obtaining very common and standardized certificates, so that trainings have specific durations (for example, a professional skill qualification called VAE, which always lasts 24 hours). In these few cases, we define the per-hour subsidy cap by dividing the cap on total subsidy by the mode duration of the training. Moreover, two industry financing agencies (FAFSEA and OPCA 3+) did not establish any subsidy cap for the pre-reform period, as they were in theory willing to cover any per-hour cost of training. A third one (OPCA Transport) did not define a conversion rate for all trainings but only for two quite popular types (VAE and common cars driving licence). All these training-financing center pairs, not linkable to a specific per-hour subsidy cap, were then excluded from the analysis (6.2% of the sample).

[12]In Appendix B, we show how this can happen for example in the case of high non-monetary costs of training and large subsidies, making demand for training inelastic and concave.

especially when the subsidy cap is higher. We will return to this in Section 3.2. As a second consideration, caps to per-hour subsidy are quite variable, and almost always above the new per-hour conversion set by the 2019 reform (15 Euros per hour). Looking at the ranking of financing centers on the horizontal axis, one can see how richer financing centers (see Figure 12 in the appendix for the correspondence between the agency name and the industry they represent) tend to be more generous, although there is quite a variability across different kinds of training.

A second interesting descriptive is reported in Figure 3, which plots the distribution of the share of the total training cost which is covered by workers CPF credits, without discretionary additions, in 2017, 2018 and 2019. Clearly, the reform of 2019 represents a dramatic cut in the capability of CPF to cover the cost of training: while before the reform CPF was fully covering the cost of training for almost 80% of the training episodes reported, after the reform this share almost halves. While pre-reform the distribution is almost fully bunched at 1, with a slight left tail, in 2019 is bimodal, with one fourth of the training episodes having between 20% and 40% of the cost covered by CPF subsidy.

Finally, Figure 4 gives an example of the effect of the reform on training prices for two among the 10 most popular kind of training, the BULATS language certificate and the lifeguard certificate. In the former, the subsidy cap falls to 15 euros in every industry in 2019, but the average price remains widely heterogeneous for workers coming from different training agencies. This suggests different financing centers should be sometimes seen as different markets, with different prices and potentially different marginal costs (due to e.g. different areas, different level of qualification, ...). Conversely, in the case of lifeguard certificate prices converge to a much more similar level after equalization of the subsidy.

3 Identification

3.1 Specification at the Training Course and Industry Level

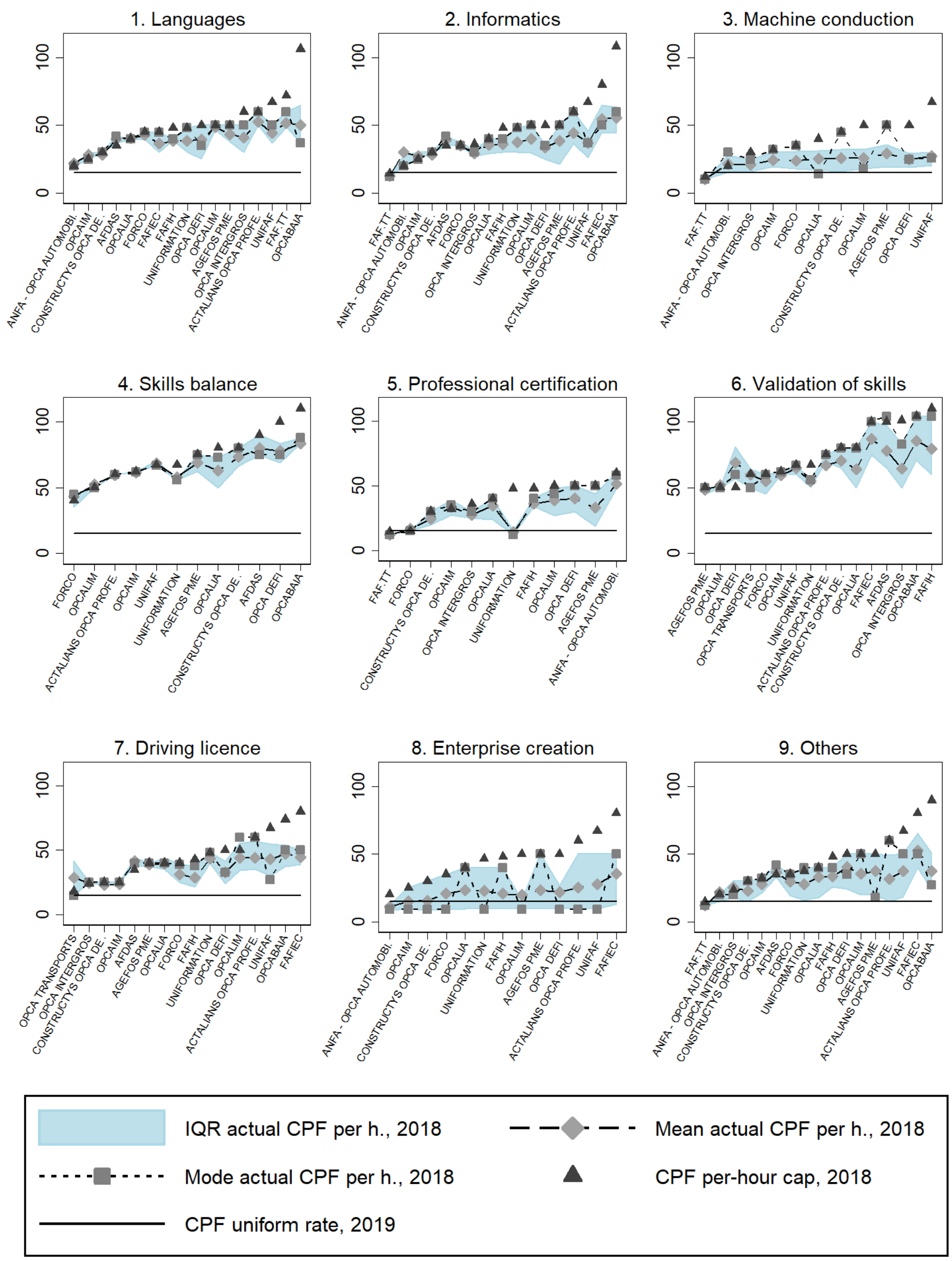
In our data, for every training episode i we directly observe the episode duration x_i, the total cost P_i, the euro amount of the subsidy from a worker CPF credits C_i , and discretionary additions by the industry financing center A_i. Instead, our dataset doesn't provide directly information on the hourly price p_i and on the effective per-hour subsidy used c_i. Concerning hourly prices, we can recover them as $p_i = \frac{P_i}{x_i}$. Concerning effective per-hour subsidy, this includes both direct subsidy and discretionary additions, so we can recover them as $c_i = \frac{C_i+A_i}{x_i}$. Finally, we denote as $c_{q,\tilde{f},t}$ the industry-specific per-hour subsidy cap, directly observed in the ad-hoc dataset built using training agencies documentation.

To study the effect of the subsidy on the quantity and prices of training, our unit of analysis will be the "training course": a cell defined by different training typologies q (which are obtained as the combination of the title of the training and whether it is run online or in person), industry financing center f, and training establishment j (obtained as combination of enterprise and local labor market). Our baseline model to be estimated is:

$$y_{q,j,f,t} = \beta_y c_{q,f,t} + \gamma_{q,j,f} + \tau_t + \varepsilon_{q,j,f,t} \tag{1}$$

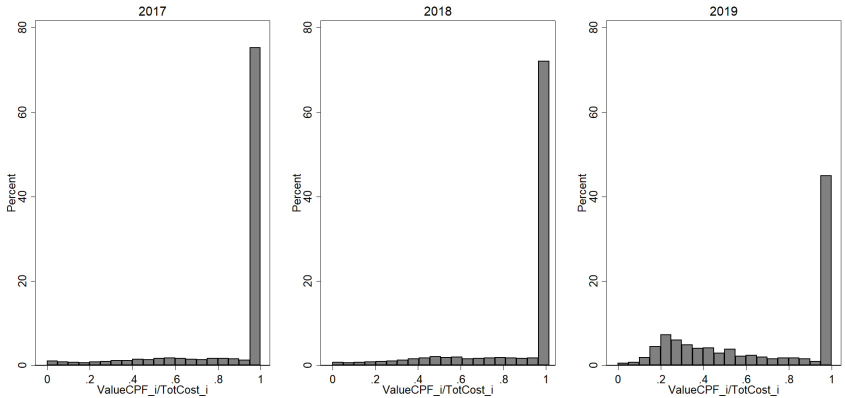
Where $y_{q,j,f,t}$ is the outcome and $c_{q,f,t}$ is the averaged effective subsidy c_i for training kind q and industry financing center of the worker f. $\gamma_{q,j,f}$ are fixed effects for training kind interacted with industry financing

Figure 2: Differences in per-hour training subsidy across industries



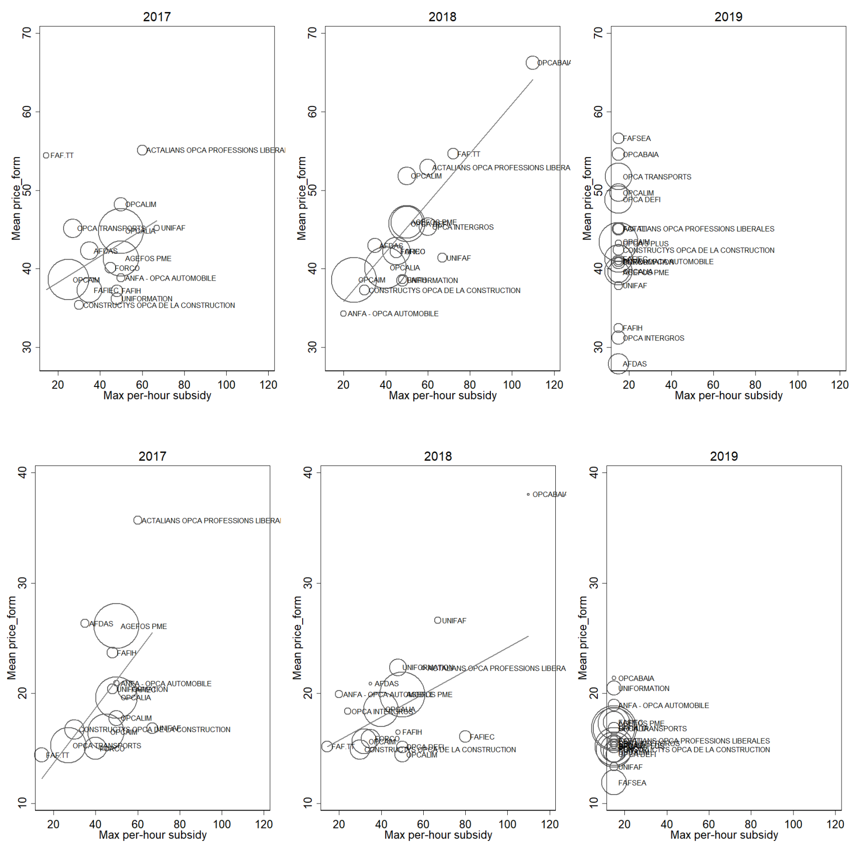
Notes. The figure reports the per-hour subsidy caps, and average actual amount of CPF subsidy used per-hour (average, mode, and IQR), for different industry financing centers and according to training type. The per-hour subsidy caps are determined by industry financing centers until the reform of 2019, which harmonizes the subsidy at 15 Euros per hour. The actual amount of CPF subsidy used per-hour is calculated, for every training episode in SI-CPF, as the ratio of the total value of CPF used C_i over the total hours of CPF debited to the worker x_i^{CPF}.

Figure 3: Percentage of total training cost covered by CPF subsidy



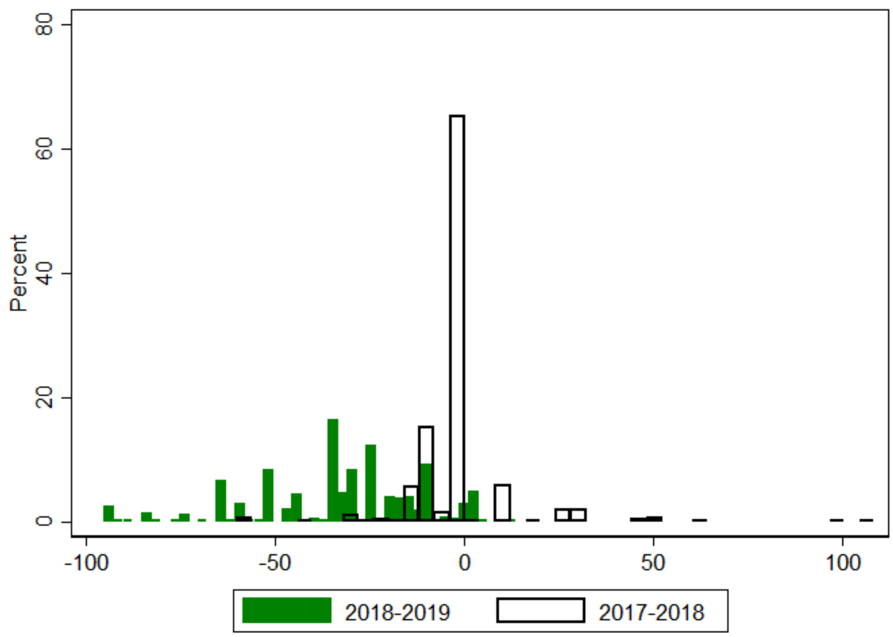
Notes. The figure reports the distribution of the ratio of the total value of CPF C_i to the total cost of the training P_i, by year, for every training episode observed in SI-CPF.

Figure 4: Effect of the reform on training prices for two among the 10 most popular kind of training, the BULATS language certificate (top) and the lifeguard certificate (bottom)



Notes. The plots the mean price and the per-hour subsidy cap $c_{q,\tilde{f},t}$ for two of the ten most popular trainings, the BULATS language certificate and the lifeguard certificate, for different industry financing centers. The size of the bubble for each observation is proportional to the number of training episodes from that center.

Figure 5: Distribution of $\Delta c_{q,\tilde{f},t}$



Notes. The figure reports the distribution of the change in the maximum subsidy rate allowed by different industry financing centers for different training kinds. The changes in 2018-2019 are the result of the reform of 2019, while those of 2017-2018 are decided by industry training financing centers.

center and establishment, and τ_t is the fixed effect for the year when the training occurs. Our estimand, β_y, is the average unit effect of a euro change in the per hour subsidy on outcome y.

Note that the model in 1 is not identified simply by using a fixed-effects model (FE), as changes in $c_{q,f,t}$ don't satisfy strong exogeneity *a-priori*, for at least two reasons. First, before 2019 the subsidy rate can be endogenously set by industry financing centers. To tackle this, we will exploit the unexpected exogenous change in subsidy rates generated by the reform of 2019, and focus only on 2018-2019. Second, even in 2018-2019 discretionary additions A_i can arise endogenously from decisions by financing centers. As they are often guaranteed only if CPF doesn't cover the whole amount of the training costs, discretionary additions can attenuate changes in the subsidy rate generated by the reform, especially for richer industries. To assess this concern, we will use an Instrumental Variable strategy, instrumenting $c_{q,f,2018}$ with $c_{q,\tilde{f},2018}$, the subsidy cap fixed by each industry financing center. Figure 5 reports the variation in our instrument for the pre-reform period 2017-2018 and the period of the reform 2018-2019.

Then, the first stage will be the linear projection of the endogenous variable, the effective subsidy rate gross of discretionary additions, on our instrument, the subsidy caps, and covariates (Wooldridge, 2010), before and after the 2019 reform:

$$c_{q,j,f,t} = \beta^{FS} c_{q,\tilde{f},t} + \gamma_{q,j,f} + \tau_t + \varepsilon_{q,j,f,t} \qquad \text{if} \quad t = 2018, 2019 \tag{2}$$

And the reduced form is obtained by replacing our instrument in the structural equation of interest:

$$y_{q,j,f,t} = \beta_y^{RF} c_{q,\tilde{f},t} + \gamma_{q,j,f} + \tau_t + \varepsilon_i \qquad \text{if} \quad t = 2018, 2019 \tag{3}$$

We will estimate both the first stage and the reduced form using simple fixed-effects estimators and obtain our structural equation in regression 1 using IV. For inference, Standard errors are clustered at the level where variation in the instrument occurs, which is the interaction between industry financing centers and the training kind category.

Finally, our identification strategy relies on the assumption that industries that will experience larger changes in $c_{q,\tilde{f},t}$ in 2018-2019 did not report significantly different evolution in the outcome variable in previous years. To test the implications of this assumption, it is not straightforward to run a placebo test on pre-shock dates, because even between 2017 and 2018, the year before the exogenous change of the reform, several changes in the per-hour subsidy cap were enacted by industry financing centers. These changes are potentially endogenous, for example if industry financing centers change the 2018 subsidy cap following higher prices.

To circumvent this issue, I will partial-out the effect of endogenous pre-shock changes in the subsidy under the null of our reduced-form estimate, before running the placebo. Namely, I first estimate $\hat{\hat{y}}_{q,j,f,t} = y_{q,j,f,t} - \hat{\beta}_y^{RF}\tilde{c}_{q,f,t}$ where $\hat{\beta}_y^{RF}$ is the estimated reduced-form coefficient for the relationship between the instrument and the outcome. Then, I will test that the future change implied by the reform is unrelated to the outcome in the pre-shock years, partialled out of $\hat{\hat{y}}_{q,j,f,t}$:

$$y_{q,j,f,t} - \hat{\hat{y}}_{q,j,f,t} = \beta_y^{PL}\tilde{c}_{q,f,t+1} + \gamma_{q,j,f} + \tau_t + \varepsilon_{q,j,f,t} \quad \text{if} \quad t = 2017, 2018 \tag{4}$$

To not reject our identifying assumption, under the null that it's valid, the placebo coefficient β_y^{PL} should not be significantly different from zero[13].

3.2 Specifications at the Training Provider and Training Kind Level

For detecting the effect of the subsidy on training suppliers' revenues, costs and profits, we will use use as unit of analysis the training provider company J. This means that information at the training episode level from SI-CPF will be aggrgated for all training episodes from the same provider. Hence, our instrument will be $\tilde{c}_{Jt} = \sum_{i\in J} \frac{x_i p_{i,t_0}}{\sum_{i\in J} x_{i,t_0} p_{i,t_0}} \tilde{c}_{i\in(q,f),t}$, the average subsidy cap allowed for a supplier's customers, weighted by the share of CPF revenues that each training accounts for, and the endogenous variable will be $c_{Jt} = \sum_{i\in J} \frac{x_i p_{i,t_0}}{\sum_{i\in J} x_{i,t_0} p_{i,t_0}} \tilde{c}_{i\in(q,f),t}$. Note also that $\sum_{i\in J} x_{i,t_0} p_{i,t_0}$ includes only CPF training, while training centers might of course provide trainings also outside of CPF scope, which we don't see in our data. The variation in $\tilde{c}_{Jt}$ in the years of interest is reported in Figure 6.

Our structural equation at the training provider level thus is:

$$\ln y_{J,t} = \beta_y \ln c_{J,t} + \gamma_J + \tau_t + \varepsilon_{J,t} \qquad \text{if} \quad t = 2018, 2019 \tag{5}$$

Where $y_{J,t}$ are different producer-level outcomes (e.g. revenues, profits, labor costs, ...). Again, the reduced form will be identical with $\tilde{c}_{J,t}$ instead of c_{Jt}, and the first stage will have c_{Jt} as outcome and $\tilde{c}_{J,t}$ on the right hand side. We take logs of instrument and of the dependent variable to interpret the results in terms of elasticities. Standard errors are clustered at the training provider level.

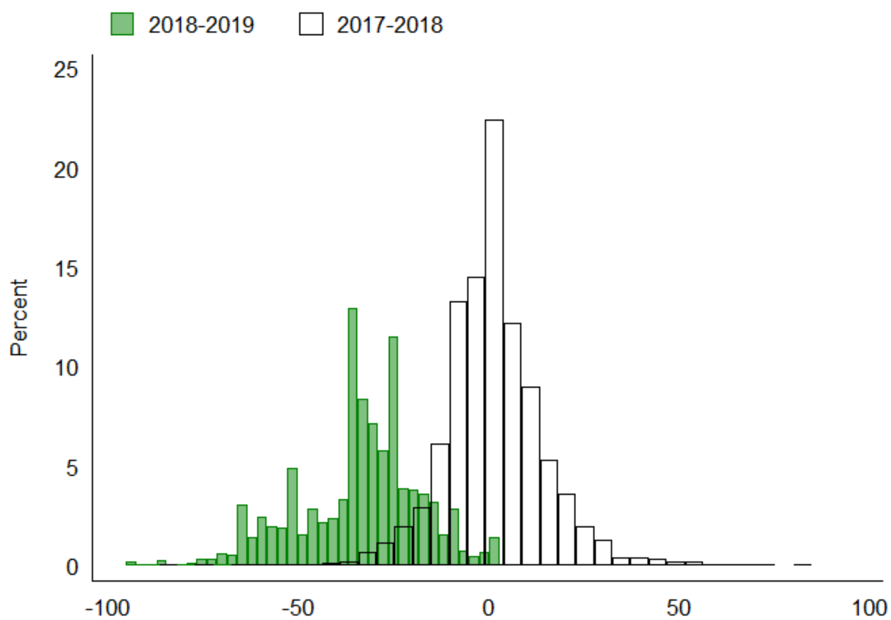
Finally, to study the effect of changes in the subsidy on the number of firms offering a specific training, we specify a model at the training-kind level:

$$\ln n_{q,t} = \beta_y \ln c_{q,t} + \gamma_q + \tau_t + \varepsilon_{q,t} \qquad \text{if} \quad t = 2018, 2019 \tag{6}$$

Where $n_{q,t}$ is the number of firms offering training kind q.

[13]The same test is also run using IV, instrumenting a lead of the effective subsidy with the lead of the subsidy cap

Figure 6: Distribution of the average subsidy cap for trainings offered by training suppliers



Notes. The figure reports the distribution of the change in the average subsidy rate that customers of training providers face (as they come from different industry financing centers). The changes in 2018-2019 are the result of the reform of 2019 harmonizing all subsidy rates to €15, while the changes in 2017-2018 are arising from decisions of industry training financing centers.

4 Results

4.1 Changes in CPF Subsidy Don't Affect Training Participation

In Table 1 we report the estimates of the effect of the changes in CPF subsidy entailed by the 2019 reform on the quantity of training undertaken for training kind q, training supplier j, and industry f. Column (1) reports our first stage, signaling that a Euro decrease in CPF maximum per-hour subsidy leads to a significant .18 Euro decrease in the effective average per hour subsidy, gross of discretionary additions. Columns (2) to (7) report the reduced form and Instrumental Variable estimates on the effect of CPF subsidy on total amount of training in terms of hours $X_{q,j,f,t}$, the average duration of a training episode $x_{q,j,f,t}$, and the number of training episodes $N_{q,j,f,t}$. Since we take the natural logarithm of the outcome variables, the estimates should be interpreted as the percentage change in the outcome following a euro change in the subsidy rate. All estimates indicate a quite precisely estimated zero effect of changes in the subsidy cap on the quantity of training taken up. In fact, the coefficient of the regressions mean that for a one euro change in the subsidy, the total amount of hours decreases by 0.4% and it's not significant with a standard error of 1.5%. Since the reduced form coefficient in Column (2) is -0.07% (standard error of 0.3%), and the mean decrease in the subsidy cap is €33, we can exclude with 95% confidence that the effect on total quantity of training following the reform of 2019 will exceed 10% in absolute values. Given that subsidy caps were on average reduced by 104% by the reform between 2018 and 2019, this is a remarkably precise zero effect of the reform. Subsequently, one can check the identification with a placebo as in Equation 4. In column (1)-(4) of Table 7 in the Appendix we find that no significant pre-trend or anticipation exists in the setting.

Table 1: Impact on Average Quantities of Training of the CPF Subsidy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	c_{qjft}	$\ln X_{qjft}$	$\ln X_{qjft}$	$\ln x_{qjft}$	$\ln x_{qjft}$	$\ln N_{qjft}$	$\ln N_{qjft}$
$\tilde{c_{qft}}$	0.180***	-0.000676		-0.000521		-0.000186	
	(0.0172)	(0.00283)		(0.00129)		(0.00199)	
c_{qft}			-0.00375		-0.00289		-0.00103
			(0.0147)		(0.00629)		(0.0108)
Observations	49,038	49,038	49,038	49,038	49,038	49,038	49,038
R-squared	0.819	0.836		0.914		0.840	
Years	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019
Estimation	FE	FE	IV	FE	IV	FE	IV

Notes. Column (1) reports the first-stage relationship between the instrument - subsidy caps - and the effective subsidy rate. Columns (2), (4) and (6) report reduced form estimates of the relationship between subsidy caps and log total training quantity, log average training episode duration, and log total number of training episodes respectively. Columns (3), (5) and (7) report the IV estimates of the effect of a change in the effective subsidy on log total training quantity, log average training episode duration, and log total number of training episodes respectively. All regressions include fixed effects for year and for training course (an interaction of the training title, online/offline, and training establishment). Standard errors are reported in parentheses and clustered at the interaction between industry financing centers and the training kind category. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.2 Changes in CPF Subsidy Are Partially Captured by Training Producers Through Changes in Prices

We then turn to study the effect of the CPF subsidy on prices. Column (1) in Table 2 reports again our first stage, while column (2) and (3) report respectively the reduced form and IV estimates of the effect of the subsidy rate on prices. The coefficients in Columns (1) and (2) suggest that a .18 Euro decrease in the subsidy leads to a 9% decrease in the average price. The positive sign of the coefficient is consistent with our expectations that a reduction (resp. increase) in the per-hour subsidy leads to a decrease (resp. increase) in the price. In Column (3), the IV estimate implies that for every Euro of effective change in the subsidy following the reform of 2018, prices changed by .53 Euros, so that the pass-through rate of the subsidy to consumers (i.e. the reduction in the net price of training) is 47%. For prices as well, placebo estimates in column (5) of Table 7 in the Appendix report no significant pre-trend or anticipation.

Table 2: Impact on Average Prices of Training of the CPF Subsidy

	(1)	(2)	(3)
VARIABLES	c_{qjft}	p_{qjft}	p_{qjft}
$\tilde{c_{qft}}$	0.180***	0.0956***	
	(0.0172)	(0.0172)	
c_{qft}			0.530***
			(0.132)
Observations	49,038	49,038	49,038
R-squared	0.819	0.846	
Years	2018-2019	2018-2019	2018-2019
Estimation	FE	FE	IV

Notes. Column (1) reports the first-stage relationship between the instrument - subsidy caps - and the effective subsidy rate. Columns (2) reports reduced form estimates of the relationship between subsidy caps and per-hour training price. Column (3) reports the IV estimates of the effect of a change in the effective subsidy on the training price. All regressions include fixed effects for year and for training course (an interaction of the training title, online/offline, and training establishment). Standard errors are reported in parentheses and clustered at the interaction between industry financing centers and the training kind category. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.3 Changes in CPF Subsidy Affect Producer Revenues and Profits, Not Costs

Finally, we use our training producer-level specification to study the effect of the CPF subsidy on log revenues ($\ln REV_{J,t}$), log costs ($\ln COST_{J,t}$), log profits ($\ln \pi_{J,t}$), log labor costs ($\ln L_{J,t}$), and the log of the number of workers employed in training centers ($\ln E_{J,t}$). The coefficients should thus be interpreted as the percentage changes in the provider-level outcome following a unitary change in the average subsidy guaranteed to a supplier's customers. Table 3 reports the results, with IV estimates in the upper panel and reduced form in the lower panel. The magnitude of the coefficients suggest that we observe a 0.6% decrease in revenues for a supplier for each 1 Euro decrease in the effective subsidy (i.e., in the lower panel, a 1 Euro reduction of the subsidy cap leads to a .21 Euros reduction in the effective subsidy and to a 0.13% decline in revenues). Conversely, the effect on costs is smaller and not significant, although still positive. Accordingly, we also find a small significant positive effect on profits: when subsidies decrease, profits decrease by a magnitude that roughly corresponds to the difference in reactions of costs and revenues. The zero effect on costs corresponds to a zero effect on labor costs and number of employees of the training center. Hence, the part of incidence of the subsidy which falls on producers seems to be eventually shifted to owners of capital invested in training centers. Table 8 report placebos for this producer-level specification, again finding no significant effect. Finally, in Table 9 in the Appendix we show that the relationship is unchanged using a log transformation to correct for the skewness of $\tilde{c}_{Jt}$ and c_{Jt}.

Table 3: Impact of changes in CPF subsidy on producers' revenues, costs, profits, labor costs and number of teachers

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	$\ln c_{Jt}$	$\ln REV_{Jt}$	$\ln COST_{Jt}$	$\ln \pi_{Jt}$	$\ln L_{Jt}$	$\ln E_{Jt}$
$\ln \tilde{c}_{Jt}$	0.242***					
	(0.0174)					
$\ln c_{Jt}$		0.261***	0.0852	0.169**	-0.0534	-0.0150
		(0.0796)	(0.107)	(0.0791)	(0.110)	(0.0943)
Observations	9,604	9,604	8,900	8,816	8,472	8,792
Years	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019
Estimation	FE	IV	IV	IV	IV	IV

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	$\ln c_{Jt}$	$\ln REV_{Jt}$	$\ln COST_{Jt}$	$\ln \pi_{Jt}$	$\ln L_{Jt}$	$\ln E_{Jt}$
$\ln \tilde{c}_{Jt}$	0.242***	0.0630***	0.0202	0.0401**	-0.0126	-0.00361
	(0.0174)	(0.0189)	(0.0252)	(0.0185)	(0.0260)	(0.0227)
Observations	9,604	9,604	8,900	8,816	8,472	8,792
R-squared	0.846	0.970	0.964	0.822	0.954	0.957
Years	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019
Estimation	FE	FE	FE	FE	FE	FE

Notes. The upper panel reports the IV estimate of the effect of an increase in the average effective training subsidy for a firms' customers on log revenues, costs, profits, labor costs and employment in the training firm. The lower panel of the table reports the reduced-form estimate of the effect of an increase in the average subsidy cap for a firms' customers on log revenues, costs, profits, labor costs and employment in the training firm. All regressions include year and training firm fixed effects and are weighted by the total value of the firm revenues. Standard errors are reported in parentheses and clustered at the traning firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Intuitively, the relationship between log revenues and the average subsidy cap is mediated by how much of a supplier's revenues is coming from CPF trainings. The share of revenues from CPF can vary across suppliers, as different training centers may target individuals with no CPF (like youth or self-employed at the time of the reform) or as some trainings are simply not eligible for CPF. Table 4 reports estimates the effect of the 2019 cut in CPF on suppliers with different share of revenues coming from CPF. The estimates signal that, as expected, the effect of the decrease of the subsidy on profits increases with the share of revenues due to

CPF. This is reassuring on the fact that the effect on revenues is actually due to policy changes in CPF, since significant effects materialize only for top two quartiles (which correspond to when CPF revenues are >20% of total revenues). A similar pattern emerges from regressions using profits as outcome.

Table 4: Impact of changes in CPF subsidy on producers' revenues: heterogeneity by importance of CPF revenues over total revenues

	(1)
VARIABLES	$\ln REV_{Jt}$
$\ln \tilde{c}_t * \mathbb{1}(\frac{RevCPF}{TotRev_{jt_0}} < p20)$	-0.00492
	(0.0197)
$\ln \tilde{c}_t * \mathbb{1}(p20 < \frac{RevCPF}{TotRev_{jt_0}} \leq p40)$	0.0241
	(0.0210)
$\ln \tilde{c}_t * \mathbb{1}(p40 < \frac{RevCPF}{TotRev_{jt_0}} \leq p60)$	0.0375*
	(0.0196)
$\ln \tilde{c}_t * \mathbb{1}(p60 < \frac{RevCPF}{TotRev_{jt_0}} \leq p80)$	0.0530***
	(0.0197)
Observations	11,470
R-squared	0.979
Years	2018-2019

Notes. Column (1) reports the first-stage effect of an increase in the average subsidy cap for a firms' customers on the average effective per-hour subsidy. Columns (2) and (3) report reduced-form estimates of the effect of an increase in the average subsidy cap for a firms' customers on log revenues and profits by quartile of the share of revenues of a firm coming from CPF. All regressions include year and training firm fixed effects and are weighted by the total value of the firm revenues. Standard errors are reported in parentheses and clustered at the training firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.4 Changes in CPF Subsidy Don't Affect Market Entry/Exit

To conclude our empirical analysis, we explore the effect of the subsidy on the number of firms offering a particular kind of training q. In light of the positive relationship of the subsidy with profits, we might expect a significant positive relationship with the number of firms as well, if lower (resp. higher) average profits would drive less (resp. more) firms into the market. However the estimated coefficient is non significantly different from zero.

Table 5: Effect on entry(/exit)

	(1)	(2)
VARIABLES	$\ln c_{qt}$	$\ln n_{qt}$
$\ln \tilde{c_{qt}}$	0.319***	
	(0.0276)	
$\ln c_{qt}$		0.640
		(0.451)
Observations	5,232	5,232
Years	2018-2019	2018-2019
Estimation	FE	IV

Notes. Column (1) reports the first-stage relationship between the average subsidy cap fo a specific training kind and the average effective subsidy rate. Columns (2) reports reduced form estimates of the relationship between subsidy caps and average number of firms offering a training kind. All regressions include fixed effects for year and for training course (an interaction of the training title, online/offline, and training establishment). Standard errors are reported in parentheses and clustered at the interaction between industry financing centers and the training kind category. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5 Mechanisms: Inelastic Demand and Imperfect Competition Can Rationalize Low Pass-Through

Our results in Section 4.1 and 4.2 pointed out an insignificant relationship between the subsidy and the total quantity of training undertaken, $\beta_X \simeq 0$ and a positive significant relationship between training subsidies and training prices $\beta_p = .53$. To understand what this implies in terms of the market structure of the training market, consider the pass-through of the subsidy to consumers, $\rho = -\frac{d(p-c)}{dc}$, defined as the change in the price paid by consumers net of the CPF subsidy, when the subsidy changes, with a minus in front, as pass-through are traditionally defined in terms of changes in taxes. This can be estimated as $\rho = 1 - \beta_p$, as $\frac{dp}{dc}$ in Equation 1 is identified by the estimand β_p.

A vast theoretical literature pioneered by Harberger (1962) studies how pass-thrugh ρ relates to the elasticities of demand and supply. Under perfect competition, pass through will be a function of demand and supply elasticities $\epsilon_d > 0, \epsilon_s > 0$, as in Fullerton and Metcalf (2002):

$$\rho = \frac{\epsilon_s}{\epsilon_s + \epsilon_d} \tag{7}$$

Generalizing this formula to allow for imperfect competition, Weyl and Fabinger (2013) show that with suppliers' market power θ ranging from zero (perfect competition) to one (monopoly) producers optimization yields:

$$\rho = \frac{1}{1 + \frac{\theta}{\epsilon_\theta} + \frac{\epsilon_d - \theta}{\epsilon_s} + \frac{\theta}{\epsilon_{ms}}}$$

where $\epsilon_{ms} \in [-\infty, +\infty]$ is the elasticity of the inverse marginal consumers' surplus, and can be interpreted as the degree of convexity of the demand function, with $\epsilon_{ms} = 1$ when demand is linear, $\epsilon_{ms} > 1$ when it's concave, $\epsilon_{ms} < 1$ when it's convex and $\epsilon_{ms} < 0$ when it's log-convex. Instead, ϵ_θ is the elasticity of the competition parameter with respect to quantity.

In light of our empirical results, we can directly recover the elasticity of demand for training:

$$\begin{aligned} \epsilon_d = -\frac{dX/X}{d(p-c)/(p-c)} &= -\beta_X/\beta_{\ln(p-c)} \\ &= \frac{\beta_X}{1-\beta_p}(p-c) \end{aligned} \tag{8}$$

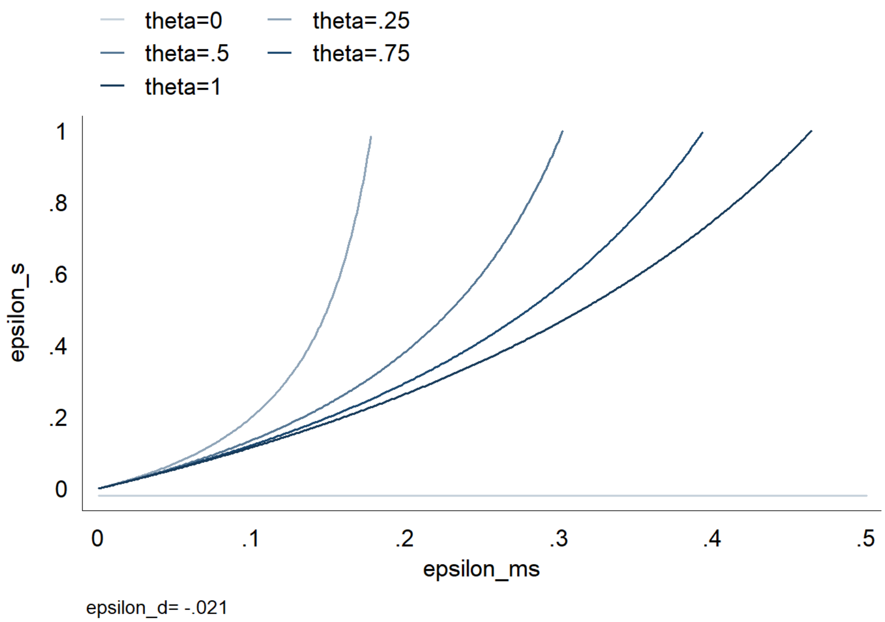
obtaining that demand for training has to be almost perfectly inelastic since $\beta_X \simeq 0$.

Then, we can assume $\theta/\epsilon_\theta = 0$, as implied by Cournot and Dixit-Stiglitz models of oligopoly, and use the fact that in our results $\epsilon_d \simeq 0$ and $1 - \beta_p \simeq 0.5$, to derive:

$$\epsilon_s = \frac{\theta - \epsilon_d}{1 - \frac{1}{\rho} + \frac{\theta}{\epsilon_{ms}}} \simeq \frac{\theta \epsilon_{ms}}{\theta - \epsilon_{ms}} \tag{9}$$

The last equation points out that once we allow market power to be present in the training market, then we cannot separately identify market power and the elasticity of supply. Figure 7 visualizes this by plotting all different values of ϵ_s, θ and ϵ_{ms} that can rationalize our results.

Figure 7: Values of the estimated elasticity of the supply of training ϵ_s as a function of market power θ and the elasticity of consumers' marginal surplus ϵ_{ms}



Notes. The Figure reports the values of the elasticity of supply (epsilon_s) in terms of market power theta and elasticity of consumers' marginal surplus, epsilon_ms (which measures the concavity of the demand function), obtained by substituting the estimates of the elasticity of demand and of pass-through from our data, in the equation of pass-through with market power derived by Weyl and Fabinger (2013).

On the other hand, , Sections 4.3 showed that a decrease (resp. an increase) in the subsidy generates a decrease (rep. an increase) in producers profits, $\beta_\pi > 0$. This result doesn't constitute evidence of imperfect competition in the training market per-se: an industry can still be competitive and when a subsidy affects profits, capturing a reduction in the producers surplus and in the remuneration of capital invested. Yet, we also show that despite the significant change in profits generated by the subsidy, no effect on entry/exit of firms is observed ($\beta_{EXIT} \simeq 0$). This suggest that the market for training might be less than perfectly competitive.

A possible source of market power in the training market is asymmetric information about training quality. DARES (2018) highlights that poor quality of a training course was one of the most significant concerns of CPF users. Consumers might thus face high switching costs to ascertain the quality of a competitor. Moreover, to tackle asymmetric information, and precisely to avoid that the training market becomes a market for "lemons", French regulators required public certification for training centers in order to be eligible for public subsidies. While reducing the problem of asymmetric information, this can stiff entry in the market. Finally, when the subsidy is so generous to cover the full cost of training, as often the case in CPF, consumers might simply be less responsive to price signals.

6 Welfare Effects

As a final step of our analysis we study the implication of our results for welfare. We start from the simpler case of perfect competition. The sufficient statistics approach (Chetty, 2009; Kleven, 2020) suggests that welfare consequences of policies can be derived as a function of high-level reaction of quantities to subsidy changes rather than deep primitives, maintaining validity under a wide array of assumptions about such primitives. This approach is not new in the study of taxes and subsidies: Harberger (1964) famously showed that the efficiency cost of small tax changes can be estimated using a simple elasticity-based formula. As reported in Chetty (2009), the Harberger model implies that the welfare of a representative consumer with utility $u(\boldsymbol{x})$ and monetary endowment ω given a subsidy ν on good x_1 is:

$$w(\nu) = \max_{\boldsymbol{x}}[u(\boldsymbol{x}) + \omega - \nu x_1 - \boldsymbol{p}(\nu)\boldsymbol{x}] + \max_{\boldsymbol{x}}[\boldsymbol{p}(\nu)\boldsymbol{x} - COST(\boldsymbol{x})] - \nu x_1$$

As a first step, we can adapt Harberger's approach to CPF subsidies. This requires taking the above expression for individual welfare, and allow the effective subsidy to be the maximum between the hourly price and the cap to per-hour subsidy. Assuming that welfare weights are equal across individuals and normalized to one, total welfare can be calculated as the sum of individuals' welfare. Finally, we assume that $u(\boldsymbol{x}) = \phi(x_i) + m_i$ where $\phi(x_i)$ is the utility from training episode i and m_i is the value of leftover money:

$$\begin{aligned}
W(\boldsymbol{c}) &= \sum_i \max_{x_i}[\phi(x_i) + m_i + \min(p_{q,f,t}, c_{\widetilde{q,f},t})x_i - p_{q,f,t}x_i)] + \max_{x_i}[p_{q,f,t}x_i - COST(x_i)] - \min(p_{q,f,t}, c_{\widetilde{q,f},t})x_i \\
&= \begin{cases} \sum_i \max_{x_i}[\phi(x_i) + m_i + c_{\widetilde{q,f},t}x_i - COST(x)] - c_{\widetilde{q,f},t}x_i & \text{if} \quad p_{q,f,t} \geq c_{\widetilde{q,f},t} \\ \sum_i \max_{x_i}[\phi(x_i) + m_i + p_{q,f,t}x_i - COST(x)] - p_{q,f,t}x_i & \text{if} \quad p_{q,f,t} < c_{\widetilde{q,f},t} \end{cases} \\
\frac{dW(\boldsymbol{c})}{d\boldsymbol{c}} &= \begin{cases} \sum_{q,f}\sum_{i\in q,f,t} -x_i + x_i - c_{\widetilde{q,f},t} \cdot \frac{dx_i}{dc_{\widetilde{q,f},t}} & \text{if} \quad p_{q,f,t} \geq c_{\widetilde{q,f},t} \\ \sum_{q,f}\sum_{i\in q,f,t} -\frac{dp_{q,f,t}}{dc_{\widetilde{q,f},t}}x_i + \frac{dp_{q,f,t}}{dc_{\widetilde{q,f},t}}x_i - p_{q,f,t} \cdot \frac{dx_i}{dc_{\widetilde{q,f},t}} & \text{if} \quad p_{q,f,t} < c_{\widetilde{q,f},t} \end{cases} \\
&= \sum_{q,f} -\frac{d\ln X_{q,f,t}}{dc_{\widetilde{q,f},t}} X_{q,f,t} \min(p_{q,f,t}, c_{\widetilde{q,f},t})
\end{aligned}$$

The last two lines write down how to recover the change in aggregate welfare for one extra euro of CPF subsidy for each eligible training hour in the sample, which we can recover using estimates of the reaction of total quantities to changes in the maximum cap of the subsidy, as in Table 1, and the actual subsidy used by each individual and in each industry/financing center. Then, one can divide by the number of hours of training to to obtain $\frac{dW(c)}{dc} = \frac{dW(\boldsymbol{c})}{d\boldsymbol{c}} / \sum_{q,f} X_{q,f,t}$, the average change in aggregate welfare from an additional Euro spent in CPF. Such estimates of are thus reported in Table 1. Not surprisingly, as the reaction of quantities is close to zero, the estimated impact on welfare of an additional Euro of CPF subsidy is also low.

Chetty (2009) shows that also in the presence of heterogeneity of preferences and discrete choice models the elasticity of the equilibrium quantity of the taxed/subsidized good with respect to the tax/subsidy is a sufficient statistic for estimating the change in welfare due to a marginal change in the tax/subsidy. However, this approach fails for large changes in a tax/subsidy, since behavioral responses $\frac{dx_i}{dc}$ in the consumer problem might not be ignored anymore. Kleven (2020) starts from the consideration that one can write a discrete welfare change, if welfare is a function of a policy variable, as the integral of the marginal welfare changes between initial and final values of the policy. This allows to derive a formula for changes in welfare following a change in the policy, with corrections for changes in tax wedges and elasticities. Assuming iso-elastic preferences, Kleven (2020)'s formula adapted to our case is:

$$\frac{\Delta W(\boldsymbol{c})}{\Delta \boldsymbol{c}} \approx \sum_{q,f} \frac{d \ln X_{q,f,t}}{d \tilde{c_{q,f,t}}} X_{q,f,t} \Big\{ \frac{c_{q,f,t-1}}{p_{q,f,t-1}} + \frac{1}{2} \left[\min(1, \frac{\tilde{c_{q,f,t}}}{p_{q,f,t}}) - \min(1, \frac{c_{q,f,t-1}}{p_{q,f,t-1}}) \right] \Big\}$$
$$\cdot \left[\min(p_{q,f,t}, \tilde{c_{q,f,t}}) - \min(p_{q,f,t-1}, c_{q,f,t-1}) \right] \tag{10}$$

Since this quantities can all be estimated, in the last line of Table 1 we can report $\frac{\Delta W(c)}{\Delta c} = \frac{\Delta W(\boldsymbol{c})}{\Delta \boldsymbol{c}} / \sum_{q,f} X_{q,f,t}$, the average change in aggregate welfare from one euro more invested in CPF, which remains close to zero.

Finally, we can study the welfare effects of CPF in the case of imperfect competition. Adachi and Fabinger (2022) study welfare effects under imperfect competition of an increase in taxes, showing that market power amplifies the deadweight loss arising from a per-unit tax. Conversely, in the case of subsidies market power can reduce the deadweight loss, as it increases the quantity consumed closer to the efficient level (up to making a subsidy welfare-improving, as noted already by Auerbach and Hines, 2001). Nonetheless, in our results we find a null reaction of quantities to subsidies, and an elasticity of demand close to zero. This corresponds to a corner solution in Adachi and Fabinger (2022), so that even with imperfect competition the subsidy should have no effect on aggregate welfare.

7 Conclusions

In this paper we studied the effect of training subsidies on training participation, their incidence and welfare effects. To summarize, our empirical analysis delivers five results. First, the change (mostly a decrease) in the per-hour CPF subsidy occurred in 2019 did not significantly affect training participation. Second, this happened as the change in the subsidy was partially absorbed by prices, and the subsidy was passed-through to consumers only by 47%. Hence, we can infer that more than half of the incidence of the CPF training subsidy falls on training producers. Third, we show that producers suffer a reduction of revenues and profits, with no effect on costs, including labor costs and employment of trainers. Fourth, this can be rationalized by inelastic demand for training, and by either inelastic supply or imperfectly competitive training markets, which we argue is a more likely scenario. Fifth, in the case of CPF, training subsidies were a simple transfer to training producers and consumers, with no effect on aggregate welfare.

Our paper is an important insight for the literature studying on-the-job training and training policy. Scholars never considered until now that training subsidies are often implemented through a training market, and that general equilibrium effects of training subsidies on prices might attenuate the effect of the subsidy on training participation. Concerning future paths for research, one implication of our results is that demand for training is quite inelastic. This seems at odds with the claim that there is a large potential demand for training which is under-financed, and suggests the importance of understanding what are the reasons for which demand for training is inelastic. Another implication is that either supply of training is inelastic or the market for training is imperfectly competitive. Again, the determinants behind both of these two explanations are also left to future research.

Finally, this paper has relevant implications for training policy. We show how subsidies like CPF risk ending up in a transfer, mostly to producers, if supply is relatively inelastic or the market is less than competitive. Policy makers who want to support human capital investment must – before subsidizing it – ensure that supply is sufficiently elastic and the market competitive. Interestingly, regulators might face a tradeoff between the need to guarantee training quality (Acemoglu and Pischke, 1999) and the risk that certifications become an entry barrier, reducing competition. To sustain lifelong learning, it might not be sufficient to simply assign enough resources to general-skills training, but an effective human capital policy should take into comprehensive consideration the design of the training market.

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A Additional tables and figures

Table 6: Initial sample selection carried out by the Ministry of Labor

	nb of training episodes		
SI-CPF data (sept-2020)		5 309 119	
restriction to CPF data		4 123 472	
restriction to training which started		2 829 975	
restriction to years 2016 to 2019		2 129 073	
restriction to workers		1 195 601	
additional restrictions (dossiers non financed by training agency, duplicates, dossiers without CPF credit, CPF de transition, etc.)		1 098 487	
	2017	**2018**	**2019**
sample by year w/o 2016	251 032	359 990	310 483

Notes. The first line of the table corresponds to the number of training episodes in the extraction of the SI-CPF from September 2020. We first restrict to CPF data, because the SI-CPF is also used for keeping track of training financed with other devices. Then we restrict to training which started to remove draft training episodes. The restriction to workers is very important because a good share of CPF users are unemployed, although this share has decreased between 2015 and 2018. Then, we remove duplicates, training episodes without CPF credits (which must be an error), and *CPF de transition dossiers* as it is a different device. We also remove training episodes which are not financed by training agencies as our study focus on the changes of per-hour values of the CPF subsidy operated by training agencies. This leads to the removing of *PAD (parcours d'achat direct) dossiers* as they are financed by the public bank. *PAD dossiers* are a new type of CPF consumption, available from November 2019 where an individual can use its CPF on his own, on an app.

Table 7: Placebo estimates, training course specification

VARIABLES	(1) $X_{qjft} - \hat{\hat{X}}_{qjft}$	(2) $\ln x_{qjft} - \ln \hat{\hat{x}}_{qjft}$	(3) $\ln N_{qjft} - \ln \hat{\hat{N}}_{qjft}$	(4) $p_{qjft} - \hat{\hat{p}}_{qjft}$
c_{qft+1}	-0.0177	0.000559	-0.0172	-0.154
	(0.0172)	(0.00207)	(0.0165)	(0.125)
Observations	17,760	17,760	17,760	17,760
Years	2018-2019	2018-2019	2018-2019	2018-2019
Estimation	IV	IV	IV	IV

VARIABLES	(1) $X_{qjft} - \hat{\hat{X}}_{qjft}$	(2) $\ln x_{qjft} - \ln \hat{\hat{x}}_{qjft}$	(3) $\ln N_{qjft} - \ln \hat{\hat{N}}_{qjft}$	(4) $p_{qjft} - \hat{\hat{p}}_{qjft}$
$c_{q\tilde{f}t+1}$	-0.00354	0.000264	-0.00359*	-0.0594
	(0.00223)	(0.000518)	(0.00202)	(0.0371)
Observations	17,760	17,760	17,760	17,760
R-squared	0.885	0.937	0.878	0.916
Years	2018-2019	2018-2019	2018-2019	2018-2019
Estimation	FE	FE	FE	FE

Notes. The upper panel reports placebo tests, obtained by estimating an IV regression of the relevant outcome in the pre-treatment period (2017-2018), residualized by the effect of any change in the subsidy cap in that period, on a lead of the effective subsidy instrumented by a lead of the subsidy cap. All regressions include year and training firm fixed effects and are weighted by the total value of the firm revenues. The lower panel reports placebo tests, obtained by estimating a reduced-form regression of the relevant outcome in the pre-treatment period (2017-2018), residualized by the effect of any change in the subsidy cap in that period, on a lead of the instrument. Column (1) uses as outcome total hours of training, Column (2) the average training duration, Column (3) the number of training courses, and Column (4) per-hour training prices. Regressions include fixed effects for training course and year. Standard errors are reported in parentheses and clustered at the training firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8: Placebo estimates, training firm specification

VARIABLES	(1) $\ln REV_{Jt}$	(2) $\ln COST_{Jt}$	(3) $\ln \pi_{Jt}$	(4) $\ln L_{Jt}$	(5) $\ln E_{Jt}$
c_{Jt+1}	-0.00228	-0.00368	0.000393	-0.00950***	0.000185
	(0.00226)	(0.00263)	(0.00180)	(0.00309)	(0.000205)
Observations	7,174	6,792	6,742	6,478	6,884
Years	2017-2018	2017-2018	2017-2018	2017-2018	2017-2018
Estimation	IV	IV	IV	IV	IV

VARIABLES	(1) $\ln REV_{Jt}$	(2) $\ln COST_{Jt}$	(3) $\ln \pi_{Jt}$	(4) $\ln L_{Jt}$	(5) $\ln E_{Jt}$
$\tilde{c}_{Jt+1}$	-0.000506	-0.000810	8.73e-05	-0.00212***	4.24e-05
	(0.000571)	(0.000663)	(0.000461)	(0.000779)	(5.37e-05)
Observations	9,322	8,916	8,866	8,501	8,900
R-squared	0.973	0.980	0.907	0.971	1.000
Years	2017-2018	2017-2018	2017-2018	2017-2018	2017-2018
Estimation	FE	FE	FE	FE	FE

Notes. The upper panel reports placebo tests, obtained by estimating an IV regression of the relevant outcome in the pre-treatment period (2017-2018), residualized by the effect of any change in the subsidy cap in that period, on a lead of the effective subsidy instrumented by a lead of the subsidy cap. All regressions include year and training firm fixed effects and are weighted by the total value of the firm revenues. The lower panel reports placebo tests, obtained by estimating a reduced-form regression of the relevant outcome in the pre-treatment period (2017-2018), residualized by the effect of any change in the subsidy cap in that period, on a lead of the instrument. Columns use as outcomes revenues, costs, profits, total labor costs and total number of employees. Regressions include fixed effects for training course and year. Standard errors are reported in parentheses and clustered at the training firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9: Impact of changes in CPF subsidy on producers' revenues, costs, profits, labor costs and number of teachers

VARIABLES	(1) $\ln c_{Jt}$	(2) $\ln REV_{Jt}$	(3) $\ln COST_{Jt}$	(4) $\ln \pi_{Jt}$	(5) $\ln L_{Jt}$	(6) $\ln E_{Jt}$
$\ln \tilde{c}_{Jt}$	0.242***					
	(0.0174)					
$\ln c_{Jt}$		0.261***	0.0852	0.169**	-0.0534	-0.0150
		(0.0796)	(0.107)	(0.0791)	(0.110)	(0.0943)
Observations	9,604	9,604	8,900	8,816	8,472	8,792
Years	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019
Estimation	FE	IV	IV	IV	IV	IV

VARIABLES	(1) $\ln c_{Jt}$	(2) $\ln REV_{Jt}$	(3) $\ln COST_{Jt}$	(4) $\ln \pi_{Jt}$	(5) $\ln L_{Jt}$	(6) $\ln E_{Jt}$
$\ln \tilde{c}_{Jt}$	0.242***	0.0630***	0.0202	0.0401**	-0.0126	-0.00361
	(0.0174)	(0.0189)	(0.0252)	(0.0185)	(0.0260)	(0.0227)
Observations	9,604	9,604	8,900	8,816	8,472	8,792
R-squared	0.846	0.970	0.964	0.822	0.954	0.957
Years	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019
Estimation	FE	FE	FE	FE	FE	FE

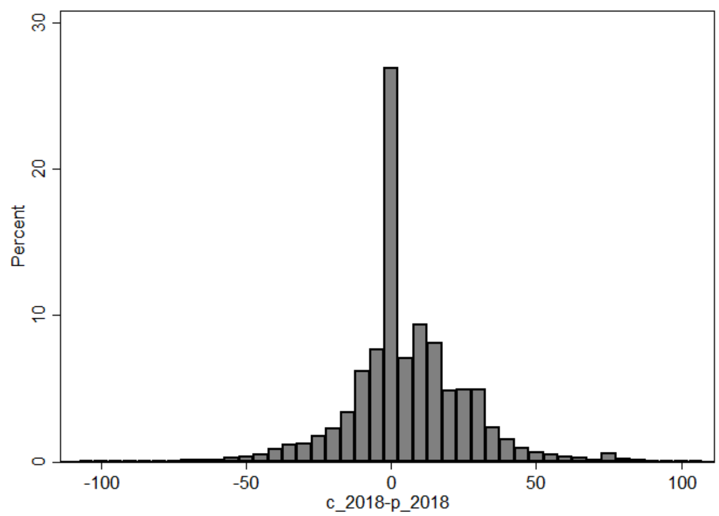
Notes. The upper panel reports the IV estimate of the effect of an increase in the natural log of the average effective training subsidy for a firms' customers on log revenues, costs, profits, labor costs and employment in the training firm. The lower panel of the table reports the reduced-form estimate of the effect of an increase in the natural log of the average subsidy cap for a firms' customers on log revenues, costs, profits, labor costs and employment in the training firm. All regressions include year and training firm fixed effects and are weighted by the total value of the firm revenues. Standard errors are reported in parentheses and clustered at the traning firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 10: Effect on net prices

	(1)
VARIABLES	p_{qjft}
c_{qft}	-0.0923***
	(0.0268)
Observations	49,038
Years	2018-2019
Estimation	IV

Notes. The table reports the IV estimates of the effect of a change in the effective subsidy on the training price. All regressions include fixed effects for year and for training course (an interaction of the training title, online/offline, and training establishment). Standard errors are reported in parentheses and clustered at the interaction between industry financing centers and the training kind category. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 8: Distribution of the difference between maximum subsidy rate and prices



Notes. The figure reports the histogram with width fixed at 5 of the difference between subsidy caps fixed by industry-specific financing centers and price of training episodes observed in the SI-CPF data in 2018.

Figure 9: Example of conversion table

Critères de prise en charge OPCA sur le CPF

Identification OPCA

Raison Sociale OPCA : ACTALIANS
Branche (s) professionnelle(s) couverte(s) par l'OPCA [2] : Professions libérales, Hospitalisation Privée, Enseignement Privé
Numéro (s) CCN :
Et/ ou
Code(s) IDCC : 2264,2691,2101,1951,1996,1147,1619, 2564,1875,959,2543,1726,2332, 2205,1921,2785,2706,240,1000,1850,

I. Informations CPF sur site institutionnel de l'OPCA

Informations générales sur le CPF [3] : http://www.actalians.fr/employeurs/cpf.asp
Conditions de prise en charge du CPF : [3] http://www.actalians.fr/employeurs/iso_album/dpc_cpf_ref2452_version_web.pdf

II. Conditions de prise en charge des OPCA au titre de l'agrément du 0.2 % CPF

A. Coût pédagogiques au titre de l'agrément 0.2% CPF

La prise en charge des coûts pédagogiques est-elle plafonnée ? : oui

Si oui, quel est le montant plafonné de prise en charge du coût horaire pédagogique (en euros HT) ?

	Heures compteur CPF	
	Coût horaire plafonné	Plafond global [4]
Pour l'accompagnement VAE	75 euros	24 h
Pour les actions CléA	27 euros	150 h
Liste COPANEF	60 euros	150 h
Liste COPAREF		
Liste CPNE	60 euros	150 h
Liste CPNE avec CPF abondé	[illegible]	[illegible]

Figure 10: Number of accounts by number of hours in the CPF account

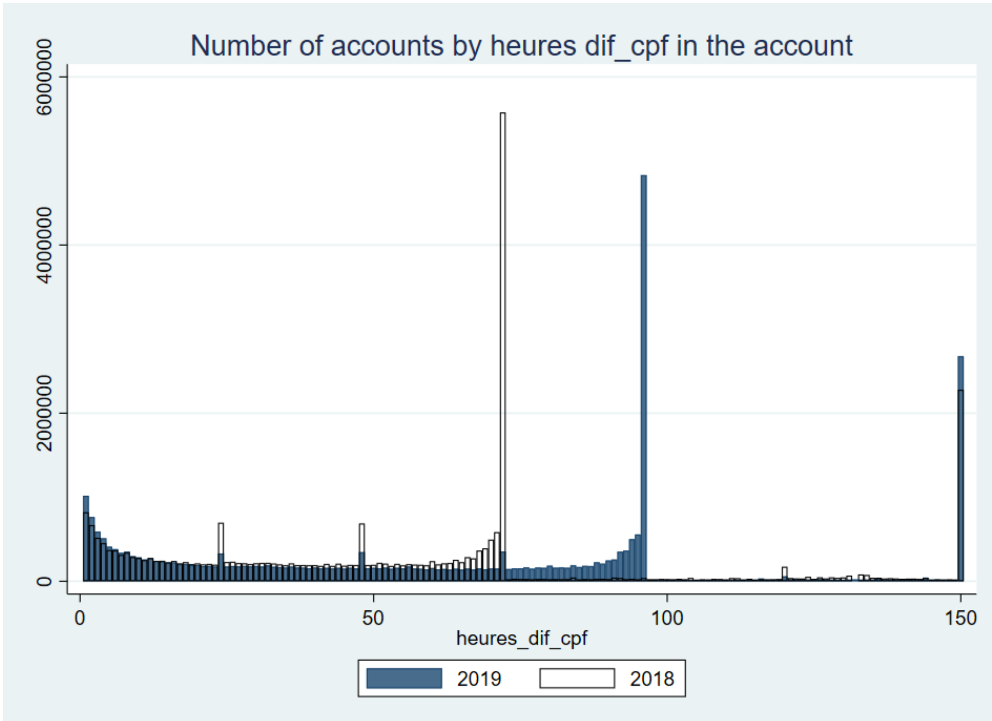


Figure 11: Time series of total cost of trainings undertaken and number of trainings started each week, in 2018 and 2019, breaking down 2019 into trainings validated by industry financing centers and those initiated through the centralized mobile app

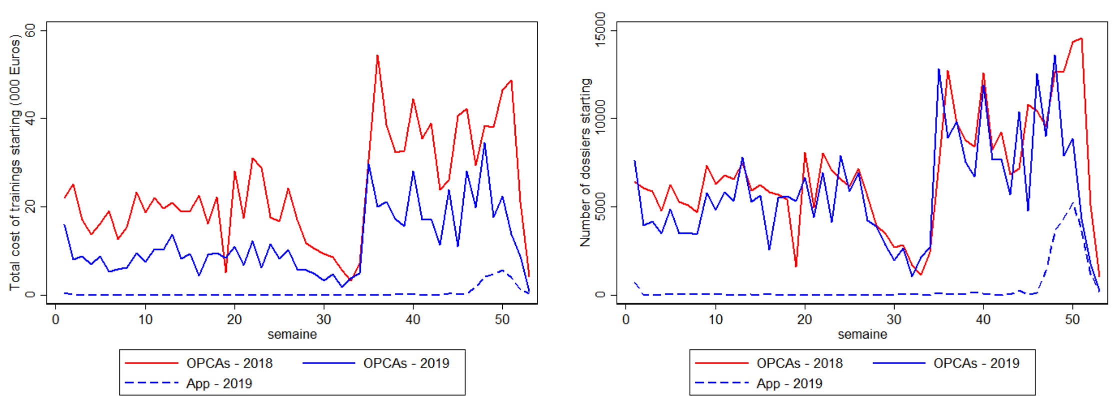


Figure 12: Link between agencies and their industry

Correspondence betwen the industry agency and industry

Industry agency	Industry
ACTALIANS	Independant workers
AFDAS	Culture, communication, media, leisure
AGEFOS	Inter-industry and interprofessionnal
ANFA	Auto services
CONSTRUCTYS	Construction
FAFIEC	Engineering, studies and consulting companies
FAFIH	Hotels and restaurants
FAFSEA	Agricultural enterprises
FAFTT	Temporary work
FORCO	Retail and distribution
INTERGROS	Wholesale and international trade
OPCA 3+	Furniture, wood, construction materials and industry and the paper and cardboard intersector
OPCA DEFI	Chemicals, petroleum, pharmaceuticals, parapharmacy / veterinary, plastics
OPCA TRANSPORT	Transport
OPCABAIA	Banks, insurance companies, mutual insurance companies, general insurance agencies, assistance companies
OPCAIM	Metallurgy industries
OPCALIA	Inter-industry and interprofessionnal
OPCALIM	Food industry
UNIFAF	Health, social and medico-social sector
UNIFORMATION	Social economy

B A Model of CPF with Discrete Choice and High Non-Monetary Training Costs

This Appendix sketches a simple model of CPF with discrete choice and high non-monetary costs of training to better understand a) why prices can be sometimes below the maximum subsidy cap, and b) why this should still not be a problem for IV estimation. For simplicity, let us ignore discretionary additions, $A_i = 0$. Assume then that training is discrete, i.e. consumers can either train for a fixed amount of hours $\bar{x}_q < \overline{x^{CPF}}$ or not train. Assume quasi-linear preferences with m_i as numeraire, and that consumers are heterogeneous in their utility from training $\phi_i(\bar{x_q}) = \phi(\bar{x_q}) + \eta_i$, where η_i can be interpreted as different benefits from training or different opportunity costs and is distributed as extreme values. Utilities from training and from not training are thus:

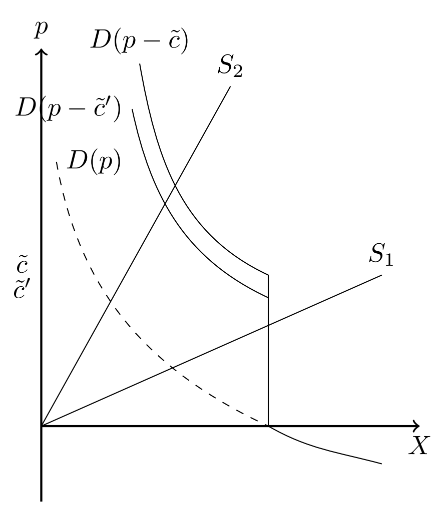
$$
\begin{aligned}
U_{i\bar{x_q}} &= \omega - \max(p - \tilde{c}, 0) \cdot \bar{x_q} + \phi(\bar{x_q}) + \eta_i \\
U_{i0} &= \omega
\end{aligned}
$$

Normalizing $\omega = 0$, and keeping all other assumptions like in the previous section, McFadden et al. (1973) shows that aggregate demand is:

- If $p > \tilde{c}$, then $X^d(p) = n\bar{x_q} \cdot e^{-p\cdot\bar{x_q}+\tilde{c}\cdot\bar{x_q}+\phi(\bar{x_q})}/(1 + e^{-p\cdot\bar{x_q}+\tilde{c}\cdot\bar{x_q}+\phi(\bar{x_q})})$
- If $p \leq \tilde{c}$, then $X^d(p) = n\bar{x_q} \cdot e^{\phi(\bar{x_q})}/(1 + e^{\phi(\bar{x_q})})$

That is, when a CPF subsidy $\tilde{c}$ is introduced, demand shifts up only for those individuals who were already willing to pay some monetary costs to train, while those consumer who were unwilling to pay any price to train, possibly due to zero returns or high opportunity cost, remain in fact unwilling to train even if the subsidy covers the whole monetary cost.

Figure 13: Equilibrium with training as discrete choice and some individuals not willing to pay any monetary cost



Now, what is the equilibrium price and effective subsidy rates, when the subsidy cap $\tilde{c}$ varies? Suppose producers charge prices equal marginal costs (i.e., they can't discriminate consumers with CPF, for example if they are only part of their customers). Then, we will have a non linear first-stage, in red in Figure 14: prices will tend to react to changes in the per-unit subsidy only when it “bites”, i.e. when the subsidy is lower than the price and the effective subsidy changes. For example, when subsidies are reduced from $\tilde{c}$ to $\tilde{c}'$, and demand lowers from $D(p - \tilde{c})$ to $D(p - \tilde{c}')$, if supply is like S_2 and equilibrium prices were above the subsidy rate the cut will “bite” and lower price and quantity according to the elasticities of demand and supply. Conversely, when the per-unit subsidy is higher than the price, the cut in the subsidy doesn’t bite, and the reaction of prices in equilibrium is null. Our IV estimator will necessarily use only instances where a variation in $\tilde{c}$ generates a variation in the effective subsidy c, and estimate the effect of the change of c on prices (i.e. the average slope of the black line left of the kink).

Figure 14: Equilibrium prices as a function of per-hour value of the subsidy, with training as a discrete choice