The Equilibrium Effects of General Training Subsidies: Evidence from a French Individual Learning Account

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Abstract

Governments often subsidize general skills training, but providers may partly capture these subsidies through higher prices. We study the equilibrium effects of the French Individual Learning Account, which grants workers training credits. The subsidy strongly affects training prices, with providers capturing 78% of its value. The subsidy also significantly increases providers' revenues and profits. While we estimate moderately inelastic demand for training, the results imply that training supply is also inelastic. Accounting for the cost of financing the subsidy, the policy is not cost-effective unless each euro of training generates positive externalities worth several times its cost.

Keywords: training subsidies, pass-through, incidence, human capital, imperfect competition

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

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1 Introduction

Workers' training is widely regarded as a key instrument to sustain workers' productivity and facilitate their reallocation following technological changes or cyclical downturns. At the same time, the cost of training that raises a worker's productivity beyond the current employer (*general* training) should largely be borne by the worker (Becker, 1964). However, substantial non-monetary costs, uncertain private returns, and the presence of externalities can lead to underinvestment in general training (Bassanini et al., 2005), particularly among credit-constrained individuals. Motivated by these considerations, governments often provide subsidies to promote investment in general training by workers (OECD, 2020).

Yet, what are the equilibrium effects of general training subsidies? The incidence literature in public finance (Jenkin, 1872; Harberger, 1962) suggests that subsidies may translate into higher equilibrium prices of the subsidized goods, thus limiting the expansion in quantities consumed. This may undermine the initial policy objective of stimulating training and instead benefit training providers, including owners of training centers (through higher profits) or their employees. While the literature on training subsidies has largely focused on small programs or limited-scale experiments, this paper studies the equilibrium effects of training subsidies on prices, participation, and providers' balance sheets in a quasi-experimental, economy-wide setting.

We derive our results by evaluating the impact of a national training subsidy for workers, the French *Compte Personnel de Formation* (CPF), using administrative data combined with information on CPF rules. The CPF is an "Individual Learning Account", a form of universal training voucher scheme that is gaining renewed momentum in Europe and is present at different scales across advanced economies (OECD, 2025).[1] Workers accumulate CPF training credits proportionally to their years of employment, and can then spend them on a market of certified providers. Consistent with its focus on workers, CPF credits are mostly spent on general training (e.g. language, digital/ICT skills, and professional skills certifications).

To assess the effects of the CPF, we exploit a reform that replaced industry- and training-specific subsidy caps with a uniform rate of 15 euros per hour in 2019. We find that a €1 change in the effective subsidy leads to a €0.78 change in training prices charged to workers in the year following the reform, implying that only 22% of the subsidy is passed through to trainees. The implied changes in the net price paid by consumers for CPF-subsidized training have only a modest effect on total training hours, pointing to moderately inelastic demand. Consistent with the observed declines in prices and quantities following a €1 decrease in the average hourly subsidy, we show that training providers' revenues fall by 2.2%, and, since firms' costs do not change significantly, profits also decrease significantly. This suggests that subsidy benefits mostly accrue to training providers, through higher profits.

We use our impact evaluation to provide estimates of training demand and supply elasticities. We directly estimate training demand in our data, finding it to be moderately inelastic, and leverage theoretical results in the incidence literature to infer the corresponding supply elasticity. Under the assumption of perfectly competitive training markets, our results suggest that supply is less elastic than demand. Because training markets could be characterized by asymmetric information and switching costs, we also calculate the implied supply elasticity under imperfect competition (Weyl and Fabinger, 2013), still obtaining low supply elasticity.

[1] Examples of individual learning account schemes include Singapore's *SkillsFuture* Credit, and pilot schemes in Croatia, Czechia, and Lithuania. Other voucher schemes targeting broad sub-populations include Scotland's *Individual Training Accounts*, Tuscany's *Carta ILA*, Flanders' *Opleidingscheques*, and Portugal's *Cheque-Formação*. Past examples include Germany's *Bildungsprämie*, the Netherlands' *STAP* voucher scheme, and Maine's 2006 *Lifelong Learning Accounts* pilot. In the United States, eligible participants may also receive training vouchers through WIOA Individual Training Accounts.

These results allow us to compute the Marginal Value of Public Funds (MVPF) for the subsidy (Hendren and Sprung-Keyser, 2020; Adachi and Fabinger, 2022), which compares the benefit of the subsidy to workers and training providers as revealed by their training demand and price reaction, to the cost for the government. However, such MVPF framework may omit other equilibrium effects of training, for instance positive externalities on co-workers' productivity (De Grip and Sauermann, 2012), or more generally cases where training demand is reduced by frictions preventing workers from fully internalizing the returns to general training (Acemoglu and Pischke, 1999). While we remain agnostic about the magnitude of these externalities, we show that, for the subsidy to break even once its distortionary financing costs are taken into account, each euro spent on training would need to generate external benefits 1.8 to 3.5 times as large in our baseline calibration. This value can reach 6-8 if the CPF subsidy covers almost all of the price of training, as observed in the data. These required external benefits appear high relative to existing estimates of returns to training to employees, and spillovers to co-workers, which are typically only a fraction of the cost of training (Goux and Maurin, 2000; De Grip and Sauermann, 2012).[2]

Our results contribute to the literature on policies to sustain training by offering, to our knowledge, the first evidence of how demand and supply reactions may undermine the effectiveness of training subsidies. The empirical literature has largely been unable to study the equilibrium effects of training subsidies on participation and prices jointly, focusing instead on their impact on training participation alone. For instance, evaluations of training vouchers (Hidalgo et al., 2014; Van den Berg et al., 2020; Görlitz and Tamm, 2017; Schwerdt et al., 2012) find some positive effects on training take-up but also that recipients mostly use the subsidy for training they would have undertaken anyway. These studies typically focus on small experimental shocks, which are unlikely to affect market prices. Studies of tax deductions for training expenditures (van den Berge et al., 2022; Leuven and Oosterbeek, 2004) also do not observe training prices, and since deductions are often directed at firms they are more likely to support firm-specific rather than general training.

We also relate to the broader literature on workers' training.[3] Seminal theoretical work has examined whether on-the-job human capital accumulation, including both formal and informal training, may be under-financed (Acemoglu and Pischke, 1999, 2000), thereby providing a rationale for (or against) subsidy policies. However, empirical studies focusing on the narrower subset of formal training programs, which are easier to define and are more often the object of policy intervention, find uncertain and relatively low private returns (Goux and Maurin, 2000; Bassanini et al., 2005). Our finding of moderately inelastic and concave demand is consistent with possibly low private returns to training, suggesting training demand responds only weakly to price reductions, while it may decline sharply when net prices increase.

Finally, our study contributes to the incidence literature in public economics (Harberger, 1962; Fullerton and Metcalf, 2002), and in particular to empirical work on the pass-through of subsidies. We extend this literature to a pivotal domain for labor and productivity policies, namely lifelong human capital investment. We find that the incidence of training subsidies falls largely on suppliers, consistent with evidence from Turner (2012) in the market for college education. Low pass-through to consumers was documented in settings with inelastic or constrained supply, such as housing markets (Gibbons and Manning, 2006; Fack,

[2] A more optimistic result is provided by Martins (2021), who find that EU-funded training subsidies to firms, worth on average €28,000, raise firms' value added by about 10% from a baseline of roughly €5 million, as well as employment. However, the study focuses on employer-provided training, which may differ substantially from training chosen by workers for their own returns, as suggested by the null effects they find on wages.

[3] This is distinct from the literature on training for unemployed individuals, which is generally supported by public employment services and more often subject to evaluations (Card et al., 2010).

2006).[4] At the same time, the pass-through rate may also reflect market power among participants (Weyl and Fabinger, 2013), an insight emerging from applied studies of subsidies for agriculture (Kirwan, 2009), health insurance (Cabral et al., 2018), and solar energy (Pless and van Benthem, 2019). We investigate this channel, but find that market power of training providers matters relatively little for the implied supply elasticities and aggregate cost-effectiveness of the subsidy.

The rest of the article is structured as follows. Section 2 presents our empirical setting: the institutional context, and the data. Section 3 presents the quasi-experimental results. Section 4 discusses the implications for the structure of the training market, including training demand, supply, and cost-effectiveness of subsidies. Section 5 summarizes and concludes.

2 Empirical setting

2.1 The French CPF and the 2019 Reform

The *Compte Personnel de Formation* (CPF) gives workers training credits that accumulate with each year of social security contributions. Credits can only finance courses offered by eligible providers, are held in a "personal" account, accessible only to the worker, and are "portable", i.e. remaining available even when changing employer.[5] Consistent with its design as a tool primarily controlled by workers, the CPF tended to finance training focused on general skills. Figure B.1 in the Appendix presents a broad categorization of the topics of CPF-financed training in 2018: the most frequent courses were in foreign languages (16%) and ICT skills (6%). Moreover, to be eligible for CPF, training programs have to either lead to a government- or industry-recognized certificate (which, consistent with the definition of general training, can improve workers' re-employment prospects with new employers) or be a compulsory training for performing specific professions or tasks (e.g. first aid, equipment operation certification). Finally, the CPF could be used to finance skills assessment or to obtain a certificate of skills acquired in past experience (recognition of prior learning), to attend training for starting a business, and for driving license, provided it is needed for a job-related plan.

Introduced in 2015, the scheme initially 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 2018. This study focuses on the private sector, where identifying variation is available, and that accounts for the vast majority of CPF trainings, since it had been covered by the CPF for longer. By 2018, the program's annual cost was around €869 million, corresponding to 5.7% of total public expenditures in training in France.[6] Although CPF accounts for only a minority share of training expenditure in France, which includes training for the unemployed and employer-sponsored training if financed through industry agencies, it remains the main training instrument for workers, thus likely to finance *general* training. Moreover, qualitative evidence from practitioner blogs suggests that the market for CPF-eligible training is relatively separate from other training

[4] Related evidence from construction markets during post-COVID supply bottlenecks includes Corsello and Ercolani (2024), and Accetturo et al. (2025).

[5] By contrast, the previous system (*Droit Individuel de Formation – DIF*) was physically reported in each employment contract, so credits from previous employment spells could only be recovered through a cumbersome procedure, and were often lost. Moreover, monitoring and activating DIF credits required asking the employer. Instead, the CPF could be mobilized autonomously by the account holder, provided that the training was conducted outside working hours.

[6] CPF expenses exclude supplementary top-ups. Total training expenses exclude apprenticeships and insertion, and cover all spending by both central and local governments, Public Employment Services, except direct expenses from public administration for own employees training. Source: *Jaune Budgetaire* for budget year 2021.

programs because of the associated administrative and regulatory burden.[7]

Between 2015 and 2018, CPF credits were measured in hours. Full-time workers accrued 24 hours per year up to 120 (then 12 per year up to 150), except for low-qualified workers, who received 48 hours per year up to 400. To use their credits, workers had to access an online platform (*"Mon Compte Formation"*) where their credits are recorded, select a training from those listed, and submit a request to the relevant industry-specific training agency.[8] These industry training financing agencies are sectoral bodies tasked with supporting workforce training and apprenticeships, jointly managed by employer organizations and trade unions. Financing agencies paid the training provider for the subsidized amount, deducting the corresponding hours from the worker's CPF account. Each agency covers a specific number of industry sectors, although one of them serves SMEs across several industries.[9] This pre-reform system is illustrated in Panel A of Figure B.2 in the Appendix.

Importantly, industry-specific training financing agencies were not willing to finance CPF-eligible training at any rate. Instead, they set subsidy caps for each type of training. We denote these as *rule-based subsidy caps*, which are most often defined in per-hour terms, although sometimes they can be in terms of overall cost of the training. These caps were reported in several official (information tables on government websites, government reports) and unofficial sources (training providers' websites, blogs).[10] For example, suppose a worker in 2018 has 120 CPF hours and wants to take a 50-hour training costing €80 per hour, for a total of €4,000. If the training agency of his industry has set a subsidy cap of €60 per hour for this training, €3,000 would be covered using 50 CPF hours, leaving 70 hours in the worker's account. To cover the remaining €1,000 costs, workers could be guaranteed *supplementary top-ups*. These are additional lump-sum financing amounts that depend on the type of training and the worker's characteristics, and are often subject to the agency's discretion on a case-by-case basis. If top-ups were unavailable or insufficient, the worker paid the remaining costs personally. However, the amount of top-ups available is validated before the training application is finalized, and trainees incorporate the availability of supplementary top-ups, or the need to pay out of pocket, in their final decision.

Before 2019, industry-specific training financing agencies were particularly generous in determining CPF subsidy caps. The program was funded through state-mandated contributions of 0.2% of the wage bill from all employers in the industry, earmarked for CPF training. Leftover funds were mutualized in a common public fund for jobseekers' and disadvantaged workers' training across industries. As a result, industry training agencies had incentives to avoid leaving CPF funds "on the table" and often set high subsidy caps to keep funds within the industry. Supplementary top-ups required instead a discretionary financing decision by the OPCA or another co-funder, and were often financed with other funding streams.

The CPF underwent a major reform in January 2019.[11] The main change was the "monetization" of credits: all CPF accounts were re-denominated in euros rather than hours, simply multiplying the amount of hours available by €15 for all workers. Consequently, industry-specific per-hour subsidy caps were abolished.

[7] For example, practitioner blogs note that some providers charge higher prices for CPF-funded training to cover "complex administrative management costs, certification costs, and very long payment delays", https://www.coopererpourformer.fr/formation-cpf-plus-chere.

[8] We call industry-specific training financing agencies what in French is known as *Organisme Paritaire Collecteur Agréé, OPCA*, renamed *Opérateurs de compétences, OPCO* in 2019.

[9] Jobseekers are instead covered by a state fund, but they account for a small share of total CPF training programs as unemployed individuals in France can access funding for training through several other schemes available at Public Employment Services.

[10] Figures B.3 and B.4 in the Appendix report two examples of official and unofficial sources, respectively.

[11] *Loi pour la liberté de choisir son avenir professionnel*, September 5, 2018.

An hour of CPF, which previously had different implicit values across industries and training kinds, became uniformly worth €15.[12] Importantly, for the first year after the reform, CPF functioned basically in the same way as the pre-reform system, except that the per-hour subsidy harmonized at €15 across industries (Panel B of Appendix Figure B.2 in the Appendix). Workers still submitted requests for approval of CPF funding to their industry training agency, but the subsidy was guaranteed at a fixed rate of €15 per hour. Industry training agencies could also still provide supplementary top-ups to cover residual costs. Because most pre-reform per-hour caps exceeded €15, the reform led to a substantial reduction in CPF subsidies. Accordingly, the share of training requiring supplementary top-ups also increased. This was a transition period in which the available subsidy changed through €15-per-hour monetization, while most other elements of the reform were delayed until the end of 2019. These included, most importantly, the introduction of the new CPF app, which allowed trainees to pay providers directly through a mobile application, bypassing industry training agencies entirely. From 2020 onward, the Covid-19 pandemic further changed the role of the CPF, as the scheme became more salient during a period of rapid growth in online training and underwent further changes and was reinforced by post-pandemic recovery policies.[13]

2.2 Data

Our main data source is an extraction of SI-CPF (*Système d'information du CPF*), an administrative database recording all CPF training episodes since 2017. Managed by the French Public Bank (*Caisse de dépôts et consignations*), it is used by authorities to monitor CPF usage and produce official statistics. Between 2017 and 2019, the SI-CPF collected information from employers to calculate CPF credits and from industry training financing agencies to track consumption.[14] The dataset includes beneficiary characteristics (ID, sex, age, industry, and CPF credits) and details of each CPF-financed training (title, duration, provider's identifier, total costs, part financed through CPF and other financing sources, including paid by the trainee). We derive gross training price as the ratio of the total training cost to the duration. We remove training episodes with extreme values in duration or price (below 1% or above 99%) and CPF training financed by employers directly, regions or public employment services (1.2% of observations).

Our second source is official and unofficial documentation on the CPF subsidy caps set by training agencies. We constructed a small database from official documents published by the inter-industry organization (*FP-SPP*), a few unofficial sources on websites and blogs, previous reports by the Ministry of Labor and by the national training council (*CNEFOP*), and written requests that we sent in 2019 with the French Labor Ministry to industry training agencies. The dataset records pre-reform subsidy caps for every industry training agency, varying across 10 training type groups[15], agency (in some cases, across specific industries within the agency) and year. We assign to each industry-specific financing agency (or sub-industry, if specified) and training group the *rule-based subsidy cap* in hourly terms that is reported on the tables. When only a cap on total financing is provided, we convert it to an hourly value. For *Skills Assessments* and *Recognition of Prior Learning* we use their standard 24-hours duration to obtain the hourly cap, while we use the total

[12] Although the reform was present in Macron's political manifesto, the details and the new uniform subsidy cap were uncertain until the final decree in December 2018, set to apply from January 2019. Anticipation was thus limited, and Appendix Figure B.5 in the Appendix shows only minor bunching of CPF-subsidized training at the end of 2018.

[13] Appendix Figure B.5 shows that training occurring through the mobile app in December 2019 was negligible. December 2019 was also an atypical month due to historically harsh strikes.

[14] We use a data extraction from 2020 built in collaboration with the French Ministry of Labour and Social Affairs (DARES) that covers private-sector workers only (Table A.1).

[15] These groups are defined following the distinctions for financing policies used by industry financing agencies, and are detailed in Appendix Table A.2.

hours cap if specified or the modal duration for all other training groups. We code as missing instances where the subsidy cap is not specified or explicitly unlimited, and trim our subsidy caps at 99%.[16]

We merge the subsidy-cap dataset with SI-CPF based on the industry training financing agency, year, and training kind for which the source is valid. We obtain a non-missing subsidy cap for 83.7% of the training episodes recorded in SI-CPF in 2017 and 79.5% in 2018. We harmonize net-of-tax and gross rule-based rates in our collection of CPF caps consistently with the way they are reported in the SI-CPF, depending on whether they appear as net or gross there.

Beyond subsidy caps, we can define two other important variables tracking the use of CPF, derived from SI-CPF. The first is the total euro amount of subsidy associated with the use of CPF hours, excluding supplementary top-ups. Dividing this amount by the number of CPF hours used gives what we call the *realized CPF per-hour subsidy*. This captures the component of the subsidy that derives directly from CPF hours converted under the applicable cap rules and is therefore, in principle, guaranteed to all applicants satisfying the regulatory requirements and not subject to further discretion by the industry agency. This realized per-hour value of CPF can in principle be either lower than the rule-based subsidy cap (in case the price of the training is below the cap), or equal to the maximum rule-based subsidy cap (when the training price is high enough that the subsidy reaches the cap). Appendix Figure B.7 shows that in 45% of the training episodes the subsidy cap exceeded the realized per-hour value of CPF, indicating that the training price was below the maximum subsidy cap, and coincided with the cap in 34% of cases, when the cap was binding.[17] Second, we observe supplementary top-ups, which are granted under specific rules and often involve agency discretion, as well as the total subsidy amount, defined as the value of CPF hours plus top-ups. Dividing this total amount by the number of CPF hours used gives what we call the *effective per-hour subsidy*.

Our final source is BPF (*bilans pédagogiques et financiers*), an administrative dataset providing key balance-sheet information for training centers. Collected by the Ministry of Labor from mandatory declarations by all providers using public subsidies, BPF is used for official statistics and government supervision. Compared to tax-based balance-sheet data, it is more up-to-date and detailed, covering financial data (revenues, costs, subsidies), cost breakdowns (employee wages, teacher wages, external consultants), and staff information (number of teachers and consultants). These data cover all training episodes at French training centers, including unsubsidized or non-CPF subsidized courses. We use the version from early 2021, which reliably covers fiscal year 2019. BPF is merged with SI-CPF via the training providers' tax identifier, with 93.3% of 2018 and 95.1% of 2019 training episodes successfully matched. To handle outliers, we trim revenues, costs, profits, and CPF revenues at the 99$^{\text{th}}$ percentile and drop profits below 1$^{\text{st}}$ percentile.

[16] This is mostly trimming caps from the finance industry, which are expressed in total amounts and end up being extremely high in hourly terms. 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 (3.7% of the sample), so they are excluded.

[17] The value of CPF hours exceeds the maximum implied by the rule-based per-hour caps in 21% of the cases, sometimes with large differences (e.g. above €10/h in 8.8% of the cases). This may reflect errors in the data: for example, the per-hour value often varies within training program and financing agency, although the rule-based subsidy and the price should be constant. Or, it can reflect errors in our collection of the subsidy caps. Our IV strategy in the next section accounts for measurement error in the observed CPF value, and we will use weak instrument tests to assess whether measurement error in the caps, which we use as instruments, biases the first stage.

2.3 Changes in Subsidy Rates Induced by the 2019 Reform

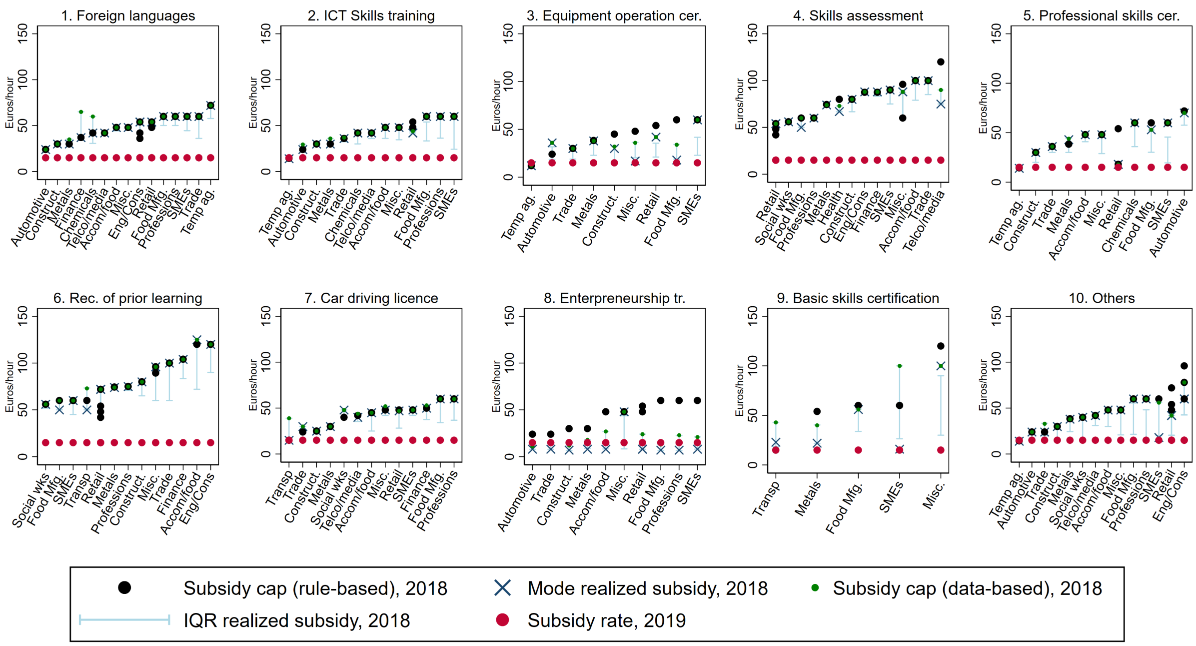
Figure 1 summarizes the evolution of effective CPF hourly subsidy rates and their caps. The black dots show the rule-based hourly subsidy caps applied in 2018, reconstructed from our data collection, across industry financing agencies and the ten training groups for which agencies set explicit caps. When multiple rule-based rates apply to a given industry and training type, they reflect different worker subgroups or more detailed industry classifications within the same agency. The figure reveals substantial variation across industries and training types. The equalization at €15 following the 2019 reform thus provides significantly different variation in CPF subsidies across industries and training episodes between 2018 and 2019. For example, the subsidy for ICT skills training barely changed for workers in the Temporary staffing agencies sector and for workers in the Automotive industry, while it fell by 75% for workers in Food Manufacturing, Professional Services or in SMEs. At the same time, the 2018 rule-based rates are in almost all cases above the uniform €15 hourly rate introduced in 2019 (the red dots), indicating that the reform generally reduced CPF subsidy rates, although to different extent across industries and training types.

Figure 1 also reports the mode of the rounded effective hourly CPF subsidy actually used to finance training, together with its interquartile range (IQR). The modal hourly subsidy is a useful reference because we expect bunching at the maximum subsidy cap whenever the cap is below the training price. For example, Appendix Figure B.9 zooms in, in the upper panel, on the distribution of realized subsidies for Foreign language training episodes financed by the Automotive industry financing agency (in Figure 1, this is summarized by the second data point from the left in the upper-left panel). Appendix Figure B.9 shows that for those training episodes the realized subsidy coincides with the cap in 80% of cases. This bunching is a common case: in Figure 1 the modal effective hourly subsidy often coincides with the cap. Note also that in many instances bunching is so pronounced that the IQR collapses to the mode. The frequent coincidence between the cap and the mode is therefore reassuring, suggesting our collection of caps based on official and unofficial sources corresponds to meaningful patterns in the administrative CPF data.

In other cases, realized subsidies vary more within an industry-by-training-group cell, either because training prices themselves vary, so that prices and the effective subsidy rate are sometimes below the cap. In such instances, bunching may be less visible and the subsidy cap may no longer coincide with the mode. This is, for example, the case for training programs financed by the agency of SMEs in the residual "Others" group, shown in Appendix Figure B.9, which zooms in on the third-to-last data point in the bottom-right panel of Figure 1. Still, the IQR of realized subsidy rates remains below the cap, suggesting that most training episodes recorded in the administrative data do not exceed the subsidy cap. This is again reassuring for the accuracy of our data collection.

Overall, most subsidy caps from our collection coincide with the mode and almost always lie above the upper bound of the IQR. However, there are a few cases in which the 2018 rule-based subsidy cap does not coincide with the mode or the upper limit of the IQR exceeds our cap. This pattern points to potentially meaningful inconsistencies between the rule-based caps we collected and the effective hourly subsidies observed in the data, either because some exceptions to the rules were not reported in the documentation we gathered or because of mismeasurement in the SI-CPF. To assess the robustness of our results, we therefore construct a *data-based subsidy cap*, defined in the pre-reform period as the maximum of the mode and the 75th percentile of the realized subsidy distribution (green dots in Figure 1). The intuition is that, when realized subsidy rates bunch sharply at a given value, this likely indicates that the value corresponds to the binding subsidy cap and that prices substantially exceed that cap, subject to the requirement that the inferred cap lies above the bulk of realized subsidy rates.

Figure 1: Per-hour subsidy caps (rule-based and data-based) and realized CPF per-hour subsidy, by training kind group and industry



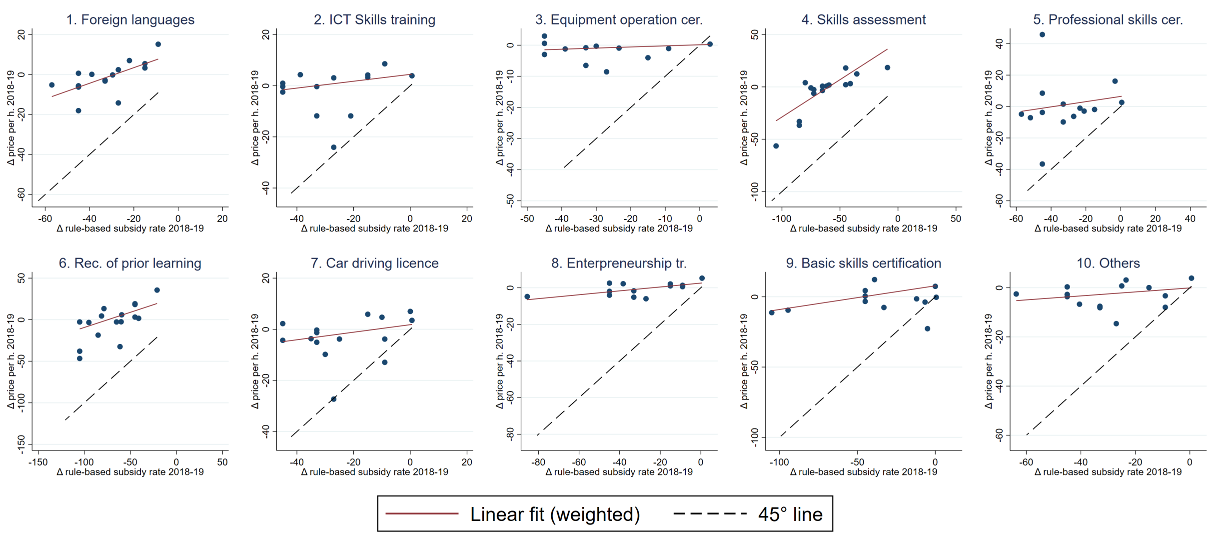
Notes. Rule-based CPF subsidy caps (black dots) in 2018 are defined by industry financing agencies to convert CPF hour credits of trainees into euro of subsidy. They are collected by the authors based on official and unofficial documentation. Realized subsidy rates are the euro amount of subsidy coming from the use of CPF hours, divided by the CPF hours, as reported in SI-CPF. The Figure reports IQR and mode. Data-based subsidy caps (green dots) correspond to the maximum of the mode and the 75th percentile of the realized subsidy distribution. The subsidy rate in 2019 (red dots) is set at €15 by the 2019 reform. The ten training groups are: (1) Foreign languages (e.g. *TOEIC, BULATS, LILATE*); (2) ICT skills training (e.g. *TOSA, PCIE*); (3) Mandatory equipment operation certification (*CACES*); (4) Skills assessment (*Bilan de compétences*); (5) Professional skills certification (*CQP*); (6) Recognition of prior learning (*VAE*); (7) Car driving licence (*Permis B*); (8) Entrepreneurship training (e.g. *SPI,formation créateurs d'entreprise*); (9) Basic skills certification (*CléA*); and (10) Others, a residual category including all remaining eligible training programs.

3 Quasi-Experimental evidence

3.1 CPF Training Subsidies Are Largely Passed Through to Producers via Prices

Descriptives. We start by presenting descriptive evidence on the impact of changes in CPF rule-based subsidy caps following the 2019 reform on training prices. Figure 2 plots, on the horizontal axis, the change in the rule-based subsidy cap per hour across industries for the 10 groups of training subject to different subsidy caps in 2018, and, on the vertical axis, the corresponding change in per-hour gross prices. Gross prices include both the portion financed through the CPF and the portion paid out of pocket by trainees. A 45-degree line is included for reference. The relationship is positive across all training groups, suggesting that, as the reform harmonised subsidy caps across industry financing agencies and training types, larger reductions in subsidy caps were associated with declines in prices. The strength of the relationship varies across different kinds of training: for some training kinds, such as skill assessments, the decrease appears close to one-for-one, while for others the relationship is less steep, such as in the residual category in the bottom right panel.

Figure 2: Changes in rule-based subsidy and prices over 2018-2019, by industry and training kind group



Notes. The figure plots changes in rule-based CPF subsidy caps per hour against changes in training prices across training groups and industries following the 2019 reform. Each point corresponds to a training group–industry cell. The linear fit in red is weighted by the number of training episodes behind each observation in 2018. The 45-degree line indicates full pass-through. Changes are computed relative to pre-reform levels.

Results. To formally study the effect of the CPF subsidy on training prices, we consider that they evolve according to the following model:

$$p_{q,f,t} = \beta c_{q,f,t} + \alpha_q + \gamma_{k,f} + \delta_{k,t} + \zeta_{f,t} + \varepsilon_{q,f,t} \tag{1}$$

where $p_{q,f,t}$ denotes the average price for training program q (identified by its title) paid by participants from industry financing agency f. $c_{q,f,t}$ is our key object of interest, as it represents the effective per-hour subsidy, including both the CPF subsidy and supplementary top-ups provided by industry financing agencies. It therefore captures the total subsidy effectively received by trainees and shaping their final training decision. The equilibrium price $p_{q,f,t}$ is the price *gross* of the subsidy, i.e. the amount paid to training providers.[18] We also consider as outcome in the same model the net price, $p^{NET}_{q,f,t} = p_{q,f,t} - c_{q,f,t}$, with $p^{NET}_{q,f,t} \geq 0$. The

[18]While training providers may offer courses to both CPF-eligible and non-CPF trainees, they often charge uniform prices across these two groups. Evidence from the French training market suggests that providers routinely charge higher prices for CPF-funded courses than for privately-paid ones, and often maintain separate courses for each group. Providers justify these price differences by the additional administrative burden associated with CPF-funded courses, including delayed reimbursement by the Caisse des Dépôts and mandatory certification costs. We therefore treat the CPF and non-CPF segments as distinct markets throughout the analysis.

coefficient β measures the average effect of a one-euro increase in the per-hour subsidy on the outcome. The term α_q refers to training program fixed-effects, accounting for differences in the level of prices, which are set at the training program level, and structural differences across programs. In addition, $\gamma_{k,f}$ represents fixed effects for financing agency f, interacted with each of the 10 training kinds k for which financing agencies set different subsidy caps. This controls for potential differences in subsidization rules by training financing agencies. Finally, $\delta_{k,t}$ and $\zeta_{f,t}$ capture training-kind- and financing-agency-specific time trends, respectively.

The total subsidy per hour for a specific training program $c_{q,f,t}$ in Equation 1 may not be exogenous. First, prior to 2018-2019, changes in subsidy policies limiting the maximum euro-value of CPF hours were set by industry financing agencies, potentially endogenously. To address this concern, we will focus our main estimation only on the exogenous change in subsidy caps generated by the 2019 reform and restrict the analysis to the 2018–2019 period. The inclusion of training kind fixed effects interacted by financing agency controls for any possible ad-hoc subsidy cap by specific financing agencies, and identification stems only from the changes entailed by the reform. We test the presence of any residual pre-reform trend using placebos.

Second, even in 2019, financing agencies were still able to guarantee supplementary top-ups in addition to CPF hours, included in the effective per-hour subsidy $c_{q,f,t}$ for each training program. For instance, trainees in 2019 from higher-income industries, where agencies have more available funds, or those in particular training programs considered priority skills by the industry, may obtain larger top-ups to compensate for the cut in the value of CPF hours following the reform. To address this second concern, one could instrument the effective per-hour subsidy $c_{q,f,t}$ with the *realized CPF per-hour subsidy*, i.e. the amount of subsidy coming purely from the use of CPF hour credits, excluding supplementary top-ups, which is reported in our data.

However, a third issue arises: by construction, the *realized CPF per-hour subsidy* is mechanically related to the price of the training, because CPF hours are converted in euros either at the maximum rule-based subsidy cap, or at the price of the training if the price is below the rule-based maximum rate. In cases where training programs are relatively inexpensive but some industries offer relatively high CPF subsidy caps, the CPF component of the effective per-hour subsidy may coincide with the gross price, introducing a correlation between our outcome (prices) and the component of the effective per-hour subsidy.[19] Therefore, in all cases (both when prices are above the maximum rule-based subsidy cap and when they are below) we use as an instrument for $c_{q,f,t}$ the *rule-based per-hour subsidy cap*, $\tilde{c}_{k,f,t}$, which was determined by industry training financing agencies in 2018, and set uniformly to 15 euros in 2019. These rule-based caps vary across training kinds k, each encompassing several programs $q \in k$, and also by industry financing agency and year, as shown in Figure 1.[20]

To implement our IV strategy, we thus estimate the following first-stage and reduced-form equations:

$$c_{q,f,t} = \beta^{FS} \tilde{c}_{k,f,t} + \alpha_q + \gamma_{k,f} + \delta_{k,t} + \zeta_{f,t} + \varepsilon_{q,f,t} \qquad \text{for } t = 2018, 2019 \quad \text{[First stage]} \tag{2}$$

[19] For example, a training course could cost 40 euros per hour, even if some industries could allow higher CPF subsidy per hour, e.g. 50 euros per hour. In this case the subsidy is "constrained" by low prices. This situation can happen as providers may not be able to raise prices exactly up to the cap for each trainee, for instance because they do not observe trainees' subsidy caps, or because they serve trainees facing different subsidy caps and cannot price-discriminate across them.

[20] Because $\tilde{c}_{k,f,t}$ can exceed the effective per-hour subsidy $c_{q,f,t}$ in instances where the rule-based cap for CPF per-hour value is above the training price, changes in $c_{q,f,t}$ may be smaller than changes in the instrument, analogously to non-compliance in an IV setting. Appendix Section Appendix C: discusses this aspect more formally. Figure B.8 in the Appendix reports the variation of rule-based CPF subsidy caps, suggesting that over 2018-2019 subsidy caps drop considerably, by almost €100 per hour in some cases.

$$p_{q,f,t} = \beta^{RF} \tilde{c}_{k,f,t} + \alpha_q + \gamma_{k,f} + \delta_{k,t} + \zeta_{f,t} + \varepsilon_{q,f,t} \qquad \text{for } t = 2018, 2019 \quad \text{[Reduced form]} \tag{3}$$

We present both reduced-form and first-stage results, estimated using a fixed-effects within estimator, as well as estimates of Equation 1 obtained via two-stage least squares. Standard errors are clustered at the level at which the instrument varies, namely the training kind group–by–industry financing agency level. We weight each q, f pair by the pre-reform number of training episodes in 2018, yielding a weighted-average effect of CPF subsidies, which is more representative of the average effect for each training episode, but we also provide robustness checks using unweighted regressions.

Table 1 reports the results. Column (1) presents the first stage, suggesting that a one-euro decrease in the CPF rule-based cap on the per-hour subsidy, $\tilde{c}_{k,f,t}$, leads to a significant €0.39 decrease in the effective average per-hour subsidy. The coefficient is strongly significant, and the F-statistic suggests that weak instruments are unlikely to be a concern. It is also substantially below one. The fact that a one-euro change in the rule-based cap on the per-hour subsidy does not translate one-for-one into a change in the effective per-hour subsidy $c_{q,f,t}$ reflects two factors that motivate our IV approach. First, supplementary top-ups can partially offset changes in the cap, attenuating the effective treatment. Second, variations in subsidy caps may exceed changes in realized subsidies when the cap is non-binding because it is above gross prices in 2018, so that adjustments in the rule-based maximum do not fully pass through to the effective subsidy received.[21]

Columns (2) to (5) show that the CPF subsidy is significantly affecting training prices, both gross and net of the subsidy. The coefficient in column (2) indicates that the reduced-form effect of the CPF rule-based subsidy cap on the per-hour gross price, $p_{q,f,t}$, is 0.3 and highly significant, implying that for every one-euro change in the rule-based subsidy cap, gross prices adjust by €0.3. Column (3) shows that the effect on net prices, equal to the difference between the effect on gross prices and that on the effective per-hour subsidy, is also significant, suggesting a reduction of net prices following an increase in the subsidy. In addition, Columns (4) and (5) report 2SLS estimates of the effect on prices of the total effective subsidy, $c_{q,f,t}$. The estimates imply that a one-euro increase (decrease) in the subsidy raises (reduces) gross training prices by about €0.78 on average, while net prices decrease (increase) by only €0.22. Thus, the share of the subsidy passed through to trainees appears to be extremely low, at only 22%.

[21] See Section Appendix C: for a discussion.

Table 1: Impact of the CPF Subsidy on Training Prices

VARIABLES	(1) c_{qft}	(2) p_{qft}	(3) p_{qft}^{NET}	(4) p_{qft}	(5) p_{qft}^{NET}
$c_{\tilde{k}ft}$	0.388***	0.304***	-0.0844***		
	(0.0601)	(0.0612)	(0.0174)		
c_{qft}				0.782***	-0.218***
				(0.0539)	(0.0539)
Observations	11,659	11,659	11,659	11,659	11,659
Years	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019
Estimation	OLS	OLS	OLS	2SLS	2SLS
F Stat.	41.74				

Notes. Column (1) reports the first-stage relationship between the rule-based hourly subsidy cap and the effective hourly subsidy, including supplementary top-ups. The Kleibergen–Paap F-statistic is also reported. Columns (2) and (3) report the reduced-form relationship between the rule-based hourly subsidy cap and the hourly training price, measured respectively gross and net of the subsidy. Columns (4) and (5) report the corresponding 2SLS estimates of the effect of the effective hourly subsidy on gross and net prices. Each cell is weighted by the number of training episodes observed in SI-CPF for that financing agency and training program in 2018. The number of observations corresponds to the number of training programs by industry financing agency by year in the regression. Standard errors are reported in parentheses and clustered by industry financing agencies and training kind group. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Heterogeneity. We explore heterogeneity across different groups of training (see Appendix Table A.3). First, high pass-through is driven by foreign languages, ICT skills training, and skills assessments, among the most frequent types of training. Pass-through estimates are not statistically significant for equipment operation certificates and professional skills certificates, but this is due to an insignificant first stage, as reduced-form estimates still point to a positive relationship between rule-based subsidies and gross prices. This suggests that financing agencies may offset reform-induced changes through supplementary top-ups in these training categories. An outlier is car driving licenses, where the subsidy appears to be passed through largely to consumers, potentially reflecting a relatively more elastic supply for these training episodes. For the residual category "others", pass-through to trainees is also higher than elsewhere, at around 43%.

Robustness and Placebos. We provide a number of robustness checks. First, we re-estimate Table 1 without using weights for the number of training episodes in each q, f group (Appendix Table A.4). The unweighted average effects on prices remain large, positive and strongly significant, but are somewhat smaller and imply larger pass-through to trainees. This can suggest a smaller adjustment of prices and a larger pass-through to trainees for training programs less commonly financed with CPF, or for industry financing agencies with less CPF trainees. Intuitively, providers may adjust prices more for programs that are more frequent or more frequently financed through CPF, and all providers may react more when larger industry financing agencies change subsidy caps vs. when small ones do.

Second, to address potential concerns arising from our data collection of rule-based subsidy caps from industry financing agencies, we run regressions using as instrument the alternative data-driven subsidy cap for 2018 CPF described in Section 2.3 (Appendix Table A.5). The results are very similar to our preferred specification, both when weighted and when unweighted. Third, the results remain robust and significant when prices and subsidies are expressed in logs (Appendix Table A.6). Fourth, in Table A.7 we check the robustness of the results to dropping those training groups for which the first stage was not significant in our heterogeneity analysis in Table A.3. We find a pass-through of 19% which is lower but similar to the one obtained on the whole sample.[22]

We also conduct placebo tests to strengthen the credibility of our identification strategy. First, to ensure that our results are not driven by underlying trends, and focusing on the 2018–2019 reform period, we estimate a specification which has a similar source identification as Equation 3, but using monthly units of analysis, indexed by m, and monthly average gross and net prices as outcomes.

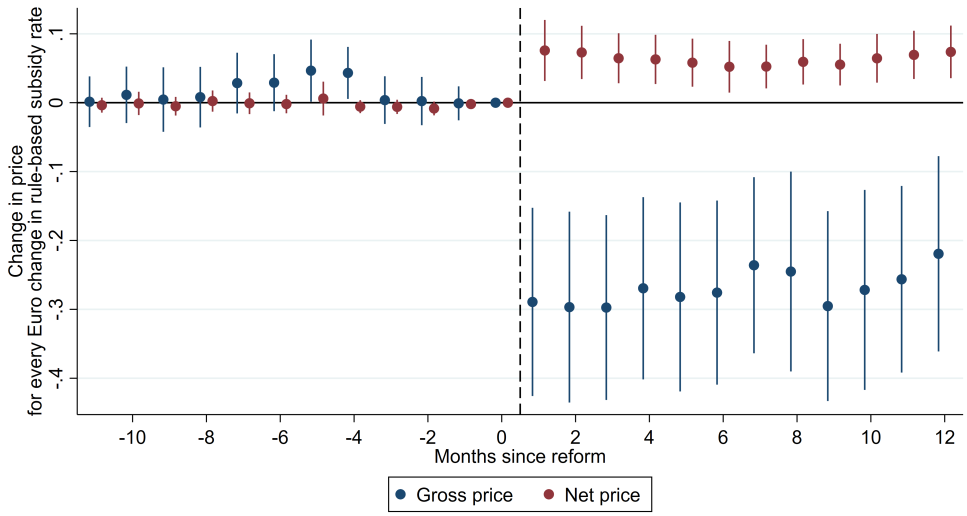
$$p_{q,f,m} = \sum_{g \neq 0} \beta_g^{RF} (-\Delta \tilde{c}_{k,f,2019-18}) \cdot \mathbb{1}[m = \text{Dec } 2018 - g] + \alpha_q + \gamma_{k,f} + \delta_{k,t} + \zeta_{f,t} + \varepsilon_{q,f,m} \tag{4}$$

The treatment variable $-\Delta \tilde{c}_{k,f,2019-18}$ is the cut in the subsidy cap induced by the reform. This reform-induced change in the subsidy cap is then interacted with a full set of monthly lead and lag dummies, excluding December 2018, which is the last month before the reform came into effect.

Figure 3 reports the results. It shows clearly that the treatment variable becomes significant with the reform, with larger cuts in the subsidy cap translating into higher net and lower gross prices. The effect is quite immediate and stable, suggesting that even if we can evaluate the effects of the reform only one year after it, the results may remain valid at longer horizons. By contrast, in the pre-reform period there are no economically significant differences across training programs and industries that would later experience differential shocks with the reform. This supports the validity of our identification strategy.

[22]We also check the robustness of the results when avoiding to harmonize net-of-tax and gross rule-based rates, which may have been misreported in the documentation. Appendix Figure B.6 shows that rule-based subsidy caps change slightly due to lack of harmonization, and are misaligned with realized rates in specific industries (this is why we prefer the corrected rates as baseline specification), but the results are virtually unchanged, as shown in Appendix Table A.8.

Figure 3: Impact of the CPF Subsidy on Training Prices, by months since reform



Notes. The figure reports coefficient estimates from a dynamic specification of Equation 3, using monthly data around the 2019 CPF reform. The treatment variable is the rule-based subsidy cap in December 2018 minus the uniform post-reform rate of €15, interacted with monthly lead and lag indicators. Blue markers denote estimates for gross prices, while red markers refer to net prices. Coefficients are reported relative to the month immediately preceding the reform. Vertical bars represent 95% confidence intervals with standard errors clustered at the training kind and industry financing agency level.

As a second placebo test, given that our data cover 2017-2019, we can assess the plausibility of the parallel-trends assumption by testing directly Equation 1 for pre-trends over the 2017-2018 period. In particular, we implement a placebo exercise examining whether reform-induced changes in subsidy caps over 2018-2019 predict outcome dynamics in the pre-reform 2017-2018 period. However, a complication arises because, in 2017-2018, many rule-based subsidy caps were already changing due to agency decisions, which may confound standard placebo tests.

To address this issue, we first partial out the reduced-form effect of the subsidy cap prior to conducting the placebo test. Specifically, we construct:

$$\hat{y}_{q,f,t} = y_{q,f,t} - \hat{\beta}^{RF}\tilde{c}_{k,f,t},$$

where $\hat{\beta}^{RF}$ denotes the estimated reduced-form coefficient for the outcome, taken from Table 1. We then estimate the following placebo specification:

$$\hat{y}_{q,f,t} = \beta^{PL}\tilde{c}_{k,f,t+1} + \alpha_q + \gamma_{k,f} + \delta_{k,t} + \zeta_{f,t} + \varepsilon_{q,f,t}, \quad \text{for } t = 2017, 2018. \tag{5}$$

Failure to reject the null hypothesis $\beta^{PL} = 0$ provides support for our identifying assumption. Columns (1) and (2) of Appendix Table A.9 report the results; in both cases, we find no evidence of statistically significant pre-trends. We also implement, in the same Table, an analogous placebo test using instrumental variables, instrumenting a lead of the effective subsidy with a lead of the subsidy cap and using $\beta^{\hat{IV}}$ instead of $\hat{\beta}^{RF}$ from Table 1. Finally, we consider an alternative placebo specification that directly regresses $\hat{y}_{k,f,t}$ on the lead of the subsidy cap while controlling for the contemporaneous value of $\tilde{c}_{k,f,t}$ (Appendix Table A.10). The effect of $\tilde{c}_{k,f,t+1}$ is never significant, so none of these exercises suggests evidence of significant pre-reform trends in 2017-2018.

3.2 Training Prices Mildly Affect Training Participation

We then turn to estimate training demand. Because net prices are often zero when the subsidy covers the full cost of training, we approximate a log-demand specification using the inverse hyperbolic sine transformation of net prices, which is defined at zero and closely approximates the logarithm (Bellemare and Wichman, 2020; Fabra et al., 2021).[23] Specifically, we estimate:

$$\ln X_{q,f,t} = F\big(\text{asinh}\big(p^{NET}_{q,f,t}\big)\,;\boldsymbol{\beta}\big) + \alpha_q + \gamma_{k,f} + \delta_{k,t} + \zeta_{f,t} + \varepsilon_{q,f,t}, \tag{6}$$

where $X_{q,f,t}$ is the total amount of training hours of a training program q undertaken by trainees from an industry agency f, and the fixed effects are the same as in Equation 1. In our preferred specification, $F\Big(\text{asinh}\Big(p^{NET}_{q,f,t}\Big)\Big) = \beta\,\text{asinh}\Big(p^{NET}_{q,f,t}\Big)$. However, we also explore a specification including a quadratic term of prices, i.e. where $F\Big(\text{asinh}\Big(p^{NET}_{q,f,t}\Big)\Big) = \beta_1\,\text{asinh}\Big(p^{NET}_{q,f,t}\Big) + \beta_2\,\text{asinh}\Big(p^{NET}_{q,f,t}\Big)^2$, to allow for flexible demand curvature and to evaluate the presence of potential log-concavity or log-convexity, which is required to relate structural elasticities to pass-through rates under imperfect competition, following Pless and van Benthem (2019). As in that paper, we address the simultaneity between prices and quantities by instrumenting training prices with changes in the rule-based CPF subsidy (including quadratic subsidy caps as instruments when the quadratic price term is present). This requires the additional assumption that, conditional on training-program fixed effects, training kind and training agency time trends, reform-induced variation in subsidies affects training hours primarily through changes in the net price paid by trainees.[24]

Table 2 reports the results. Columns (1) and (2) present the first-stage and 2SLS estimates without a quadratic term. The first stage is strong and significant in this baseline specification, and demand appears mildly inelastic, with a coefficient of -0.43, significant at 90% confidence. To investigate the presence of concavity in demand, columns (3) and (4) show that the first stage remains significant when adding the quadratic term, with F-statistics above 10. The 2SLS coefficients of this quadratic demand specification in column (5) are consistent with log-concave demand, although they are not statistically significant (note that our conservative clustering yields only 283 clusters).

The reduced-form relationship between subsidies and net prices in the first stage may change when subsidy caps exceed the gross training price, that is, when trainees' net prices are effectively driven to zero and become unresponsive to the subsidy. In columns (6) and (7), we therefore expand the set of instruments by adding an interaction of the rule-based subsidy with a dummy indicating whether baseline prices exceed the rule-based subsidy.[25] The first stage remains statistically significant, although the F-statistic is now slightly below 10, suggesting some caution in interpreting the results. This weakening appears to be driven by prices very close to zero, since already when we use indicators for prices above €0.1, rather than strictly above zero, the F-stat increases above 10, as shown in Appendix Table A.13. The resulting 2SLS estimates in column (8) suggest significant concavity in demand.

[23] Following Aihounton and Henningsen (2021), we assess the sensitivity of the inverse-hyperbolic-sine transformation to the unit of measurement by comparing IHS-transformed prices with log prices among observations with strictly positive net prices. In our baseline scaling, the correlation is 0.97, which suggests that the IHS transformation closely tracks log prices over the positive-price range. We also check the robustness of our results to using $\log(1 + p^{NET})$ in Appendix Table A.11.

[24] This assumption is further supported by the fact that we focus only on 2019 as the post-reform period, before the CPF app allowed trainees to bypass industry financing agencies.

[25] This specification additionally assumes that, conditional on the fixed effects, subsequent pricing shocks are uncorrelated with the baseline price position relative to the subsidy cap. Table A.12 in the Appendix provides a validation test for this assumption using pre-reform data.

Table 2: Impact of the CPF Subsidy on Training Participation and Implied Demand for Training

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\text{asinh}\left(p^{NET}_{q,f,t}\right)$	$\ln X_{qft}$	$\text{asinh}\left(p^{NET}_{q,f,t}\right)$	$\text{asinh}\left(p^{NET}_{q,f,t}\right)^2$	$\ln X_{qft}$	$\text{asinh}\left(p^{NET}_{q,f,t}\right)$	$\text{asinh}\left(p^{NET}_{q,f,t}\right)^2$	$\ln X_{qft}$
$\tilde{c_{kft}}$	-0.013***		-0.018**	-0.121***		-0.021**	-0.129***	
	(0.003)		(0.008)	(0.043)		(0.010)	(0.046)	
$\tilde{c_{kft}}^2$			0.000	0.001*		0.000	0.001**	
			(0.000)	(0.000)		(0.000)	(0.000)	
$\tilde{c_{kft}} \times \mathbb{1}(p_{qf2018} > \tilde{c_{kf2018}})$						0.019**	0.069*	
						(0.009)	(0.036)	
$\tilde{c_{kft}}^2 \times \mathbb{1}(p_{qf2018} > \tilde{c_{kf2018}})$						-0.000	-0.001	
						(0.000)	(0.000)	
$\text{asinh}\left(p^{NET}_{q,f,t}\right)$		-0.433*			0.119			1.669*
		(0.246)			(0.883)			(0.956)
$\text{asinh}\left(p^{NET}_{q,f,t}\right)^2$					-0.130			-0.408*
					(0.199)			(0.245)
N	13,317	13,317	13,317	13,317	13,317	13,317	13,317	13,317
N clusters	283	283	283	283	283	283	283	283
Estimation	OLS	2SLS	OLS	OLS	2SLS	OLS	OLS	2SLS
F-Stat	26.24		11.81	11.80		9.05	9.15	

Notes. Column (1) reports the relationship between the rule-based subsidy cap and the inverse-hyperbolic sine transformation of hourly net training price. This can be seen as a first-stage in demand estimation, so we report Kleibergen–Paap F-statistic. Column (2) reports the 2SLS estimates of the effect of changes in IHS-transformed net prices on log total training hours. Columns (3)-(5) add a quadratic term in the instrument and in log prices. Columns (6)-(8) add as instruments an interaction with a dummy for the baseline gross training price exceeding the rule-based CPF cap (i.e. for the subsidy cap to bind). The number of observations corresponds to the number of training programs by industry financing agency by year in the regression. Standard errors are reported in parentheses and clustered at the interaction between industry financing agencies and the training kind category. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

3.3 CPF Training Subsidies Affect Providers' Revenues and Profits

We then study the effect of CPF on training providers, focusing on how the subsidy affects suppliers' revenues, costs, and profits. Let a training-providing firm be denoted by subscript j. We model the impact of CPF subsidies at the provider level as:

$$y_{j,t} = \beta \left[c_{j,t} \cdot \frac{RevCPF_{j,2018}}{Rev_{j,2018}} \right] + \theta_t \cdot \frac{RevCPF_{j,2018}}{Rev_{j,2018}} + \gamma_j + \iota_t + \varepsilon_{j,t} \quad \text{for } t = 2018, 2019, \tag{7}$$

where we will use as main outcomes $y_{j,t}$ log total revenues $\ln Rev_{jt}$, log total costs $\ln Cost_{jt}$, and profits normalized by revenues π_{jt}/Rev_{jt}. We also investigate the effect on labor costs and employment.

Intuitively, Equation 7 relates the outcome to the average CPF subsidy rate faced by trainees at provider j. Namely, changes in CPF subsidies are captured by $c_{jt} = \sum_f \sum_{q \in j} \frac{x_{q,f,2018} p_{q,2018}}{RevCPF_{j,2018}} c_{q,f,t}$, which corresponds to the average effective per-hour subsidy for a provider's customers in 2018, weighting each training episode by its cost $x_{q,f,2018} p_{q,2018}$ over total baseline revenues from CPF training for that provider. Moreover, we note that training providers may differ substantially in the importance of CPF-eligible programs in their business. To account for the varying importance of CPF training over total training activity across providers, we interact the average subsidy $c_{j,t}$ with $\frac{RevCPF_{j,2018}}{Rev_{j,2018}}$, the baseline share of total revenues derived from CPF-subsidized training, where $RevCPF_{j,2018} = \sum_{q \in j} x_{q,2018} p_{q,2018}$ from SI-CPF data and $Rev_{j,2018}$ is observed in balance-sheet BPF information. The term $\theta_t \cdot \frac{RevCPF_{j,2018}}{Rev_{j,2018}}$ controls for differential time trends by baseline share of total revenues derived from CPF-subsidized training. γ_j and ι_t are training provider and time fixed-effects, respectively. In terms of econometric intuition, Equation 7 can thus be interpreted as a triple-difference design, where we compare over time the evolution of outcomes across providers whose trainees are more or less affected by changes in $c_{j,t}$, in firms with greater reliance on CPF relative to those with lower reliance. In terms of economic interpretation, one advantage of using as the regressor of interest an interaction of the average rate times the share of trainees eligible for the subsidy is that β can be interpreted as the average effect of a euro of subsidy on producers' outcomes.

As in the previous sections, we focus on changes induced by the CPF reform over 2018-2019 for estimating the main effects. We also instrument the average effective per-hour subsidy c_{jt} with the corresponding rule-based CPF cap, $\tilde{c}_{jt} = \sum_f \sum_{q \in j} \frac{x_{q,f,2018} p_{q,2018}}{RevCPF_{j,2018}} \tilde{c}_{k,f,t}$. The variation in $\tilde{c}_{jt}$ over the relevant years is shown in Appendix Figure B.10. We cluster standard errors at the training provider level, which corresponds to the level at which the regressor of interest varies.

In Table 3 we report the coefficients estimated on the sample of firms that are present both in SI-CPF data on CPF training episodes and in BPF data on training providers' balance sheets. The first stage is positive and statistically significant, with large F-statistics. The coefficient in Column (2) implies that a €1 increase in the effective subsidy leads to a 2.3% increase in suppliers' revenues. By contrast, the estimated effect on costs is smaller and insignificant. As a result, we find a positive statistically significant effect on profitability: when subsidies increase by €1, the profit-to-revenue ratio increases by 1 percentage point. This pattern suggests that the relatively large share of the subsidy passed through to producers, highlighted in Table 1, is ultimately captured by the owners of capital invested in training centers.[26]

[26] Importantly, the positive relationship between subsidies and profits in the year following the reform, is not sufficient to identify the degree of competition in the training market. For example, these patterns are consistent with models featuring either perfect competition with fixed costs and adjustment frictions, or monopolistic competition with heterogeneous firms. Under perfect competition with fixed costs (Hopenhayn, 1992), training providers earn zero economic profits in the long-run, and a subsidy cut can lower prices below average costs for marginal providers. A negative effect on average profits could be observed if some firms with negative profits remain active one year after the reform, for instance due to exit frictions or because the shock is perceived as temporary. Under monopolistic competition (Melitz, 2003), infra-marginal firms earn positive profits. A subsidy cut compresses these rents, and raises the zero-profit productivity cutoff, thereby reducing profits among surviving firms.

Table 3: Impact of changes in CPF subsidies on producers' revenues, costs, profits, labor costs, employment, and exit

VARIABLES	(1) c_{jt}	(2) $\ln Rev_{jt}$	(3) $\ln Cost_{jt}$	(4) π_{jt}/Rev_{jt}	(5) $\ln L_{jt}$	(6) $\ln E_{jt}$	(7) $Exit_{jt}$
$\tilde{c}_{jt} \cdot \frac{RevCPF}{Rev_{jt_0}}$	0.221***						-0.000976
	(0.0306)						(0.000781)
$c_{jt} \cdot \frac{RevCPF}{Rev_{jt_0}}$		0.0230***	0.0115	0.0101*	0.00362	0.000449	
		(0.00689)	(0.00833)	(0.00575)	(0.00920)	(0.00587)	
Observations	9,392	9,392	9,392	9,392	8,906	8,708	10,280
Years	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019
Estimation	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	OLS
F Stat.	31.06						

Notes. The table shows the effect of changes in CPF subsidies on provider-level outcomes. Column (1) reports the first-stage regression of the average rule-based subsidy cap for trainees of a given training provider (weighted average by revenue share of the training), interacted with the overall share of revenues of the provider coming from CPF, on the effective hourly subsidy. The Kleibergen–Paap F-statistic is also reported. Columns (2)–(7) report 2SLS estimates of the effect of the effective hourly subsidy on training providers' log revenues, log costs, profits as a share of revenues, log labor costs, log employment, and net exit. Standard errors, reported in parentheses, are clustered at the training-provider level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Columns (5) and (6) of Table 3 report the effects on log labor costs $\ln L_{jt}$ and log employment $\ln E_{jt}$. The absence of an effect on total costs reflects a similarly null effect on labor costs and on the number of employees at training centers. We also conduct placebo tests over 2017–2018 by regressing outcomes on the subsequent 2018–2019 subsidy change, after partialling out contemporaneous subsidy changes. Table A.14 presents these placebo estimates for the provider-level specification and again shows no significant effects.

Finally, the last column of Table 3 examines the effect of the subsidy on firms' net exit. We focus on firms active in 2018 and expand the data into a panel, assigning a value of one in 2019 to firms that disappear from the BPF data, which we interpret as market exit, and zero otherwise. We assign to firms exiting the market $\tilde{c}_{j2019} = 15$ and interact it with their 2018 share of CPF revenues, like the other firms surviving. We thus evaluate, in line with our firm-level reduced-form specification, how a firm's exit relates to the rule-based CPF cap of its trainees in 2018 and the uniform €15 cap in 2019, mediated by the 2018 share of CPF training revenues in the firm.[27] Given the positive relationship between subsidies and profits, we might expect subsidy cuts to increase exit if lower profits push marginal providers out of the market. While the sign is consistent with an increase in exit following a subsidy reduction, the estimated coefficient is small and not significantly different from zero.

Spillovers to non-CPF training. The analysis until now has focused only on CPF-eligible training. This is a small part of the French training market, where most training providers do not offer CPF-eligible programs at all, focusing on other segments such as vocational education, unemployment training, or apprenticeships. Some training programs are also not eligible for CPF due to lack of official certification, some

[27] Note that we cannot estimate the 2SLS specification as we cannot observe supplementary top-ups of trainees in firms that exited the market.

trainees are not historically eligible for CPF (e.g. self-employed) and some eligible trainees may simply choose not to use CPF for financing their training. Consistently with these facts, about 88% of firms in the BPF do not correspond to any firm code associated with CPF training episodes in the SI-CPF data.

Although qualitative evidence suggests that the market for CPF training is considered as a distinct one by providers, one may still wonder if potential spillovers to non-CPF training exist, implying that our estimates partly miss the whole equilibrium effects of the subsidy. However, thanks to the fact that BPF data cover total training revenues of all French training providers, including revenues from training not financed through CPF and providers not using CPF at all, we can test the presence of spillovers in the firm-level outcomes and assess the extent to which the CPF market is segmented from the rest of the training market.

First, we re-estimate Equation 7 on the full sample of training providers reported in BPF, assigning $RevCPF_{j,2018} = 0$ to providers not matched to SI-CPF. The results, reported in Appendix Table A.15, are not significantly different from those obtained on the sample of CPF-using firms matched to SI-CPF in Table 3. This suggests that changes in CPF subsidies over 2018-2019 did not generate significant spillovers to providers that did not operate in the CPF market during that period.

Second, the estimated effect of a one-euro increase in the subsidy on providers' log revenues in Column 2 of Table 3, using BPF data for firms with some CPF revenues, is extremely close in magnitude to the sum of the estimated effects on log gross prices and log training hours, estimated using a specification as in Equation 1 on CPF training episodes recorded in SI-CPF (Appendix Table A.16). This highlights the consistency of our results across two very different specifications, involving different datasets. It also suggests that, within CPF-using firms, there is limited substitution between CPF-financed and non-CPF-financed training episodes. If a large share of trainees were switching from CPF-financed training programs within the same provider to non-CPF training, as the reform cuts CPF subsidies, one would expect the decrease in log total firm revenues to be substantially smaller than the combined decrease in log prices and log training volumes observed in the CPF segment. Together with the qualitative evidence discussed in Section 2, these two results indicate that the estimates in Tables 1–3, based on CPF-eligible training episodes, capture nearly all of the equilibrium effect of CPF training subsidies.

4 Market Structure and Welfare Implications

4.1 Training Demand and Supply Elasticity

Framework. The previous section provided evidence on the pass-through of training subsidies and their effects on training participation. We now turn to the implications for the underlying structure of the training market, in particular the elasticities of training demand and supply. Given training demand $D(p^{NET}) = X$, training demand elasticity is defined as $\epsilon_d(p^{NET}) \equiv -D'(p^{NET})p^{NET}/X \geq 0$. Given training supply $S(p) = X$, training supply elasticity is defined as $\epsilon_s(p) \equiv S'(p)p/X \geq 0$. We begin by deriving the relationship between pass-through and structural elasticities under the textbook case of perfect competition, and then extend the analysis to allow for market power.

Denote pass-through to net prices $\rho \equiv -\frac{dp^{NET}}{dc}$, where c is the per-unit subsidy. The minus sign makes the definition comparable to the standard tax pass-through rate used in the literature: an increase in the subsidy is equivalent to a decrease in the tax wedge, so pass-through is measured with respect to the corresponding tax change, $-dc$. Following classical results of (Jenkin, 1872; Fullerton and Metcalf, 2002), if markets are perfectly competitive, pass-through of a subsidy is approximately a function of demand and supply elasticities:[28]

$$\rho = \frac{\epsilon_s}{\epsilon_s + \epsilon_d} \tag{8}$$

Yet, the training market may well be imperfectly competitive, for example due to 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 may therefore face high search or switching costs when assessing competitors' quality. 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 limit entry in the market.

Under symmetric imperfect competition, Weyl and Fabinger (2013) show that the pass-through rate of a subsidy corresponds to:

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

where $\theta \in [0, 1]$ captures the degree of market power, with $\theta = 0$ under perfect competition and $\theta = 1$ under monopoly.[29] Note that if $\theta = 0$, then Equation 9 reduces to Equation 8. Beyond θ, Equation 9 includes as additional drivers of pass-through the elasticity of inverse marginal consumer surplus $\epsilon_{ms} = \frac{ms}{ms'X}$, where $ms = -p^{NET\prime}X$ is the marginal consumer surplus, and the response of θ to changes in the quantity consumed, ϵ_θ. Following Pless and van Benthem (2019), we assume the degree of competition is invariant to quantities consumed so $\theta/\epsilon_\theta = 0$, as implied by standard Cournot and Dixit–Stiglitz models of oligopoly, and estimate ϵ_{ms} using:

$$\frac{1}{\epsilon_{ms}(p^{NET})} = -\frac{(\log D(p^{NET}))''}{\left((\log D(p^{NET}))'\right)^2}, \tag{10}$$

Calibration and Results. We can now use Equations 9 to recover the training supply and demand elasticities implied by the results of our empirical analysis, as reported in the upper panel of Table 4. This is based on the fact that our results suggest that only 22% of the subsidy is passed-through to consumers (Table 1), so $\rho = 22\%$, as reported in the upper panel.

For the perfect-competition scenario, we evaluate demand using the linear specification without quadratic price terms reported in Column (2) of Table 2, since demand curvature does not enter the perfect-competition incidence formula. Multiplying that coefficient by $\frac{\bar{p}^{NET}}{\sqrt{1+(\bar{p}^{NET})^2}}$ to convert into log-log elasticity around the average net price yields a demand elasticity of $\epsilon_d = 0.42$, which is also close to the result in Table A.11. The corresponding supply elasticity is then obtained directly from Equation 8 and is estimated at 0.12.

[28] In equilibrium, $D(p^{NET}) = S(p)$, so totally differentiating with respect to the subsidy c yields $D'(p^{NET})\frac{dp^{NET}}{dc} = S'(p)\frac{dp}{dc}$. Since $\frac{dp^{NET}}{dc} = \frac{dp}{dc} - 1$, rearranging gives $\frac{dp}{dc} = \frac{-D'}{S'-D'} = \frac{\epsilon_d p}{\epsilon_s p^{NET} + \epsilon_d p}$. Because $\rho \equiv -dp^{NET}/dc = 1 - dp/dc$, this implies $\rho = \frac{\epsilon_s p^{NET}}{\epsilon_s p^{NET} + \epsilon_d p}$. Approximating for small wedges c such that $p \simeq p^{NET}$, this simplifies to $\rho = \frac{\epsilon_s}{\epsilon_s + \epsilon_d}$.

[29] In Weyl and Fabinger (2013), pass-through is defined as the response of the consumer price to a tax t, i.e. dp^{NET}/dt, but since in our setting, $t = -c$ then $\rho = -dp^{NET}/dc$ coincides with the pass-through object in Weyl and Fabinger (2013).

For the market-power scenario, we instead use the results of the quadratic demand specification reported in Column (8) of Table 2, evaluated at the average net price of CPF training. This gives a local demand elasticity, $\epsilon_d = 0.12$. We also use Equation 10 to compute the inverse elasticity of marginal consumer surplus, $1/\epsilon_{ms}(p^{NET})$. As explained by Weyl and Fabinger (2013), a positive value of $1/\epsilon_{ms}(p^{NET})$ implies that log demand is log-concave at the average price. Combining these demand-side objects with the formula for pass-through under market power in Equation 9, and calibrating on the extreme case of monopoly ($\theta = 1$), yields an implied supply elasticity that is virtually zero. This suggests that overall training supply is relatively inelastic, especially in case training providers hold some market power in our context.[30]

Table 4: Derivation of demand and supply elasticities and cost-effectiveness of the CPF

Panel 1 - Elasticities	Perfect competition ($\theta = 0$)		Market power ($\theta = 1$)		Source
ρ	0.218				Table 1, Column 3
ϵ_d	0.423		0.117		Table 2
$1/\epsilon_{ms}$	–		48.361		Eq. 10
ϵ_s	0.118		0.020		Eq. 8; Eq. 9
Panel 2 - Welfare	Perfect competition ($\theta = 0$)		Market power ($\theta = 1$)		
	(1)	(2)	(3)	(4)	
	$\mu = 0$	$\mu = 0.3$	$\mu = 0$	$\mu = 0.3$	Source
ν	0.40				20% VAT on net price
τ	-0.60				Calibrated wedge
ϕ	0.45				Economy-wide tax-to-GDP
MVPF($B = 0$)	0.952	0.732	1.105	0.850	Eq. 12
b (required for MVPF = 1)	0.281	1.786	-2.117	3.487	

Notes. Panel 1 summarizes the results that are directly estimated using empirical results, and references the results table from where they are taken. Panel 2 reports the calibrated parameters from external sources and their corresponding sources. Panel 3 presents the implied supply elasticity, the Marginal Value of Public Funds in the absence of externalities, and the externality required for the MVPF to equal 1 under alternative assumptions on the degree of competition and the distortionary cost of taxation.

4.2 Cost-Effectiveness and Welfare

Framework. To conclude, we assess the welfare effects of the subsidy by computing the marginal value of public funds (MVPF). The MVPF measures the ratio of marginal social welfare gains to the net social cost of public funds (Hendren and Sprung-Keyser, 2020). Values above one indicate that the policy generates more than one euro of social value per euro of cost, while an infinite MVPF corresponds to a program that pays

[30]The results rely on the usual small-wedge approximation in the literature. Appendix Table A.17 replicates the results without small-wedge approximation, assuming an initial wedge equal to the ratio of the average gross to the average net price of CPF-subsidized training episodes. This ratio can be particularly high in our data as we have seen that the average net price is 0 in many instances, so that the average gross price is ten times the average net price. With these wedges, the results remain consistent, even if they become more extreme: supply elasticities are around one in the case of perfect competition and around zero with market power.

for itself. We build on previous results, in particular Adachi and Fabinger (2022), who derive the MVPF of a per-unit tax rate or subsidy allowing for imperfect competition (captured by θ) and the presence of other pre-existing tax and subsidy wedges. In that paper, the authors define:

$$\text{MVPF} = \frac{\frac{1}{\rho} + \nu + (1-\nu)\theta}{\frac{1}{\rho} + \nu - \tau\epsilon_d}. \tag{11}$$

where ν are pre-existing ad-valorem taxes, and τ is the overall pre-existing tax wedge on the good resulting from ad-valorem and per-unit taxes/subsidies, which in our case apply to the price gross of CPF p, and which accounts for the fact that pre-existing distortions may magnify the cost of an additional tax/subsidy.

We extend the framework of Adachi and Fabinger (2022) in two directions. First, we incorporate a marginal deadweight cost of additional taxation $(1+\mu)$ required to finance CPF. As clarified by Hendren and Sprung-Keyser (2022), this is equivalent to evaluating the MVPF of a policy that combines CPF expenditures with a linear income tax used to finance them, characterized by a marginal cost of public funds μ. Second, we allow for the possibility that training generates positive externalities. Rather than estimating these explicitly, we remain agnostic and introduce a parameter B capturing the additional marginal social benefit generated by CPF-induced training. We then compute the MVPF as a function of B. We further allow externalities either to accrue as non-fiscal social benefits or to reduce government costs, for example if government is able to tax the additional external benefits generated by training, as governed by $\phi \in [0,1]$.

With these extensions, the MVPF can be written as:

$$\text{MVPF}(B) = \frac{\frac{1}{\rho} + \nu + (1-\nu)\theta \;+\; (1-\phi)B}{(1+\mu)\left(\frac{1}{\rho} + \nu - \tau\epsilon_d \;-\; \phi B\right)} \tag{12}$$

We also derive the minimum level of B required for the policy to be cost-effective, denoted $B^{MVPF=1}$.[31] We use this value to calculate the additional benefit required for the MVPF to be one per euro of CPF-induced training expenditure. Specifically, we compute:

$$b = \frac{B^{MVPF=1}}{\rho\epsilon_d \frac{\bar{p}}{p^{NET}}}, \tag{13}$$

where the denominator is an estimate of the average increase in gross training expenditure induced by the behavioural demand response to one additional euro of CPF subsidy, holding gross prices fixed.[32]

Calibration and Results. Note that in Equation 12, the MVPF of a subsidy depends on the initial level of the subsidy, which enters through τ. In our baseline, we evaluate the welfare effects of CPF at a

[31]Setting equation (12) equal to one gives

$$B^{MVPF=1} = \frac{(1+\mu)\left(\frac{1}{\rho} + \nu - \tau\epsilon_d\right) - \left(\frac{1}{\rho} + \nu + (1-\nu)\theta\right)}{1+\mu\phi}.$$

Note that when $\mu = 0$, $B^{MVPF=1}$ is invariant to ϕ.

[32]Namely, the denominator corresponds to $p\frac{dX}{d(cX)} = \frac{dp^{NET}}{dc}\frac{dX/X}{dp^{NET}/p^{NET}}\frac{p}{p^{NET}}$. Intuitively, a one-euro increase in the CPF subsidy reduces the net price paid by trainees by ρ euros, and increases training demand by $\rho\epsilon_d/p^{NET}$. Multiplying this quantity response by the gross price p gives $\rho\epsilon_d p/p^{NET}$. By holding gross prices fixed, we isolate the expenditure induced by the behavioural quantity response and exclude price-driven increases in spending for both infra-marginal and marginal trainees that mainly reflect incidence rather than additional training.

reference policy margin in which the CPF subsidy equals the net price paid by trainees, hence it is 50% of the gross price. We see this reference as a balanced one, because the additional welfare loss from the pre-existing distortion is higher than if the subsidy were zero at baseline, yet smaller than the loss under the actual average subsidy observed in the data, where gross prices are several times higher than net prices. We provide sensitivity checks in the Appendix. This implies that, based on the French 20% VAT rate applied to gross prices, the ad-valorem tax relative to net prices is $\nu = 0.4$. Since the baseline subsidy is equal to the net price, the overall wedge relative to net prices is $\tau = -0.6$. Finally, $\phi = 0.45$ based on the French tax-to-GDP ratio in 2018.

Panel 2 of Table 4 reports the MVPF (for $B = 0$) using a cost of taxation parameter $\mu = 0.3$ following Hendren and Sprung-Keyser (2022), as well as the case $\mu = 0$, corresponding to the MVPF of CPF abstracting from the cost of distortions due to taxation needed to finance it. It also reports the value of b required for the MVPF to equal one, i.e. the amount of externalities for every euro of CPF-induced training needed for the CPF subsidy to be a cost-effective policy under each scenario.

The results suggest that, when not accounting for distortive taxation ($\mu = 0$) and externalities of training ($B = 0$), the MVPF of CPF is close to one. Under perfect competition (column 1), the result is intuitive, as the combination of an estimated low elasticity of demand and even lower elasticity of supply (implied by estimated low pass-through to trainees) entails small responses of the quantity consumed to the subsidy, hence small deadweight-loss. In other words, under inelastic training demand and supply, there is low aggregate cost of the CPF arising from the classical deadweight loss associated with distortions in quantities. Therefore, the externality required for the MVPF of the CPF to reach the break-even value of 1 is relatively modest, at about 28 cents per euro spent on CPF-subsidized training. This magnitude is not implausible in light of existing evidence. For instance, De Grip and Sauermann (2012) estimate that a 10% increase in workers' training raises the productivity of co-workers by about 0.5%, suggesting that large increases in workforce training can generate such significant spillovers.[33]

It is interesting to note that the MVPF of the subsidy is actually above one in the presence of market power (Column 3). This occurs as the subsidy increases training participation that would be otherwise sub-optimally low due to providers pricing above perfect competition, an intuition already present in Auerbach and Hines (2001). No positive externality is needed in this case: the break-even value of b is negative because the CPF is already cost-effective in this calibration.

The MVPF falls significantly below one once financing distortions are taken into account (Columns 2 and 4). This occurs because, while quantity reactions are low, the subsidy is relatively large and so is taxation required to finance it. As a result, and given the limited participation response to the subsidy, the per-euro externality b generated by each additional euro spent in training would need to be very large for the policy to be cost-effective when accounting for the distortionary taxation used to finance it. In our calibration, each euro spent on training would need to generate externalities roughly 1.8 to 3.5 times larger for the subsidy to break even, which seems extreme given the available quantitative estimates in the literature (De Grip and Sauermann, 2012).

Figure B.12 in the Appendix reports a sensitivity analysis to alternative CPF subsidy wedges, ranging from

[33] The program studied by De Grip and Sauermann (2012) generates direct returns of around 10% higher productivity for participants. If training prices broadly reflect private returns to training, and if the estimated peer effects scale approximately linearly, their estimates would imply that each euro spent on training generates private returns and, in the limiting case in which training exposure increases for the whole relevant workforce, peer-productivity gains of up to about 5%, equivalent to about half the cost of training, so $b \simeq .5$.

0, which corresponds to the MVPF of the first euro spent through CPF, to about 8, roughly the average ratio of the observed CPF subsidy to net prices, since net prices are often very low relative to the subsidy.[34] The results remain qualitatively consistent. In the scenario with market power and not accounting for distortive financing taxes the MVPF is above or very close to one but never particularly high (between 0.94 and 1.13). The MVPF is instead mostly below one in all other scenarios, reaching cost-effectiveness only in the limit case of perfect competition with no distortionary cost of taxation and zero initial CPF subsidy wedge. In scenarios that account for taxation costs, the required externality b for the subsidy to break even reaches levels around 6-8 additional euros per euro of induced training when the initial CPF subsidy wedge is as high as the average observed in the data. This suggests that it is particularly unlikely that sufficient externalities justify training subsidies with wedges as high as the CPF.

Beyond overall cost-effectiveness, our results also have important distributional implications, i.e. for who ultimately benefits from the subsidy. The fact that incidence falls predominantly on producers, reflecting relatively inelastic demand and even more inelastic supply, and determining a small overall deadweight loss, suggests that training subsidies largely operate as a transfer to training providers. In particular, owners of training provider firms appear to benefit the most, as we detect a significant response in profits but no significant response in input costs, including expenditures on teachers and tutors.

5 Conclusions

In this paper, we examine the effects of training subsidies on participation and prices, and leverage the findings to study the incidence and cost-effectiveness in terms of welfare of training subsidies. Our empirical analysis yields three main findings. First, the reaction of training prices to a reform changing CPF subsidy caps in 2019 reveals that training subsidies were largely passed through to producers: about 78% via higher gross prices, and only 22% to consumers through lower net prices. Second, training prices have a modest impact on participation, with demand responding weakly and displaying a slightly negative relationship between subsidy-induced changes in net training prices and hours. Third, we find that for every euro of cut in the subsidy, producers experience a decline in revenues and profits, with a smaller and insignificant change in costs. Overall, our results are consistent with relatively inelastic training supply and demand, which makes subsidies behave like a transfer, mostly benefiting owners of training firms. Unless each euro of training generates high externalities (in the order of 1.8-3.5 times its cost), the aggregate effects of the subsidy are negative once the distortionary cost of taxation is taken into account.

Our paper suggests that equilibrium effects of training subsidies on prices might attenuate the effect of the subsidy on training participation and lower cost-effectiveness of the policy. One limitation we emphasize is that because further reforms intervene at the end of 2019 and the Covid crisis affects training markets starting from early 2020, we are able to observe the effects of subsidy changes only in the short run, even if the adjustment of prices to changes in subsidy rates seems quick and stable over the post-reform year we study. We leave more long-run evaluations to future research.

Our results imply that the CPF likely falls short of its objective of significantly increasing training participation, while primarily benefiting training providers. Policymakers seeking to subsidize human capital investment should thus first ensure that supply is sufficiently elastic. While this case illustrates a general

[34] The observed CPF subsidy net of supplementary top-ups is only about three times as large as net prices, closer to our baseline calibration.

risk for policies that aim to stimulate consumption through price subsidies in decentralized markets (Accetturo et al., 2025; Turner, 2012), in the specific context of training the solution may not be straightforward. Regulators and providers may face important trade-offs between ensuring training quality and reducing the marginal cost of training to more elastically expand supply. We therefore conclude by emphasizing that designing training programs that balance these objectives remains an important and open challenge for sustaining human capital investment.

References

Antonio Accetturo, Elisabetta Olivieri, and Fabrizio Renzi. Incentives for dwelling renovations: evidence from a large fiscal programme. *Fiscal Studies*, 2025.

Daron Acemoglu and Jorn-Steffen Pischke. Beyond becker: Training in imperfect labour markets. *The economic journal*, 109(453):112–142, 1999.

Daron Acemoglu and Jörn-Steffen Pischke. Certification of training and training outcomes. *European Economic Review*, 44(4-6):917–927, 2000.

Takanori Adachi and Michal Fabinger. Pass-through, welfare, and incidence under imperfect competition. *Journal of Public Economics*, 211:104589, 2022.

Ghislain BD Aihounton and Arne Henningsen. Units of measurement and the inverse hyperbolic sine transformation. *The Econometrics Journal*, 24(2):334–351, 2021.

Alan J Auerbach and James R Hines. Perfect taxation with imperfect competition, 2001.

Andrea Bassanini, Alison L Booth, Giorgio Brunello, Maria De Paola, and Edwin Leuven. Workplace training in europe. 2005.

Gary S Becker. *Human capital: A theoretical and empirical analysis, with special reference to education.* University of Chicago press, 1964.

Marc F Bellemare and Casey J Wichman. Elasticities and the inverse hyperbolic sine transformation. *Oxford Bulletin of Economics and Statistics*, 82(1):50–61, 2020.

Marika Cabral, Michael Geruso, and Neale Mahoney. Do larger health insurance subsidies benefit patients or producers? evidence from medicare advantage. *American Economic Review*, 108(8):2048–87, 2018.

David Card, Jochen Kluve, and Andrea Weber. Active labour market policy evaluations: A meta-analysis. *The economic journal*, 120(548):F452–F477, 2010.

Francesco Corsello and Valerio Ercolani. The role of the superbonus in the growth of italian construction costs. *Bank of Italy Occasional Paper*, (903), 2024.

DARES. Realisation d'une etude qualitative a partir de 2 regions sur le compte personnel de formation. 2018.

Andries De Grip and Jan Sauermann. The effects of training on own and co-worker productivity: Evidence from a field experiment. *The Economic Journal*, 122(560):376–399, 2012.

Natalia Fabra, David Rapson, Mar Reguant, and Jingyuan Wang. Estimating the elasticity to real-time pricing: evidence from the spanish electricity market. In *AEA Papers and Proceedings*, volume 111, pages 425–429. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203, 2021.

Gabrielle Fack. Are housing benefit an effective way to redistribute income? evidence from a natural experiment in france. *Labour Economics*, 13(6):747–771, 2006.

Don Fullerton and Gilbert E Metcalf. Tax incidence. *Handbook of public economics*, 4:1787–1872, 2002.

Stephen Gibbons and Alan Manning. The incidence of uk housing benefit: Evidence from the 1990s reforms. *Journal of Public Economics*, 90(4-5):799–822, 2006.

Katja Görlitz and Marcus Tamm. Information, financial aid and training participation: Evidence from a randomized field experiment. *Labour Economics*, 47:138–148, 2017.

Dominique Goux and Eric Maurin. Returns to firm-provided training: evidence from french worker–firm matched data. *Labour economics*, 7(1):1–19, 2000.

Arnold C Harberger. The incidence of the corporation income tax. *Journal of Political economy*, 70(3): 215–240, 1962.

Nathaniel Hendren and Ben Sprung-Keyser. A unified welfare analysis of government policies. *The Quarterly journal of economics*, 135(3):1209–1318, 2020.

Nathaniel Hendren and Ben Sprung-Keyser. The case for using the mvpf in empirical welfare analysis. Technical report, National Bureau of Economic Research, 2022.

Diana Hidalgo, Hessel Oosterbeek, and Dinand Webbink. The impact of training vouchers on low-skilled workers. *Labour Economics*, 31:117–128, 2014.

Hugo A Hopenhayn. Entry, exit, and firm dynamics in long run equilibrium. *Econometrica: Journal of the Econometric Society*, pages 1127–1150, 1992.

Fleeming Jenkin. 3. on the principles which regulate the incidence of taxes. *Proceedings of the Royal Society of Edinburgh*, 7:618–631, 1872.

Barrett E Kirwan. The incidence of us agricultural subsidies on farmland rental rates. *Journal of Political Economy*, 117(1):138–164, 2009.

Edwin Leuven and Hessel Oosterbeek. Evaluating the effect of tax deductions on training. *Journal of Labor Economics*, 22(2):461–488, 2004.

Pedro S Martins. Employee training and firm performance: Evidence from esf grant applications. *Labour Economics*, 72:102056, 2021.

Daniel McFadden et al. Conditional logit analysis of qualitative choice behavior. 1973.

Marc J Melitz. The impact of trade on intra-industry reallocations and aggregate industry productivity. *econometrica*, 71(6):1695–1725, 2003.

OECD. *Increasing Adult Learning Participation*. 2020. doi: https://doi.org/https://doi.org/10.1787/cf5d9c21-en. URL https://www.oecd-ilibrary.org/content/publication/cf5d9c21-en.

OECD. Advancing adult skills through individual learning accounts: A step-by-step guide for policymakers. getting skills right. *OECD Publishing*, 2025.

Jacquelyn Pless and Arthur A van Benthem. Pass-through as a test for market power: An application to solar subsidies. *American Economic Journal: Applied Economics*, 11(4):367–401, 2019.

Guido Schwerdt, Dolores Messer, Ludger Woessmann, and Stefan C Wolter. The impact of an adult education voucher program: Evidence from a randomized field experiment. *Journal of Public Economics*, 96(7-8): 569–583, 2012.

Nicholas Turner. Who benefits from student aid? the economic incidence of tax-based federal student aid. *Economics of Education Review*, 31(4):463–481, 2012.

Gerard J Van den Berg, Christine Dauth, Pia Homrighausen, and Gesine Stephan. Informing employees in small and medium sized firms about training: results of a randomized field experiment. 2020.

Wiljan van den Berge, Egbert Jongen, and Karen van der Wiel. The effects of a tax deduction for lifelong learning expenditures. *International Tax and Public Finance*, pages 1–28, 2022.

E Glen Weyl and Michal Fabinger. Pass-through as an economic tool: Principles of incidence under imperfect competition. *Journal of Political Economy*, 121(3):528–583, 2013.

Appendix A: Additional Tables

Table A.1: 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 A.2: Training groups

	English name	French name of main training programs included	Description	Freq.	%
1	Foreign languages	TOEIC, BULATS, LILATE	Training in foreign languages for professional or general purposes, generally with a certification exam.	136,943	40.12
2	ICT skills training	TOSA, PCIE	Training in digital skills, including office software, programming, and IT tools, generally with a certification exam.	40,987	12.01
3	Equipment operation certification	Certificat d'Aptitude à la Conduite En Sécurité (CACES)	Training and certification to safely operate industrial equipment (e.g. forklifts, cranes).	26,314	7.71
4	Skills assessment	Bilan de compétences	Assessment of professional skills, aptitudes, and career prospects to support career development.	19,323	5.66
5	Professional skills certification	Certificat de Qualification Professionnelle (CQP)	Industry-recognised certification validating occupation-specific skills and competencies.	12,255	3.59
6	Recognition of prior learning	Validation des Acquis de l'Expérience (VAE)	Process to obtain formal qualifications by validating skills acquired through work experience.	10,008	2.93
7	Car driving licence	Permis de conduire catégorie B	Training to obtain a standard passenger car driving licence.	9,284	2.72
8	Entrepreneurship training	Stage de Préparation à l'Installation (SPI), Actions de formation créateurs d'entreprise	Training to support business creation and management, particularly for self-employed workers and artisans.	5,519	1.62
9	Basic skills certification	Certificat CléA	Certification of core competencies, including literacy, numeracy, and basic professional skills.	1,985	0.58
10	Others		Residual category covering all other eligible training programs.	78,678	23.05

Notes. The first column reports the 10 training groups across which rule-based rates vary. The second column provides examples of the training programs included in each group. The third column describes the characteristics of training programs covered by the group. The last two columns report, respectively, the number of training episodes in the SI-CPF sample used in this paper belonging to each group and their relative frequency.

Table A.3: Impact on Training Prices of the CPF Subsidy by different training groups

	(1)	(2)	(3)	(4)	(5)	(6)
	c_{qft}	p_{qft}	p_{qft}^{NET}	p_{qft}	p_{qft}^{NET}	
VARIABLES	Reduced form			IV		N trainings
1. Foreign languages	0.512***	0.365***	-0.132***	0.728***	-0.272***	109,896
	(0.0706)	(0.0575)	(0.0327)	(0.0672)	(0.0672)	
2. ICT Skills training	0.319***	0.258***	-0.0820***	0.730***	-0.270**	27,986
	(0.0628)	(0.0263)	(0.0316)	(0.120)	(0.120)	
3. Equipment operation cer.	0.117	0.0711***	-0.0564	-0.192	-1.192	20,149
	(0.0814)	(0.0244)	(0.0368)	(1.084)	(1.084)	
4. Skills assessment	0.652***	0.420***	-0.0572**	0.853***	-0.147***	15,792
	(0.124)	(0.132)	(0.0275)	(0.0398)	(0.0398)	
5. Professional skills cer.	0.254	0.520***	-0.137	0.376	-0.624	6,566
	(0.168)	(0.126)	(0.0848)	(0.408)	(0.408)	
6. Rec. of prior learning	0.385***	0.617***	-0.0114	0.951***	-0.0494	7,853
	(0.0973)	(0.0928)	(0.0309)	(0.0705)	(0.0705)	
7. Car driving licence	0.564***	0.323***	-0.256***	0.152	-0.848**	6,446
	(0.128)	(0.0687)	(0.0746)	(0.394)	(0.394)	
8. Enterpreneurship tr.	0.202***	0.234***	-0.00472	1.156***	0.156	3,944
	(0.0654)	(0.0442)	(0.0289)	(0.242)	(0.242)	
9. Basic skills certification	0.273***	0.174***	-0.0707*	0.651***	-0.349*	1,253
	(0.0768)	(0.0498)	(0.0385)	(0.180)	(0.180)	
10. Others	0.260***	0.527***	-0.1000***	0.569***	-0.431***	47,949
	(0.0466)	(0.144)	(0.0269)	(0.0857)	(0.0857)	
Observations	11,659	11,741	11,659	11,659	11,659	
Years	2018–2019	2018–2019	2018–2019	2018–2019	2018–2019	
Estimation	OLS	OLS	OLS	2SLS	2SLS	
F Stat.	13.50					

Notes. Columns (1)-(3) report coefficients of the rule-based subsidy rate interacted with dummies for training groups, on the effective hourly subsidy rate (first stage), gross and net training prices. Columns (4)-(5) report 2SLS effects of the interaction of the effective per-hour subsidy with training group dummies. Column (6) reports the number of training episodes in each group. Regressions are weighted by the number of training episodes in each training program and financing agency in 2018. Standard errors are reported in parentheses and clustered by industry financing agencies and the training kind category. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.4: Impact of CPF on training Prices of Training – Unweighted

VARIABLES	(1) c_{qft}	(2) p_{qft}	(3) p_{qft}^{NET}	(4) p_{qft}	(5) p_{qft}^{NET}
$c_{\tilde{k}ft}$	0.223***	0.117***	-0.105***		
	(0.0332)	(0.0322)	(0.0295)		
c_{qft}				0.526***	-0.474***
				(0.117)	(0.117)
Observations	11,659	11,659	11,659	11,659	11,659
Years	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019
Estimation	OLS	OLS	OLS	2SLS	2SLS
F Stat.	45.12				

Notes. Column (1) reports the first-stage relationship between the rule-based hourly subsidy cap and the effective hourly subsidy, including supplementary top-ups. The Kleibergen–Paap F-statistic is also reported. Columns (2) and (3) report the reduced-form relationship between the rule-based hourly subsidy cap and the hourly training price, measured respectively gross and net of the subsidy. Columns (4) and (5) report the corresponding 2SLS estimates of the effect of the effective hourly subsidy on gross and net prices. The number of observations corresponds to the number of training programs by industry financing agency by year in the regression. Standard errors are reported in parentheses and clustered by industry financing agencies and training kind group. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.5: Impact on Prices of Training of the CPF Subsidy – Alternative instrument, weighted (upper panel) and unweighted (lower panel)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	c_{qft}	p_{qft}	p_{qft}^{NET}	p_{qft}	p_{qft}^{NET}
$c_{kft}^{\tilde{data}}$	0.377***	0.245***	-0.132***		
	(0.0450)	(0.0451)	(0.0209)		
c_{qft}				0.650***	-0.350***
				(0.0612)	(0.0612)
Observations	14,086	14,086	14,086	14,086	14,086
Years	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019
Estimation	OLS	OLS	OLS	2SLS	2SLS
F Stat.	70.43				

	(1)	(2)	(3)	(4)	(5)
VARIABLES	c_{qft}	p_{qft}	p_{qft}^{NET}	p_{qft}	p_{qft}^{NET}
$c_{kft}^{\tilde{data}}$	0.239***	0.111***	-0.128***		
	(0.0443)	(0.0353)	(0.0308)		
c_{qft}				0.465***	-0.535***
				(0.104)	(0.104)
Observations	14,086	14,086	14,086	14,086	14,086
Years	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019
Estimation	OLS	OLS	OLS	2SLS	2SLS
F Stat.	29.20				

Notes. Data-based subsidy caps $c_{kft}^{\tilde{data}}$ correspond to the maximum of the mode and the 75th percentile of the realized subsidy distribution for each training program and financing agency in 2018, and to €15 in 2019. Column (1) reports the first-stage relationship between the data-based hourly subsidy cap and the effective hourly subsidy, including supplementary top-ups. The Kleibergen–Paap F-statistic is also reported. Columns (2) and (3) report the reduced-form relationship between the data-based hourly subsidy cap and the hourly training price, measured respectively gross and net of the subsidy. Columns (4) and (5) report the corresponding 2SLS estimates of the effect of the effective hourly subsidy on gross and net prices. In the upper panel, each cell is weighted by the number of training episodes observed in SI-CPF for that financing agency and training program in 2018, while in the lower panel observations are unweighted. The number of observations corresponds to the number of training programs by industry financing agency by year in the regression. Standard errors are reported in parentheses and clustered by industry financing agencies and training kind group. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.6: Impact on Training Prices of the CPF Subsidy – expressing subsidies and prices in log terms

VARIABLES	(1) $\ln c_{qft}$	(2) $\ln p_{qft}$	(3) $\ln p_{qft}^{NET}$	(4) $\ln p_{qft}$	(5) $\ln p_{qft}^{NET}$
$\ln \tilde{c_{kft}}$	0.331***	0.230***	-0.616***		
	(0.0720)	(0.0554)	(0.162)		
$\ln c_{qft}$				0.696***	-1.864***
				(0.0514)	(0.391)
Observations	11,659	11,659	11,659	11,659	11,659
Years	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019
Estimation	OLS	OLS	OLS	2SLS	2SLS
F Stat.	21.08				

Notes. Column (1) reports the first-stage relationship between the log rule-based hourly subsidy cap and the log effective hourly subsidy, including supplementary top-ups. The Kleibergen–Paap F-statistic is also reported. Columns (2) and (3) report the reduced-form relationship between the rule-based hourly subsidy cap and the hourly training price, measured respectively gross and net of the subsidy. Columns (4) and (5) report the corresponding 2SLS estimates of the effect of the log effective hourly subsidy on log gross and net prices. Each cell is weighted by the number of training episodes observed in SI-CPF for that financing agency and training program in 2018. The number of observations corresponds to the number of training programs by industry financing agency by year in the regression. Standard errors are reported in parentheses and clustered by industry financing agencies and training kind group. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.7: Impact on Training Prices of the CPF Subsidy – excluding training groups where first stage is not significant

	(1)	(2)	(3)	(4)	(5)
VARIABLES	c_{qft}	p_{qft}	p_{qft}^{NET}	p_{qft}	p_{qft}^{NET}
$\tilde{c_{qft}}$	0.382***	0.309***	-0.0725***		
	(0.0589)	(0.0644)	(0.0185)		
c_{qft}				0.810***	-0.190***
				(0.0604)	(0.0604)
Observations	10,381	10,381	10,381	10,381	10,381
Years	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019
Estimation	OLS	OLS	OLS	2SLS	2SLS
F Stat.	42.12				

Notes. Column (1) reports the first-stage relationship between the rule-based hourly subsidy cap and the effective hourly subsidy, including supplementary top-ups. The Kleibergen–Paap F-statistic is also reported. Columns (2) and (3) report the reduced-form relationship between the rule-based hourly subsidy cap and the hourly training price, measured respectively gross and net of the subsidy. Columns (4) and (5) report the corresponding 2SLS estimates of the effect of the effective hourly subsidy on gross and net prices. Each cell is weighted by the number of training episodes observed in SI-CPF for that financing agency and training program in 2018. The number of observations corresponds to the number of training programs by industry financing agency by year in the regression. Standard errors are reported in parentheses and clustered by industry financing agencies and training kind group. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.8: Impact on Training Prices of the CPF Subsidy – without harmonizing for VAT

VARIABLES	(1) c_{qft}	(2) p_{qft}	(3) p_{qft}^{NET}	(4) p_{qft}	(5) p_{qft}^{NET}
$c_{\tilde{kf}t}$	0.474***	0.362***	-0.112***		
	(0.0762)	(0.0739)	(0.0225)		
c_{qft}				0.763***	-0.237***
				(0.0529)	(0.0529)
Observations	11,659	11,659	11,659	11,659	11,659
Years	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019
Estimation	OLS	OLS	OLS	2SLS	2SLS
F Stat.	38.76				

Notes. Column (1) reports the first-stage relationship between the rule-based hourly subsidy cap and the effective hourly subsidy, including supplementary top-ups. The Kleibergen–Paap F-statistic is also reported. Columns (2) and (3) report the reduced-form relationship between the rule-based hourly subsidy cap and the hourly training price, measured respectively gross and net of the subsidy. Columns (4) and (5) report the corresponding 2SLS estimates of the effect of the effective hourly subsidy on gross and net prices. Each cell is weighted by the number of training episodes observed in SI-CPF for that financing agency and training program in 2018. The number of observations corresponds to the number of training programs by industry financing agency by year in the regression. Standard errors are reported in parentheses and clustered by industry financing agencies and training kind group. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.9: Placebo tests for the presence of pre-trends in training prices in 2017-2018 - residualising outcomes for contemporaneous changes in subsidy cap

VARIABLES	(1) $p_{qft} - p_{\hat{\hat{qft}}}$	(2) $p_{qft}^{NET} - p_{qft}^{\hat{\hat{NET}}}$	(3) $p_{qft} - p_{\hat{\hat{qft}}}$	(4) $p_{qft}^{NET} - p_{qft}^{\hat{NET}}$
$c_{\tilde{kf}t+1}$	0.0369	-0.00989		
	(0.0401)	(0.0156)		
c_{qft+1}			0.000652	0.000652
			(0.0385)	(0.0385)
Observations	6,226	6,226	6,226	6,226
Years	2017-2018	2017-2018	2017-2018	2017-2018
Estimation	OLS	OLS	2SLS	2SLS

Notes. The table reports placebo tests of the effect of the lead of the CPF subsidy on training prices in the 2017-2018 period. Price outcomes are residualised by the predicted value estimated using the coefficients in Table 1. Standard errors are reported in parentheses and clustered by industry financing agencies and the training kind category. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.10: Placebo tests for the presence of pre-trends in training prices in 2017-2018 - using controls

VARIABLES	(1) p_{qft}	(2) p_{qft}^{NET}	(3) p_{qft}	(4) p_{qft}^{NET}
$c_{\tilde{kf}t+1}$	-0.0421	-0.00308		
	(0.0371)	(0.0165)		
$c_{\tilde{kf}t}$	0.0410	-0.0618**	0.0622**	-0.0602**
	(0.0365)	(0.0278)	(0.0283)	(0.0262)
c_{qft+1}			-0.0831	-0.00609
			(0.0778)	(0.0326)
Observations	6,226	6,226	6,226	6,226
Years	2017-2018	2017-2018	2017-2018	2017-2018
Estimation	OLS	OLS	2SLS	2SLS

Notes. The table shows the placebo test of the effect of lead of the CPF subsidies on provider-level outcomes, controlling for the contemporaneous change in rule-based subsidy rates. Columns (1)-(2) report OLS and (3)-(4) report 2SLS estimates on log revenues, log costs, profits as a share of revenues, log labor costs, and log employment. Standard errors are reported in parentheses and clustered by industry financing agencies and the training kind category. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.11: Impact of the CPF Subsidy on Training Participation and Implied Demand for Training

	(1) $\ln(1+p_{q,f,t}^{NET})$	(2) $\ln X_{qft}$	(3) $\ln(1+p_{q,f,t}^{NET})$	(4) $\ln(1+p_{q,f,t}^{NET})^2$	(5) $\ln X_{qft}$	(6) $\ln(1+p_{q,f,t}^{NET})$	(7) $\ln(1+p_{q,f,t}^{NET})^2$	(8) $\ln X_{qft}$
$c_{\tilde{kf}t}$	-0.011***		-0.016**	-0.085***		-0.018**	-0.088***	
	(0.002)		(0.007)	(0.031)		(0.008)	(0.032)	
$c_{\tilde{kf}t}{}^2$			0.000	0.000*		0.000	0.000**	
			(0.000)	(0.000)		(0.000)	(0.000)	
$c_{\tilde{kf}t} \times \mathbb{1}(p_{qf2018} > c_{\tilde{kf}2018})$						0.015**	0.047*	
						(0.008)	(0.025)	
$c_{\tilde{kf}t}{}^2 \times \mathbb{1}(p_{qf2018} > c_{\tilde{kf}2018})$						-0.000	-0.000	
						(0.000)	(0.000)	
$\ln(1+p_{q,f,t}^{NET})$		-0.526*			0.104			2.217*
		(0.298)			(1.154)			(1.132)
$\ln(1+p_{q,f,t}^{NET})^2$					-0.180			-0.667*
					(0.312)			(0.352)
N	13,317	13,317	13,317	13,317	13,317	13,317	13,317	13,317
N clusters	283	283	283	283	283	283	283	283
Estimation	OLS	2SLS	OLS	OLS	2SLS	OLS	OLS	2SLS
F-Stat	26.63		11.56	11.47		8.95	8.87	

Notes. Column (1) reports the relationship between the rule-based subsidy cap and the log of hourly net training price. This can be seen as a first-stage in demand estimation, so we report Kleibergen–Paap F-statistic. Column (2) reports the 2SLS estimates of the effect of changes in log net prices on log total training hours. Columns (3)-(5) add a quadratic term in the instrument and in log prices. Columns (6)-(8) add as instruments an interaction with a dummy for the baseline gross training price exceeding the rule-based cap (i.e. for the subsidy cap to bind). Standard errors are reported in parentheses and clustered at the interaction between industry financing agencies and the training kind category. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.12: Validation test for the interaction instrument

	(1)
	Pricing shock
VARIABLES	2018–2019
$\tilde{c_{kft}} \times \mathbb{1}(p_{qf2018} > \tilde{c_{kf2018}})$	0.010
	(0.006)
$\tilde{c_{kft}}^2 \times \mathbb{1}(p_{qf2018} > \tilde{c_{kf2018}})$	-0.000*
	(0.000)
Observations	13,317
R-squared	0.289
Observations	13317
R-squared	0.289

Notes. The table reports a validation test for the exclusion restriction underlying the interaction instruments used in columns (6) and (7) of Table 2. The dependent variable is the residualized change in net prices over 2018–2019, obtained after absorbing the same set of fixed effects used in the main demand specification. The regressors are the rule-based subsidy instrument and its interaction with an indicator for whether baseline gross prices exceed the rule-based subsidy cap. Standard errors are clustered at the training provider level. The test assesses whether baseline price position relative to the subsidy cap predicts subsequent pricing shocks.

Table A.13: Impact of the CPF Subsidy on Training Participation and Implied Demand for Training

	(1)	(2)	(3)
	$\text{asinh}\left(p^{NET}_{q,f,t}\right)$	$\text{asinh}\left(p^{NET}_{q,f,t}\right)^2$	$\ln X_{qft}$
$\tilde{c_{kft}}$	-0.020**	-0.126***	
	(0.010)	(0.045)	
$\tilde{c_{kft}}^2$	0.000	0.001**	
	(0.000)	(0.000)	
$\tilde{c_{kft}} \times \mathbb{1}(p_{qf2018} > \tilde{c_{kf2018}})$	0.022**	0.077**	
	(0.009)	(0.034)	
$\tilde{c_{kft}}^2 \times \mathbb{1}(p_{qf2018} > \tilde{c_{kf2018}})$	-0.000	-0.001	
	(0.000)	(0.000)	
$\text{asinh}\left(p^{NET}_{q,f,t}\right)$			1.484*
			(0.823)
$\text{asinh}\left(p^{NET}_{q,f,t}\right)^2$			-0.391*
			(0.216)
N	13,317	13,317	13,317
N clusters	283	283	283
Estimation	OLS	OLS	2SLS
F-Stat	10.34	10.02	

Notes. Column (1) reports the relationship between the rule-based subsidy cap and the inverse-hyperbolic sine transformation of hourly net training price. This can be seen as a first-stage in demand estimation, so we report Kleibergen–Paap F-statistic. Column (2) reports the 2SLS estimates of the effect of changes in IHS-transformed net prices on log total training hours. Columns (3)-(5) add a quadratic term in the instrument and in log prices. Columns (6)-(8) add as instruments an interaction with a dummy for the baseline gross training price exceeding the rule-based cap (i.e. for the subsidy cap to bind). Standard errors are reported in parentheses and clustered at the interaction between industry financing agencies and the training kind category. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.14: Placebo estimates, training provider specification

VARIABLES	(1) $\ln Rev_{jt} - \ln \hat{Rev}_{jt}$	(2) $\ln Cost_{jt} - \ln \hat{Cost}_{jt}$	(3) $\pi_{jt}/Rev_{jt} - \pi_{jt}/\hat{Rev}_{jt}$	(4) $\ln L_{jt} - \ln \hat{L}_{jt}$	(5) $\ln E_{jt} - \ln \hat{E}_{jt}$
$\tilde{c}_{jt+1} \cdot \frac{RevCPF}{Rev_{jt_0}}$	-5.74e-06	0.00218	-0.00132	-0.00203	-0.000141
	(0.00143)	(0.00220)	(0.000980)	(0.00253)	(0.000247)
Observations	9,168	9,168	9,168	8,612	8,300
Years	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019
Estimation	FE	FE	FE	FE	FE

VARIABLES	(1) $\ln Rev_{jt} - \ln \hat{Rev}_{jt}$	(2) $\ln Cost_{jt} - \ln \hat{Cost}_{jt}$	(3) $\pi_{jt}/Rev_{jt} - \pi_{jt}/\hat{Rev}_{jt}$	(4) $\ln L_{jt} - \ln \hat{L}_{jt}$	(5) $\ln E_{jt} - \ln \hat{E}_{jt}$
$c_{jt+1} \cdot \frac{RevCPF}{Rev_{jt_0}}$	-2.72e-05	0.00838	-0.00625	-0.0106	-0.000611
	(0.00679)	(0.0107)	(0.00477)	(0.0131)	(0.00103)
Observations	9,168	9,170	9,168	8,612	8,790
Years	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019
Estimation	2SLS	2SLS	2SLS	2SLS	2SLS

Notes. The upper panel reports placebo tests for the reduced-form specification, 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 rule-based 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 provider and year. The lower panel reports placebo tests, obtained by estimating an IV regression of the relevant outcome in the pre-treatment period (2017-2018), residualised by the effect of any change in the rule-based subsidy cap in that period, on a lead of the effective subsidy instrumented by a lead of the rule-based subsidy cap. 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.15: Impact of changes in CPF subsidies on producers' revenues, costs, profits, labor costs, and number of employees

VARIABLES	(1) c_{jt}	(2) $\ln Rev_{jt}$	(3) $\ln Cost_{jt}$	(4) π_{jt}/Rev_{jt}	(5) $\ln L_{jt}$	(6) $\ln E_{jt}$
$\tilde{c}_{jt} \cdot \frac{RevCPF}{Rev_{jt_0}}$	0.251***					
	(0.0284)					
$c_{jt} \cdot \frac{RevCPF}{Rev_{jt_0}}$		0.0166***	0.00510	0.00946*	-0.00128	-0.000402
		(0.00619)	(0.00826)	(0.00529)	(0.00982)	(0.00513)
Observations	90,592	90,592	90,592	90,592	70,436	82,658
Years	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019
Estimation	OLS	2SLS	2SLS	2SLS	2SLS	2SLS
F Stat.	359.7					

Notes. The table shows the effect of changes in CPF subsidies on provider-level outcomes. Column (1) reports the first-stage regression of the average rule-based subsidy cap for trainees of a given training provider (weighted average by revenue share of the training), interacted with the overall share of revenues of the provider coming from CPF, on the effective hourly subsidy. The Kleibergen–Paap F-statistic is also reported. Columns (2)-(6) report 2SLS estimates of the effect of the effective hourly subsidy on training providers' log revenues, log costs, profits as a share of revenues, log labor costs, and log employment. Standard errors, reported in parentheses, are clustered at the training-provider level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.16: Comparison of impact of CPF on providers' revenues, prices and training quantities

	(1)	(2)	(3)
	$\ln Rev_{jt}$	$\ln p_{qft}$	$\ln X_{qft}$
$c_{jt} \cdot \frac{RevCPF}{Rev_{jt_0}}$	0.0222***		
	(0.0068)		
c_{qft}		0.0130***	0.0149*
		(0.0017)	(0.0087)
Observations	9,422	15,400	15,400
Years	2018-2019	2018-2019	2018-2019
Estimation	2SLS	2SLS	2SLS

Notes. Column (1) reports 2SLS estimates of the effect of the effective hourly subsidy on training providers' log revenues, where the regression is run at the training provider level. Columns (2) and (3) report 2SLS estimates of the effect of the effective hourly subsidy on gross prices and total training hours, where the regression is run at the training program by training financing agency level. Standard errors, reported in parentheses, are clustered at the training-provider level for Column (1) and at the training kind group by industry financing agency for Columns (2) and (3). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

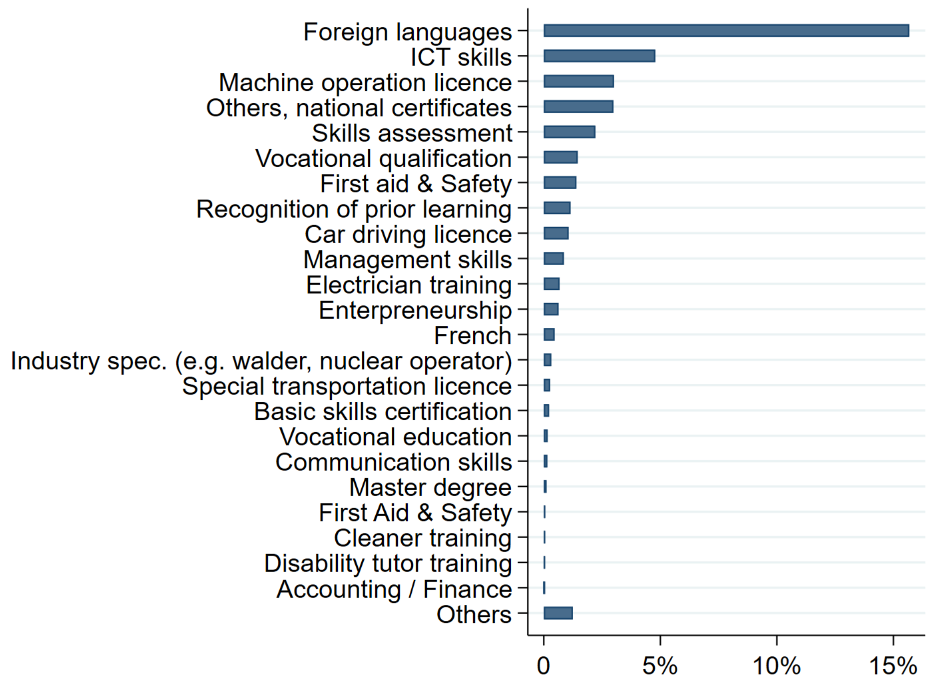
Table A.17: Derivation of demand and supply elasticities and cost-effectiveness of the CPF

Results with exact wedge correction	Perfect competition ($\theta = 0$)	Market power ($\theta = 1$)
$\bar{p}/\bar{p}^{net}$	9.81	
$\epsilon_d \times \bar{p}/\bar{p}^{net}$	4.145	1.150
$1/\epsilon_{ms}$	–	48.361
ϵ_s	1.153	-0.003

Notes. Panel 1 summarizes the results that are directly estimated using empirical results, and references the results table from where they are taken. Panel 2 reports the calibrated parameters from external sources and their corresponding sources. Panel 3 presents the implied supply elasticity, the Marginal Value of Public Funds in the absence of externalities, and the externality required for the MVPF to equal 1 under alternative assumptions on the degree of competition and the distortionary cost of taxation.

Appendix B: Additional Figures

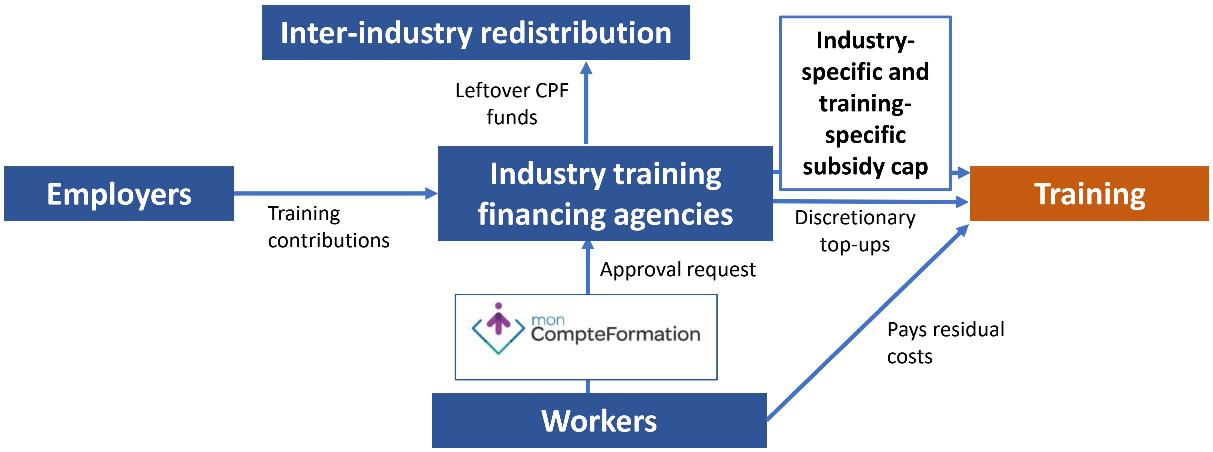
Figure B.1: CPF-financed training episodes in 2018, by topic of the course



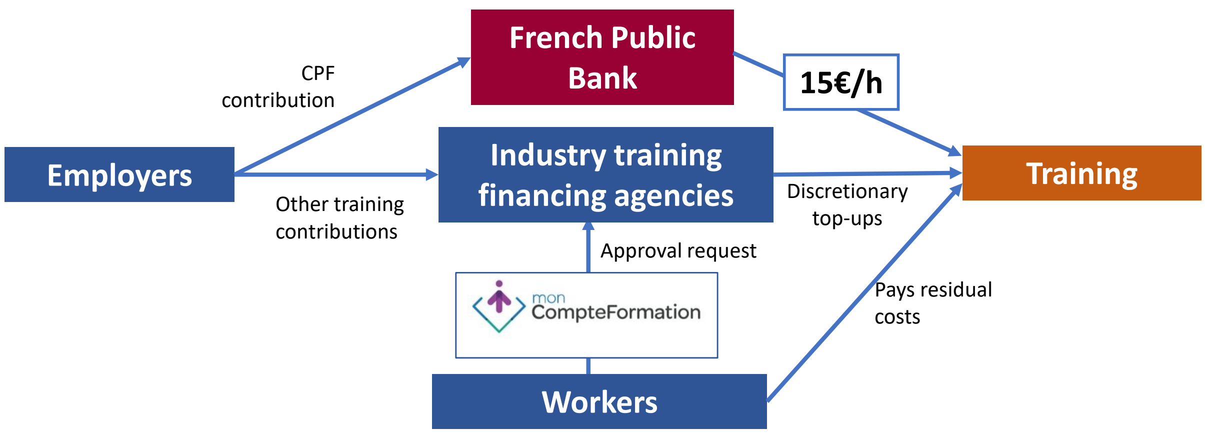
Notes. Training episodes are grouped in different topics by the authors and only training programs with more than 100 CPF-financed episodes are evaluated, the rest is included under "Others".

Figure B.2: Pre and post-reform functioning of 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 training agencies collect mandatory contributions from companies, decide per-hour rule-based 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 training agencies 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.

Figure B.3: Example of official document with CPF subsidy caps for different training kinds from the Finance industry training financing agency

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 B.4: Example of unofficial document with CPF subsidy caps for different training kinds and industry training financing agency

ATHEME MAJ LE 01/02/2018

2018 # TABLEAU RÉCAPITULATIF DES PRISES EN CHARGE CPF

OPCA	Coût horaire	Abondements ou spécificités	Source
ACTALIANS Développeur de compétences	60 € HT (liste COPANEF et branches) 75 € HT (VAE)	Si abondement au-delà de 150 h = 15 € Accompagnement VAE 24h	
Afdas.	35 € HT	Abondement lorsque le nombre d'heures dont dispose le bénéficiaire est insuffisant pour réaliser la formation	
ANFA	60 € HT : Actions visant un CQP inscrit au RNCSA et démarches VAE associées 20 € HT : Autres actions éligibles	• Abondement de 100 % des heures mobilisées si la formation préparée est un CQP inscrit au RNCSA (si le titulaire mobilise 50 heures de ses heures CPF, l'ANFA en financera au total 100). • Abondement de 50 % des heures mobilisées si la formation préparée est un titre, un diplôme ou une certification inscrite au RNCSA (si le titulaire mobilise 20 heures de ses heures CPF, l'ANFA en	
Fafiec	80 € HT Formation Langues *(hors français et langue des signes)* : 45 € HT	Abondement à hauteur de l'intégralité des heures manquantes, déduction faite du nombre d'heures inscrit sur le CPF (solde disponible des heures, DIF compris)	
FAF.TT	CPF = 12 € HT/heure CACES = 10 € HT/heure BULATS et TOEIC = 60 € HT/heure dans la limite de 150 heures		

Figure B.5: Time series of total cost of training undertaken and number of training episodes started each week, in 2018 and 2019, breaking down 2019 into training validated by industry financing agencies and those initiated through the centralized mobile app

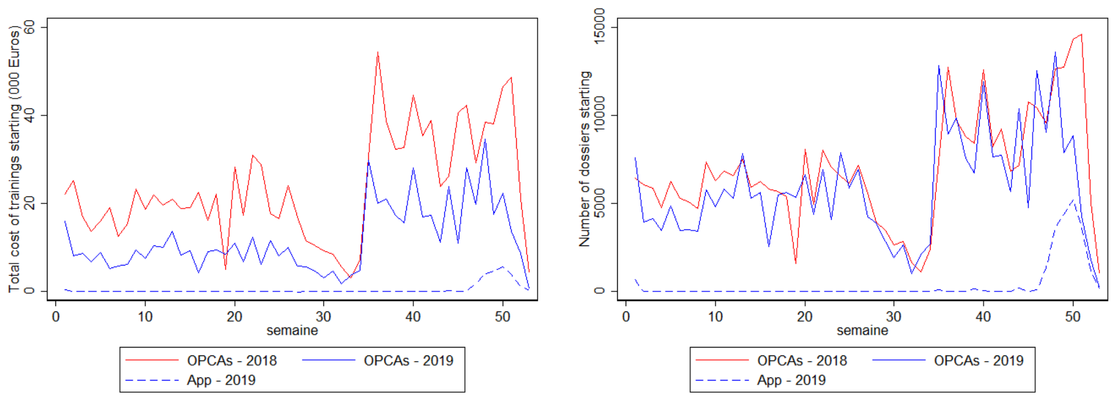
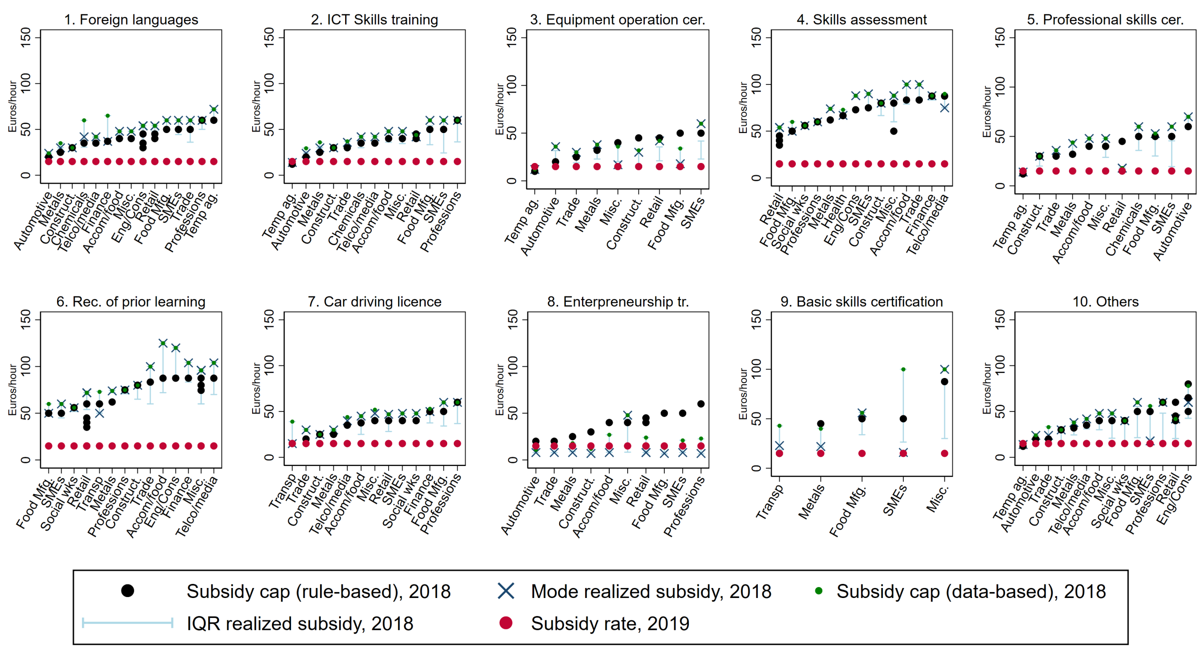
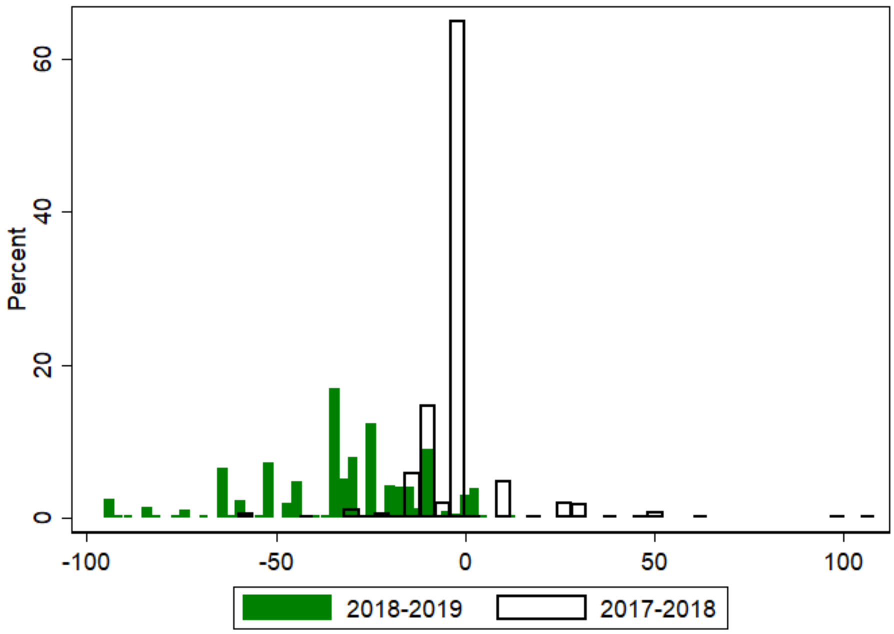


Figure B.6: Per-hour subsidy caps (rule-based and data-based) and realized CPF per-hour subsidy, by training kind group and industry – without harmonizing for VAT



Notes. Rule-based CPF subsidy caps (black dots) in 2018 are defined by industry financing agencies to convert CPF hour credits of trainees into euro of subsidy. They are collected by the authors based on official and unofficial documentation. Realized subsidy rates are the euro amount of subsidy coming from the use of CPF hours, divided by the CPF hours, as reported in SI-CPF. The Figure reports QR and mode. Data-based subsidy caps (green dots) correspond to the maximum of the mode and the 75th percentile of the realized subsidy distribution. The subsidy rate in 2019 (red dots) is set at €15 by the 2019 reform. The ten training groups are: (1) Foreign languages (e.g. *TOEIC, BULATS, LILATE*); (2) ICT skills training (e.g. *TOSA, PCIE*); (3) Equipment operation certification (*CACES*); (4) Skills assessment (*Bilan de compétences*); (5) Professional skills certification (*CQP*); (6) Recognition of prior learning (*VAE*); (7) Car driving licence (*Permis B*); (8) Entrepreneurship training (e.g. *SPI,formation créateurs d'entreprise*); (9) Basic skills certification (*CléA*); and (10) Others, a residual category including all remaining eligible training programs.

Figure B.8: Distribution of $\Delta c_{k,\tilde{f},t}$



Notes. The figure reports the distribution of the change in the maximum subsidy cap allowed by different industry financing agencies 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 agencies.

Figure B.7: Difference between per-hour rule-based subsidy cap and ratio of observed paid CPF to observed CPF hours in 2018

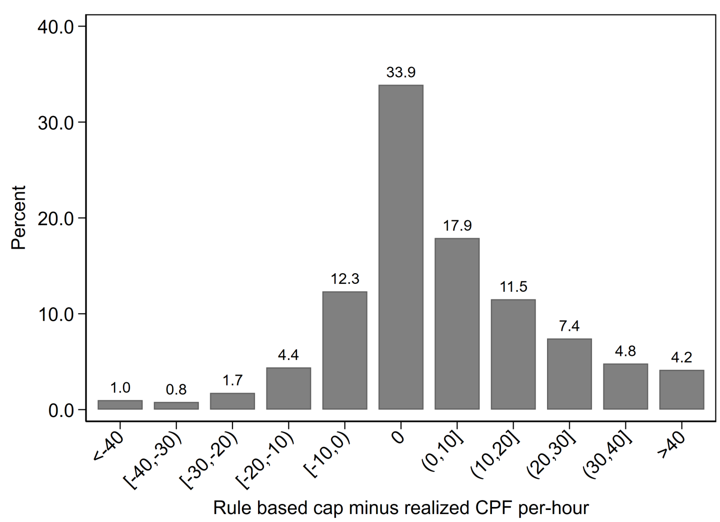
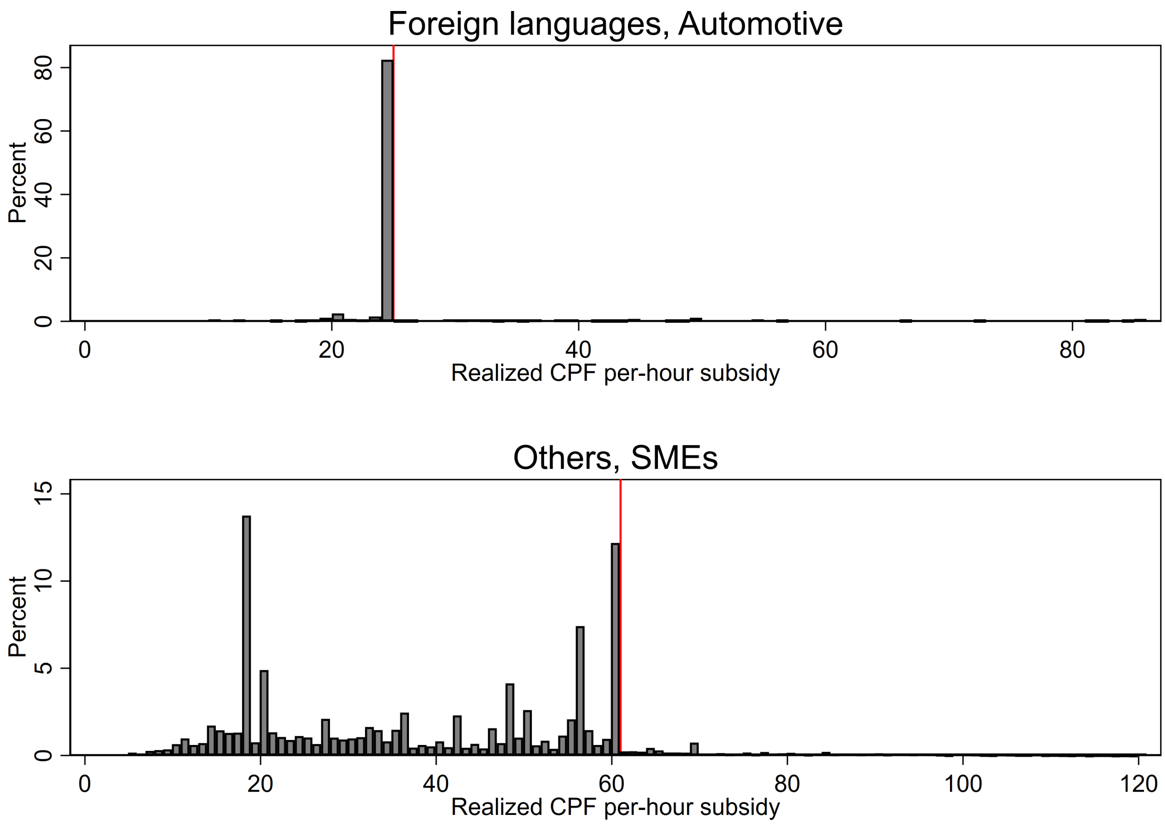
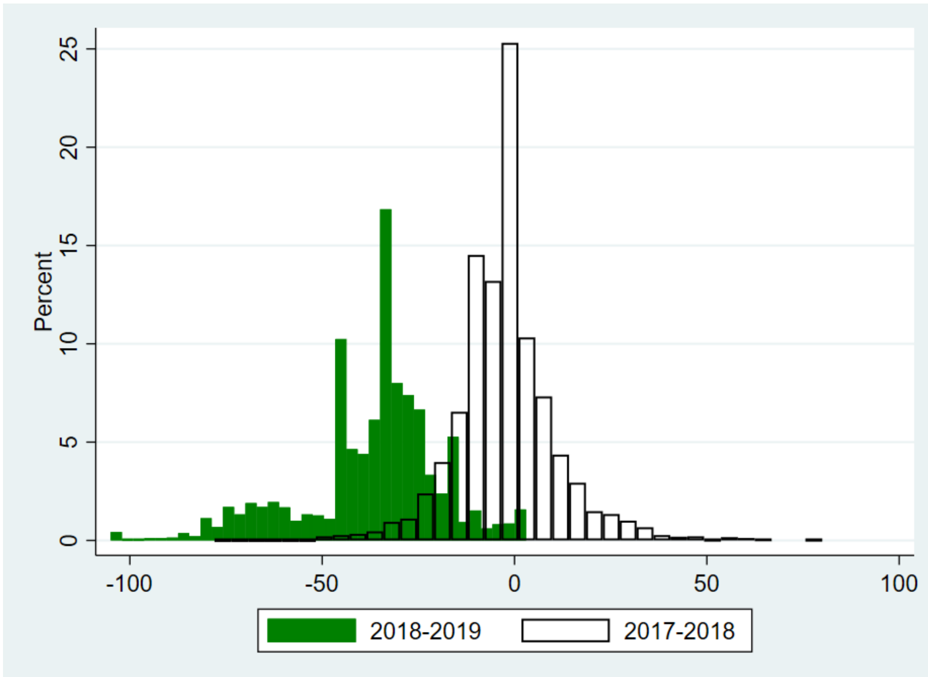


Figure B.9: Distribution of the difference between maximum subsidy cap and prices



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

Figure B.10: Distribution of the average rule-based subsidy cap faced by trainees at different training providers



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

Figure B.11: Number of accounts by number of hours in the CPF account

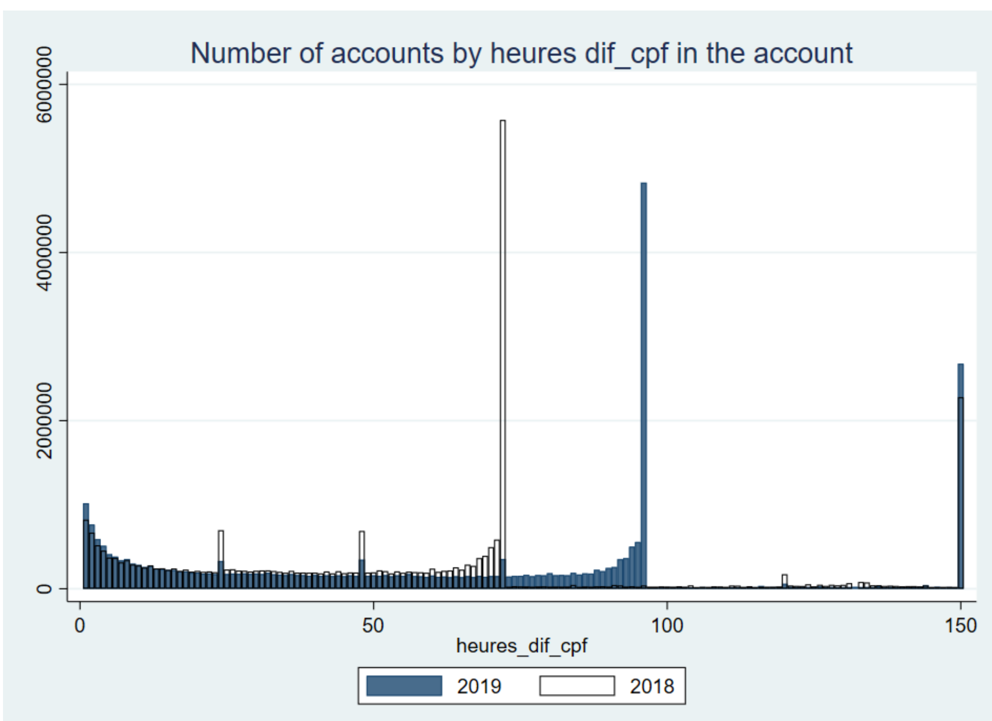
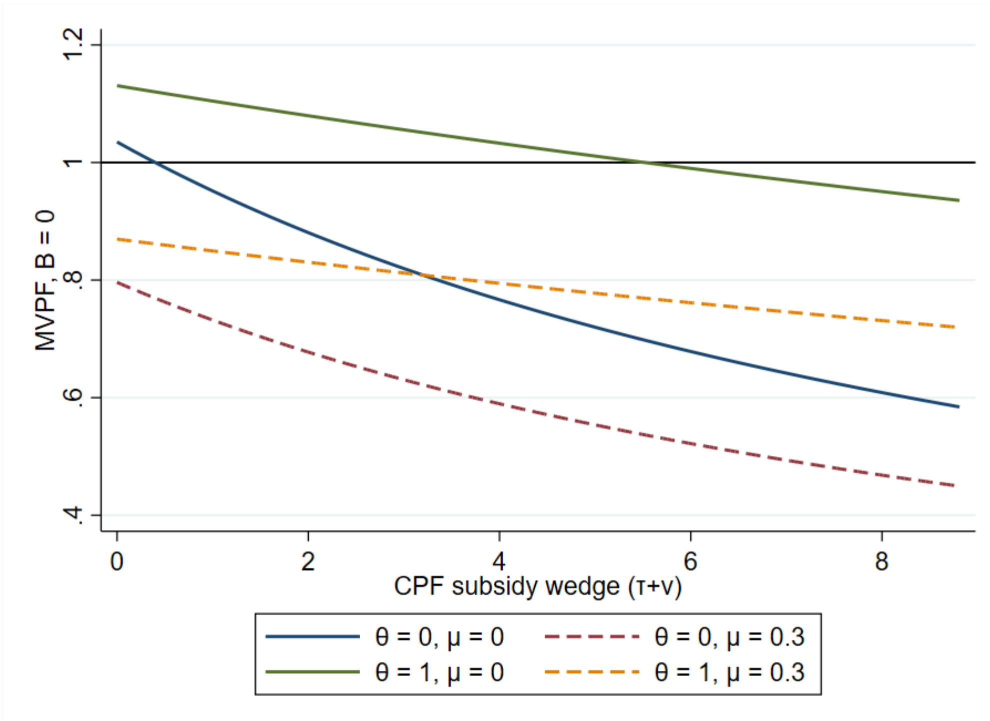
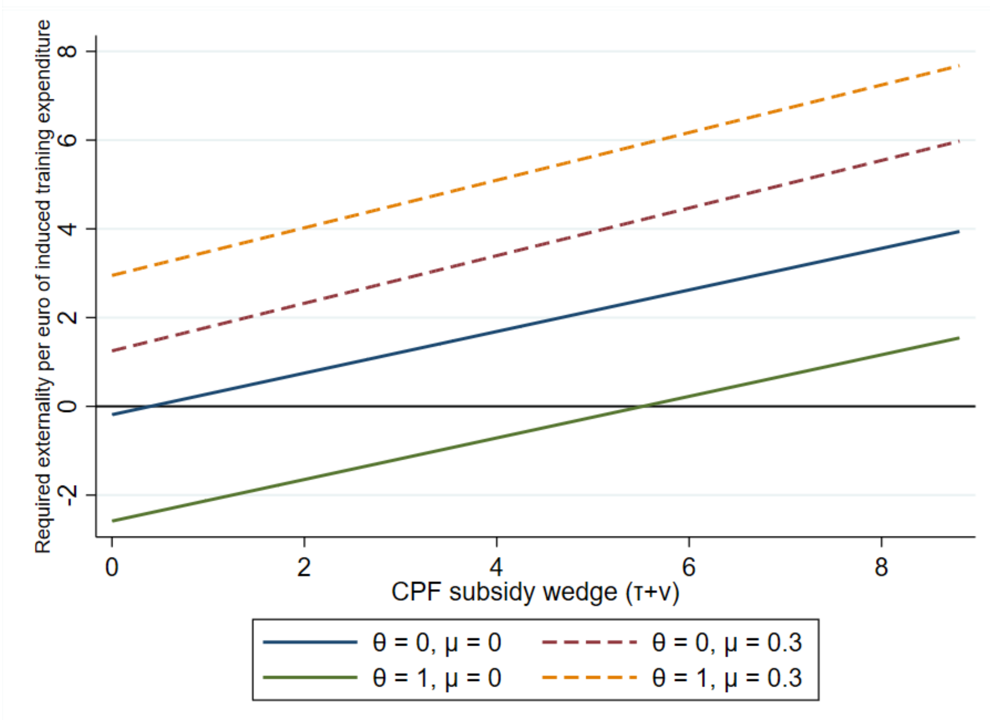


Figure B.12: Sensitivity of MVPF and b to changes in the CPF subsidy wedge





Appendix C: Relationship between of CPF Rule-Based Rates, Realized Subsidies, and Prices in a Simple Model

This Appendix presents a simple model to clarify why, among CPF-eligible training programs, gross prices are observed to be sometimes below the rule-based subsidy cap, leaving part of the subsidy unused, while in other cases they bunch at the cap (Figure B.7). It also explains why these pricing patterns should not threaten the identification of pass-through in our IV strategy.

Let training be discrete: consumers either enrol in a fixed-duration training programme or do not train. Assume that the CPF hours available in trainees' accounts are below the programme duration, $\overline{x}^{CPF} < \bar{x}_q$, as was often the case in our setting.[35] Training has a per-hour price p. The CPF rule-based subsidy cap is $\tilde{c}$, and the total effective subsidy is $c = \min(p, \tilde{c}+u)$, where u denotes supplementary top-ups. For simplicity, we abstract from supplementary top-ups for now and set $u = 0$, so that the net price of training is $\max(p-\tilde{c}, 0)$. Assume quasi-linear preferences, with m_i denoting the numeraire, and let consumers be heterogeneous in their utility from training, $\phi_i(\bar{x}_q) = \phi(\bar{x}_q) + \eta_i$. The term η_i captures differences in the returns to training or in opportunity costs, and is assumed to follow an extreme-value distribution. Utilities from training and not training are therefore:

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

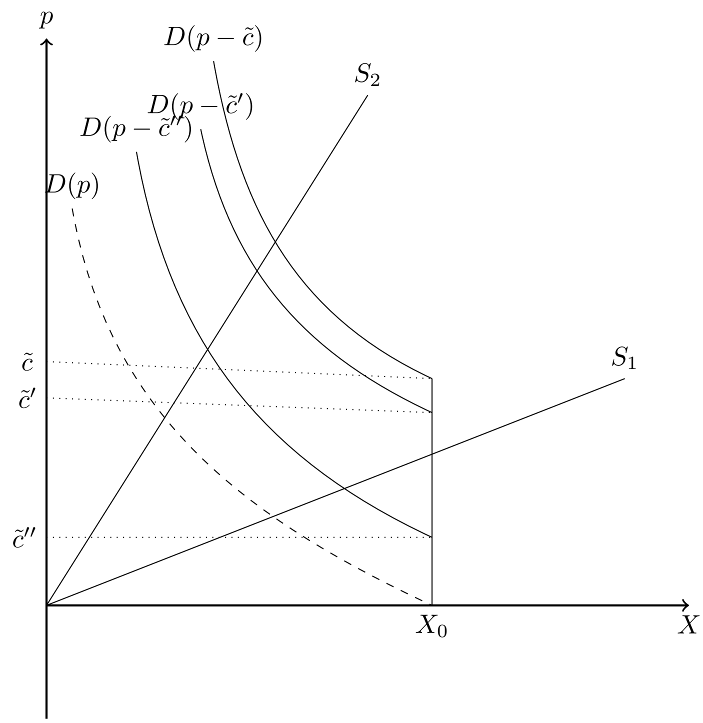
note that, because of the term η_i, for some individuals utility from training would be negative even when the net price of training is zero. Normalizing $\omega = 0$, and keeping all other assumptions like in the previous section, McFadden et al. (1973) shows that aggregate demand is:

- 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 positive net 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. This corresponds to demand curves as $D(p)$ in Figure C.13.

[35] Figure B.11 shows that most accounts were at the maximum number of hours, which corresponded to around the 75th percentile of training programme duration.

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



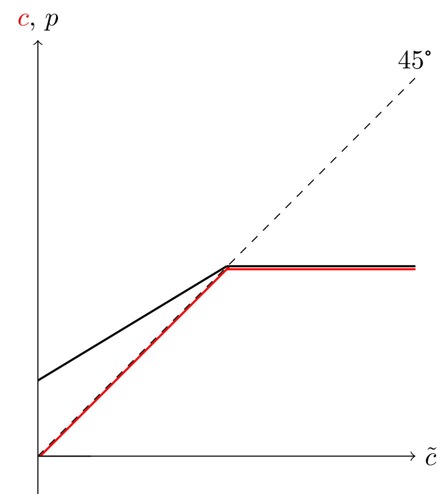
When a subsidy such as the CPF is introduced, aggregate demand shifts upward, for instance to $D(p - \tilde{c})$ or $D(p - \tilde{c}')$. However, workers who are unwilling to train at any non-negative net price remain unwilling to do so: the CPF can reduce the price paid by consumers to zero, but it cannot pay workers with a negative willingness to pay for training to enrol. The new demand with a subsidy therefore features a discontinuous jump at the point where the initial demand curve $D(p)$ reaches a zero net price, followed by a perfectly inelastic segment. Figure C.13 illustrates this case, together with two possible supply curves, S_1 and S_2, tracking the marginal cost of training.

Assume that prices are determined by the intersection of demand and supply curves, i.e. that the market is perfectly competitive. For a given marginal cost schedule, the equilibrium gross price p increases with the subsidy cap $\tilde{c}$ as long as supply intersects demand along its downward-sloping segment. If, instead, $\tilde{c}$ is sufficiently high to cover the full marginal cost of training, the gross price is in principle unresponsive to further changes in $\tilde{c}$.

To illustrate, suppose subsidies are reduced from $\tilde{c}$ to $\tilde{c}'$, shifting demand from $D(p - \tilde{c})$ to $D(p - \tilde{c}')$ in Figure C.13. If supply is given by S_2 and equilibrium prices are initially above the subsidy cap, the cut bites: it lowers both price and quantity according to the elasticities of demand and supply. Conversely, suppose supply is given by S_1, so that the initial subsidy cap $\tilde{c}$ exceeds the equilibrium price. If the cut is small, as in the move from $\tilde{c}$ to $\tilde{c}'$, it does not bite and equilibrium prices do not respond. If the cut is large, as in the move to $\tilde{c}''$, the marginal cost schedule becomes binding and the subsidy cut reduces both the equilibrium price and quantity.

Figure C.14 plots the resulting relationship between subsidy caps and prices. The figure also shows, in red, the effective subsidy schedule c: when the subsidy cap lies below the equilibrium price, the effective subsidy is equal to the cap; when the subsidy cap exceeds the equilibrium price, the effective subsidy is equal to the full price of training.[36]

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



Our first stage equations 2 and 3 aim at estimating the red and black schedule in Figure C.14, respectively. The IV relationship will be equivalent to the ratio of the two coefficients and correctly capture the average effect of changes in the subsidy cap $\tilde{c}$ only when they affect the effective subsidy c, i.e. in the upward-sloped part of Figure C.14. This reflects a standard feature of IV estimation: identification relies on the validity of the instrument, rather than on correctly specifying the underlying reduced-form or first-stage relationship. The key assumptions are that changes in the rule-based subsidy cap $\tilde{c}$ affect prices only through changes in the effective subsidy rate c (excludability), and that c is affected by $\tilde{c}$ (relevance). Training programs are "compliers" in this IV design when the rule-based subsidy cap $\tilde{c}$ falls below their equilibrium price either in the initial or final period, placing them on the upward-sloping part of the relation between prices and subsidy caps in Figure C.14.

Finally, we reintroduce discretionary top-ups, while still imposing that the subsidy gross of top-ups covers at most the full price of training, so $c = \min(p, \tilde{c} + u)$ (recall that subsidies cannot be paid to consumers on top of the training prices). In Figure C.14, this implies that the red schedule for c may lie somewhere between the red and black lines. As before, this can attenuate the first stage, in a way akin to non-compliance, and helps explain why the first stage is significantly below one, and sometimes noisy, throughout the analysis. Nevertheless, the IV estimates still recover the effect of c on p for compliers, for the same reason of robustness to misspecification of the first stage.

It is important to note that our IV estimates are locally valid only for training programs that "comply", at least to some extent, with policy-induced variation in $\tilde{c}$. These are training programs that: (i) are priced above the rule-based cap, either before or after the reform, therefore entering the upward sloped part of

[36] Firms charging prices below the subsidy cap, as in the case of S_1, may be able to increase profits by raising prices up to exactly $\tilde{c}$, provided they observe the applicable cap and can discriminate across consumers covered by different training agencies. In that case, prices and subsidies would instead follow the 45-degree line in the right-hand part of Figure C.14, after the red and solid black lines cross.

Figure C.14; and (ii) do not receive supplementary top-ups that fully offset the change in the subsidy cap. The first concern is unlikely to be quantitatively important: in 2018, less than 10% of training programs had gross prices below the 2019 rate of €15, suggesting that the reform-induced cut affected most programs. The second criterion may be more relevant, making some segments of the population not comply with changes in the subsidy cap. Table A.3 suggests that it may matter for example for two specific types of training, equipment operation certificates and professional skills certifications, for which the first stage is low and imprecisely estimated. On average, however, our first stage is strong and very significant, suggesting that a sufficient share of the variation in rule-based caps affects effective subsidies.