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

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Abstract

This paper studies the incidence of training subsidies exploiting a reform in 2019 of a French Individual Learning Account which differentially lowered the per-hour subsidy across industries. We highlight four results. First, changes in the maximum per-hour subsidy are passed through to consumers only by 48%, so that more than half of the benefit of the subsidy is captured by training producers. Second, the incidence is almost fully on producers when the cut bites more, i.e. when training prices exceeded the initial maximum per-hour subsidy. Third, the amount of training undertaken is not significantly affected by subsidy changes, so that training subsidies are eventually a simple transfer, with no effect on welfare. Fourth, we show that the reduction of the subsidy eventually translates in a reduction of producers' profits, with no effect on labor costs and employment of trainers. The results suggest that training markets are imperfectly competitive.

Keywords: training, subsidies incidence, imperfect competition

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

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1 Introduction

Adult learning is regarded as a key challenge to secure careers and improve productivity, especially when the demand for skills is changing fast. International institutions often urge governments to scale-up support to investment in on-the-job training (OECD, 2020), and subsidies to training are a common policy tool. Yet, Microeconomic theory dating back to Harberger (1962) suggests that the capacity of a subsidy to increase the consumption of a good, and the welfare effect of a subsidy, depend from the reaction of equilibrium prices. As a general rule, the benefits or costs of a tax/subsidy fall on the less elastic side of the market (Fullerton and Metcalf, 2002). For example, if markets are competitive and supply is relatively inelastic a subsidy will mostly cause an increase in prices, not in the quantity consumed, and the benefit will be mostly captured by producers. Imperfect competition can substantially modify this prediction (Weyl and Fabinger, 2013). Assessing the incidence of a subsidy remains thus a fundamentally empirical question, which can offer insights on the structural fundamentals of a market.

What is the incidence of training subsidies? The market for training is characterized by several potential departures from the standard, perfectly competitive market prototype. On the demand side, non-monetary costs of training are high, private returns are widely uncertain, and spillovers are significant (Becker, 1964; Acemoglu and Pischke, 1999; Bassanini et al., 2005). In particular, the so-called poaching externality may lead to under-financing of training by employers and workers (while possibly justifying public support to investment in training). On the supply side, asymmetric information on training quality risks making the market for training courses a market for "lemons", with low-quality training providers pushing high-quality ones out of the market. Hence signaling through reputation, repeated interaction, as well as policies such as mandatory certifications play an important role, but could in turn build entry barriers and jeopardize competition. With very inelastic supply or demand, or with imperfect competition, training subsidies risk not being able push up the quantity of training consumed as desired, and being more beneficial to providers than to consumers.

This paper studies the incidence of training subsidies by exploiting a natural experiment provided by the French *Compte Personnel de Formation* (CPF). The CPF is a national Individual Learning Account in which each French worker accumulates training credits proportionally to its years of social security contributions, which can be used to finance training by certified providers. The policy represented a significant investment for the French government and was relatively welcomed by social parties, despite the concerns that were voiced by some scholars about the effectiveness and equity of an earlier version of CPF (Cahuc and Zylberberg, 2006). Between 2015 and 2018 each industry was allowed to decide the maximum amount of subsidy guaranteed to each workers based on her accumulated training credits. Richer industries were thus offering more generous subsidies. The 2019 reform fixed instead a uniform subsidy of 15 Euros per-hour across industries, exogenously equalizing the per-hour value of the subsidy across industries. Using administrative data from the operating system of CPF, we estimate the relationship between changes in the maximum per-hour subsidy, hourly price and quantity of training undertaken by workers in different industries. In addition, we use balance-sheet information from training providers to disentangle the final incidence of the subsidy on production factors, by measuring the effect of the policy change on producers' profits and employment levels.

Our results show that more than half of the incidence of CPF falls on suppliers of training. Namely, a reduction in the per-hour cap triggers an 18% reduction in total subsidies, since discretionary additions by industry training agencies attenuate the cut of the subsidy, and a 9% decrease in prices. However, we show that due to specific features of the market the per-hour subsidy is sometimes higher than prices of training, attenuating the effect of a cut in the subsidy on prices. When prices are instead higher than the per-hour subsidy, the subsidy cut is expected to bite more, and prices react almost one-to-one. The quantity of training, measured as total hours of training in an industry-training kind pair, is instead not significantly affected, suggesting that the CPF is ineffective in increasing the amount of training undertaken. The silver lining is that, studied through the lenses of a sufficient statistics framework, the dead weight loss arising from CPF is also close to zero. Finally, we use data on revenues and expenses of training centers to highlight that the reduction of prices translated in a reduction of revenues and profits of training producers, not of costs. In particular, no effect is detected on labor costs and number of trainees. To be consistent with a perfectly competitive framework, full incidence on suppliers when the subsidy bites requires fully inelastic supply. However, a more realistic explanation can be imperfect competition in the market for training, given that we observe an effect on producers' rents and no effect on entry/exit of firms in the market.

Firstly, our results are important for the literature studying on-the-job training and human capital policy in equilibrium. This literature has often focused on the question of whether or not human capital accumulation is under-financed (Bassanini et al., 2005), so as to justify (or not) subsidization policies. Yet, scholars ignored the risk that training subsidies might have a zero pass-through to consumers. We are the first, to our knowledge, to study the incidence of training subsidies. We highlight how low elasticity of supply and/or imperfect competition can make training subsidies fail to increase the quantity of training undertaken in equilibrium. Our results support the intuition of Cahuc and Zylberberg (2006), who advocated for better targeting of training subsidies on weaker workers for longer training programs, for which demand might be more elastic.

Second, our study can be seen as part of the literature on subsidies incidence, and of the recent branch at the crossroad of IO and Public Economics that uses subsidies incidence to derive implications on market power. Classical incidence studies found that, consistently with models which assume perfect competition, subsidies mostly generate an increase in prices where marginal costs are high and supply elasticities low (e.g. in the housing market, Gibbons and Manning, 2006; Fack, 2006). Instead, when markets are imperfectly competitive, pass-through of subsidies to consumers depends on how market power interacts with the shape of the demand function (Weyl and Fabinger, 2013). Exploiting quasi-experimental variation in subsidies, studies such as Kirwan (2009); Cabral et al. (2018); Pless and van Benthem (2019) test the degree of imperfect competition in the market for agricultural land, health insurance, and solar energy systems. In this paper, we find that the incidence of training subsidies mostly falls on suppliers, with pass-through attaining zero when the subsidy fully bites, and showing a positive relationship between suppliers profits and subsidy levels. We argue that the most plausible mechanism behind our findings is the presence of market power by suppliers in the training market.

Third, our study offers theoretical insights and empirical evidence on how per-unit subsidies can make demand locally inelastic. This arises when per-unit subsidies are applied to goods with high non-monetary costs, or when the total quantity subsidizable is capped. When demand is locally inelastic, markets don't clear, some of the subsidy might be left on the table and, most importantly, the subsidy fails to increase the quantity consumed of the good. We show how this situation applies to the case of Individual Learning Accounts, which are defined as "virtual, individual accounts in which training rights are accumulated over time", and are increasingly popular in Europe, as they are often advocated by international institutions (OECD, 2019)[1]. Our study is the first empirical one showing how a large, national Individual Learning

[1] A similar scheme to Individual Learning Accounts are training vouchers. These are more diffused. Examples of voucher

Account fails to significantly increase the quantity of training consumed, similarly to what was found for small training vouchers programs (Hidalgo et al., 2014; Van den Berg et al., 2020; Görlitz, 2016; Schwerdt et al., 2012).

The rest of the article is structured as follows. Section 2 presents our empirical setting: the institutional context, the data, and some descriptives of the policy shock. Section 3 reports our empirical analysis of the effect of a change in the maximum per-hour CPF subsidy on training prices. We include a model-based heterogeneity analysis in which, using a partial equilibrium model, we show that Individual Learning Accounts generate locally inelastic demand and flatten the relationship between subsidy and prices when the subsidy rate exceeds the equilibrium price. Section 4 presents the results concerning the effect on quantities, which are also a sufficient statistic for the effect of the CPF subsidy on welfare. Section 5 looks at the effect of the subsidy cut on suppliers of training, particularly on their revenues, costs, profits and employment. Section 6 discusses the implications of our results in terms of structural fundamentals of the training market, namely the degree of competition and the elasticities of supply and demand. Section 7 discusses policy implications and concludes.

2 Empirical setting

2.1 The French CPF

Introduced in 2015, the *Compte Personnel de Formation* (CPF) provides workers with credits to be spent for training, guaranteeing a fixed amount of additional credits for every year of social security contributions, depending on personal characteristics. Credits are accumulated in a "personal" account, in the sense that only workers can access it and decide how to use it, which is also "portable", in the sense that workers maintain the credits even when changing employer[2]. Initially, the scheme covered only employees of the private sector, while workers of the public sector were added to the program from 2017, and self-employed workers from 2019. Importantly, CPF credits can be used to finance only training courses from a list of eligible providers. As of 2018, the cost of the policy was estimated about €650 Millions, roughly 10% of French government expenditures in professional training as calculated by the OECD.

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

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

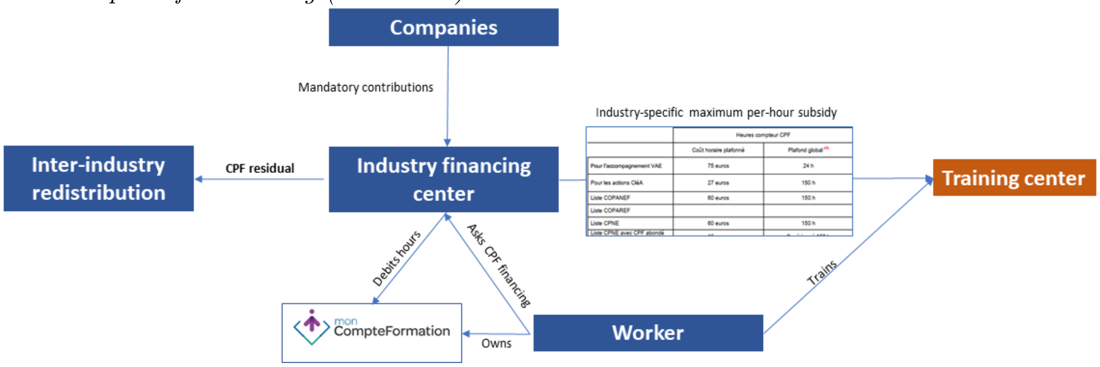
[2]By contrast, the previous device (*Droit Individuel de Formation – DIF*) replaced by CPF, was instead attached to each working contract: the employer could see the amount of training guaranteed to each employee on the payslip, the credits disappeared if the contract terminated, and the worker could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

Importantly, industry-specific training agencies would not be willing to finance a CPF-subsidized hour of training at any price, but they were fixing different caps to per-hour subsidy payable for each hour of training. These caps were reported in official tables communicated to the government (an example of these table is reported in Figure 12 in the Appendix). For instance, suppose a worker wanted to use its CPF for for financing a training which is very expensive in per-hour terms, say €80 per-hour for 50 hours of duration, so €4,000 of total cost of the training. Then, suppose that for that specific kind of training his training agency fixed a maximum subsidy up to €60 per hour. Hence, €3,000 of the training cost will be covered by 50 hours of CPF credits, while €1000 will remain uncovered. For paying costs uncovered by CPF, additional discretionary subsidies could be offered by the training agency, consisting in an extra lump-sum amount of financing. In case there would still be leftover costs to pay, the worker would finance them by himself.

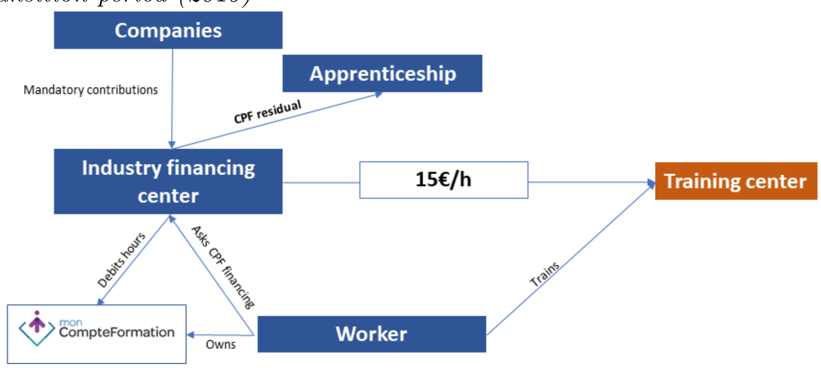
Before 2019, industry-specific training agencies had strong incentives to be generous in financing CPF. In fact, companies were paying mandatory contributions (1% of the wage bill for firms above 10 employees) to their industry training agency, of which 0,2% was mandatorily allocated to a CPF financing line. If contributions exceeded the cost of all CPF used by workers in the industry during the year, the excess funding was assigned to an inter-industry organization for being used to finance other training outside the industry. Industry training agencies had thus incentives to avoid leaving money from CPF contributions on the table, allowing high caps to per-hour subsidy, in order to keep the money within the industry. Several French regulators confirmed this mechanism. We quote a regulator from the Minister of Labor in charge of supervision of CPF: "The system pushed industry financing centers to fix whatever high per-hour subsidy cap, just to consume the CPF financing line, and avoid giving up the money". Finally, it is worth noting that CPF was underused in 2018: individuals tended to accumulate credits without using them (Figure 13 in the Appendix), so that most individuals actually reached the maximum amount of hours which could be accumulated in the account.

Figure 1: Pre and post-reform organisationof the CPF

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



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



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

The CPF was reformed in January 2019[3], and the main change was the so-called "monetization" of the credits: for all private workers, the account would be denominated in Euros rather than hours. As a consequence, industry-specific per-hour subsidy caps were abolished: an hour of CPF, once having different values in different industries according to per-hour subsidy caps defined by training agencies, became after 2019 uniformly worth 15 Euros[4]. Although the final goal of the reform was to allow workers to use CPF directly in euros, directly paying training providers through a mobile app and bypassing industry financing centers, between January and November 2019 a transition period was enacted, which in practice affected

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

[4] Although the reform was expected, the exact magnitude of the change was not clear until the very end. The discussions about the CPF reform started in January 2018, but a reform of the CPF system in the sense of a monetization was already in the electoral program of the Macron government, elected in 2017. A clear political question was the magnitude of the conversion rate: after a year of discussion and several changes due to harsh bargaining between the government and industry training agencies, the 15 Euros conversion rate was decided by Decree in December 2018, after the approval of the law, to be applied from January 2019. Consequently, large anticipation was not likely. Figure 14 in the Appendix suggests only a small bunching of CPF-subsidized trainings at the end of 2018.

almost all trainings of 2019[5]. Our analysis will focus on this transition period, during which CPF worked in an extremely similar way to the pre-reform years, but the per-hour subsidy was harmonized at 15 Euros per hour across industries. Specifically, workers still submitted requests to the training agency of their industry to pay training providers and debit their CPF account, but the value of the CPF subsidy was determined as the amount of hours available on the CPF account multiplied by the uniform 15 Euros rate (Panel B of Figure 1). Because industry-specific caps were mostly higher than €15 before the reform, the reform determined a huge drop in the CPF subsidy used. Discretionary additions were still possible from the training agency, if the CPF subsidy was not enough to cover the cost of training. In fact, some industry financing centers started using discretionary additions to increase the total value of their workers' CPF, attenuating the reform. Training agencies were nonetheless not incentivized to do so, since the reform allowed training agencies to keep the unused CPF contributions for financing apprenticeship in their industry. We can thus expect that the cut in CPF will not fully compensated by an increase in discretionary additions.

2.2 Data sources, sample selection, and cleaning

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

[5] As Figure 14 in the Appendix shows, the value of trainings undertaken through the unique mobile up in December 2019 is negligible, and most trainings are still the result of previous validation by industry financing centers. The December 2019 period is also a particular one in France, due to historically harsh strikes of public transportation.

[6] The first line of the table correspond 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 (see Figure 15 in the Appendix). 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. He doesn't have to ask the training agency anymore. This was implemented in the second part of the reform and we do not study it.

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

CPF training episodes financed by other institutions than industry-specific financing centers (1.2% of the observations)[8].

Our second data source is the official documentation on the caps to the per-hour value of the CPF subsidy allowed by training agencies. We construct a small database digitalizing publicly available documentation from the inter-industry training organization (FPSPP), the national training council (CNEFOP) and from the training agencies themselves. Through the French Labor Ministry, we also sent requests of additional information to training agencies to complete the dataset and ensure a better understanding of the process. The final dataset records 224 different per-hour subsidy caps according to the industry financing agency and the year (2017 to 2019), and for different kinds of training[9]. We merge this new dataset with SI-CPF, sucessfully assigning a subsidy cap to more than 90% of the training episodes[10].

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

[8]These are financed by employers (8 000 training episodes), regions (100 training episodes), and by the unemployment agency *Pôle emploi* (30 training episodes)

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

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

2.3 Descriptives of the shock

We conclude the introduction to the institutional context by presenting 3 descriptives of the shock to per-hour subsidies generated by the reform of January 2019. First, Figure 2 displays the maximum cap to the per-hour subsidy applied in 2018 as reported in official documentation and from interviews with industry financing centers, for the 9 most diffused groups of training kind. The graph also reports mean, mode and IQR of the average actual amount of CPF subsidy used to cover the training, in per hour terms, observed in the data. This set of figures points out two considerations. First, our data gathering of the different per-hour subsidy caps across industry looks accurate: with few exceptions, the per-hour value of the CPF subsidy actually seen in the data is never above the per-hour subsidy cap. Interestingly, although the per-hour value of the CPF subsidy is often bunched at the value of the cap, suggesting that the per-hour subsidy cap is binding, the subsidy used by consumers is sometimes below the cap, suggesting that some of the subsidy is left on the table. This happens especially when the subsidy cap is higher. We will return to this in Section 3.2. As a second consideration, caps to per-hour subsidy are quite variable, and almost always above the new per-hour conversion set by the 2019 reform (15 Euros per hour). Looking at the ranking of financing centers on the horizontal axis, one can see how richer financing centers (see Figure 16 in the appendix for the correspondence between the agency name and the industry they represent) tend to be more generous, although there is quite a variability across different kinds of training.

A second interesting descriptive is reported in Figure 3, which plots the distribution of the share of the total training cost which is covered by the CPF subsidy, in 2017, 2018 and 2019. Clearly, the reform of 2019 represents a dramatic cut in the capability of CPF to cover the cost of training: while before the reform CPF was fully covering the cost of training for almost 80% of the training episodes reported, after the reform this share almost halves. While pre-reform the distribution is almost fully bunched at 1, with a slight left tail, in 2019 is bimodal, with one fourth of the training episodes having between 20% and 40% of the cost covered by CPF subsidy.

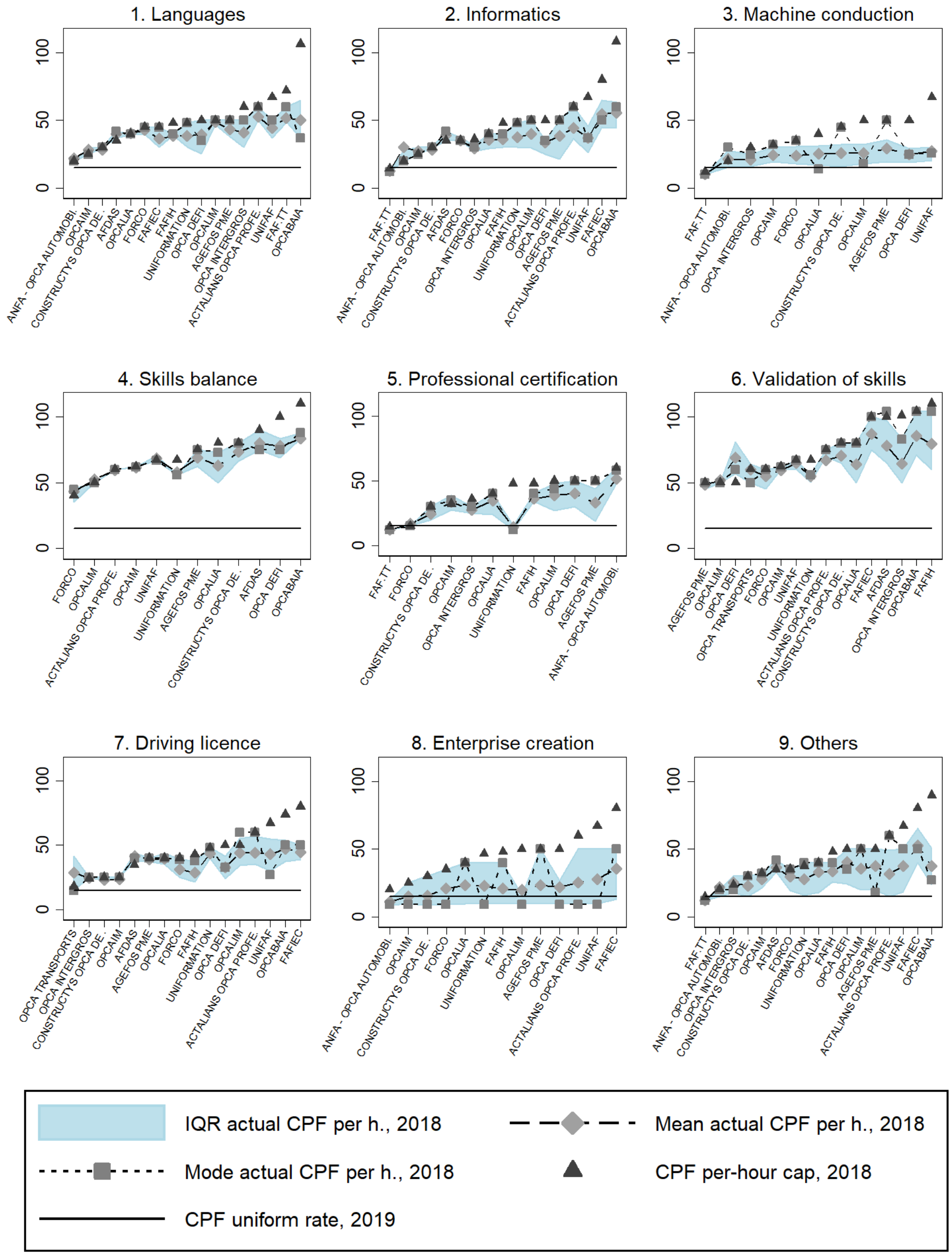
Finally, Figure 4 gives an example of the effect of the reform on training prices for two among the 10 most popular kind of training, the BULATS language certificate and the lifeguard certificate. In the former, the equalization of per-hour subsidy cap in 2019 changes the average price applied to individuals financed by different financing centers, but the price remains widely heterogeneous for workers coming from different training agencies. This suggests different financing centers should be sometimes seen as different markets in a diff-in-diff context, either due to different marginal costs (e.g. different areas, different level of qualification, ...) or to price discrimination. Conversely, in the case of lifeguard certificate prices converge to a much more similar level after equalization of the subsidy.

3 The pass-through rate of the CPF subsidy

3.1 Baseline specification

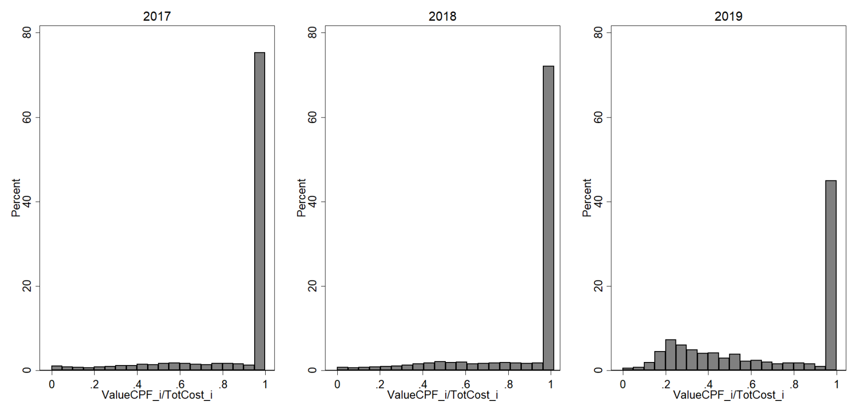
In this section, we will study the effect of CPF on training prices. Namely, our target parameter is $\rho = \frac{dp}{dc}$, the change in the hourly price p paid to the training supplier, gross of the CPF subsidy, following a change in the effective subsidy c. Equivalently, we will recover the pass-through of the subsidy to consumers $1 - \rho = -\frac{d(p-c)}{dc}$, which is the change in the price paid by consumers gross of the CPF subsidy when the

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



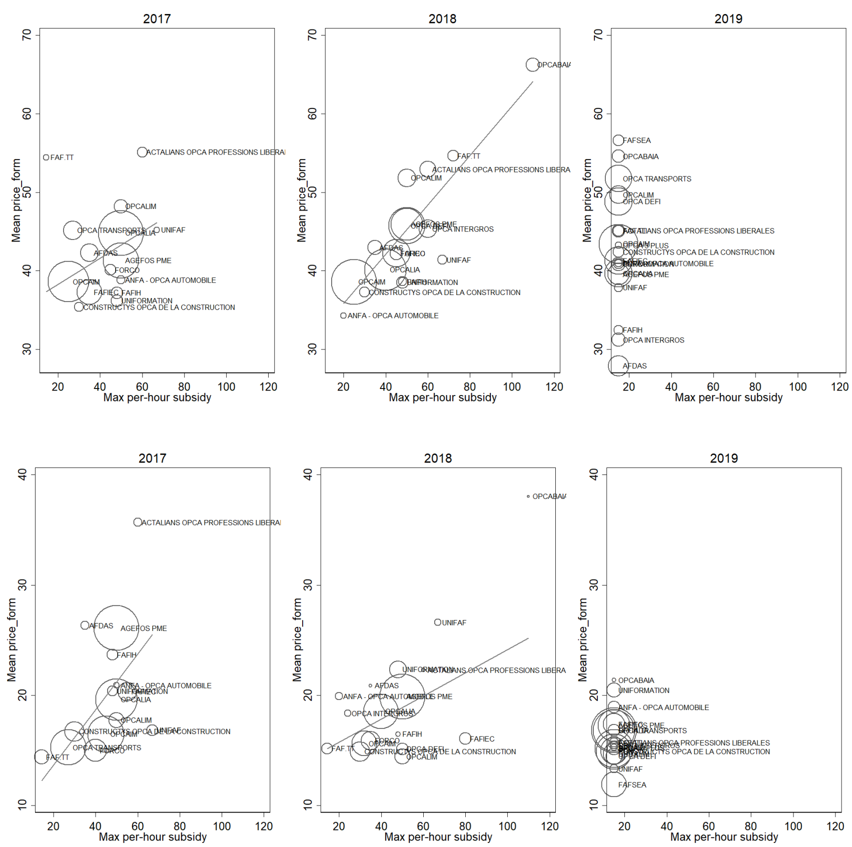
Notes. The figure reports the per-hour subsidy caps, and average actual amount of CPF subsidy used per-hour (average, mode, and IQR), for different industry financing centers and according to training type. The per-hour subsidy caps are determined by industry financing centers until the reform of 2019,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

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



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

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



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

subsidy changes (with a minus in front, as pass-through are traditionally defined in terms of changes in taxes). Our dataset doesn't provide directly information on the hourly price p_i of a training episode i and on the effective per-hour subsidy used c_i. Concerning hourly prices, we can indirectly recover them as $p_i = \frac{P_i}{x_i}$, where x_i is the duration of the training and P_i is the total cost as reported in our data. Concerning effective per-hour subsidy, this includes both the subsidy from a worker CPF credits C_i and discretionary additions by the industry financing center A_i, so we can recover $c_i = \frac{C_i + A_i}{x_i}$.

Our baseline model to be estimated is thus:

$$p_i = \rho c_i + \gamma_{q,j,f} + \tau_t + \varepsilon_i$$

Where $\gamma_{q,j,f}$ are fixed effects for "training kind", indexed by q and defined as the combination of the title of the training and whether it is run online or in person, financing center of the training, indexed by f, and training provider, indexed by j. Finally τ_t is the fixed effect for the year when the training occurs.

As explained in the previous Section, the final per-hour CPF subsidy c_i will be capped by industry-specific per-hour subsidy caps, $c_{\tilde{q,f,t}}$. Consequently, c_i will be either equal to the full per-hour price of the training, if the cap is above per-hour prices, or equal to the maximum amount of per-hour subsidy $c_{\tilde{q,f,t}}$, plus discretionary additions: $c_i = \min(p_i, c_{\tilde{q,f,t}}) + A_i$. However, discretionary additions are endogenous to our model, as they can arise from endogenous decisions by financing centers. For example, they are often guaranteed only if CPF doesn't cover the whole amount of the training costs. To tackle the threat of endogeneity, we will instrument c_i with $c_{\tilde{q,f,t}}$, the subsidy cap fixed by each industry financing center. These caps were fixed (and sometimes changed) by industry financing centers. For example, Figure 5 reports in white the change of the subsidy in 2017-2018. Yet, the industry-specific $c_{\tilde{q,f,t}}$ were exogenously changed between 2018 and 2019, when they were harmonized by the central government at 15 Euros with the CPF reform of 2019. As reported in green in Figure 5, this generated a decrease in the subsidy cap in most cases, which was larger for industry-training kind pairs having higher subsidy caps in 2018. This exogenous shock provides our source of identification given that, within training programs, different financing centers suffer different exogenous variation of the conversion rate as a consequence of the pre-reform differences and 2019 equalization of the per-hour value of the CPF subsidy.

Then, we can write our first stage of the relationship between subsidy caps and effective subsidy rates gross of discretionary additions before and after the 2019 reform:

$$c_i = \beta^{FS} c_{\tilde{q,f,t}} + \gamma_{q,j,f} + \tau_t + \varepsilon_i \qquad \text{if} \quad t = 2018, 2019 \tag{1}$$

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

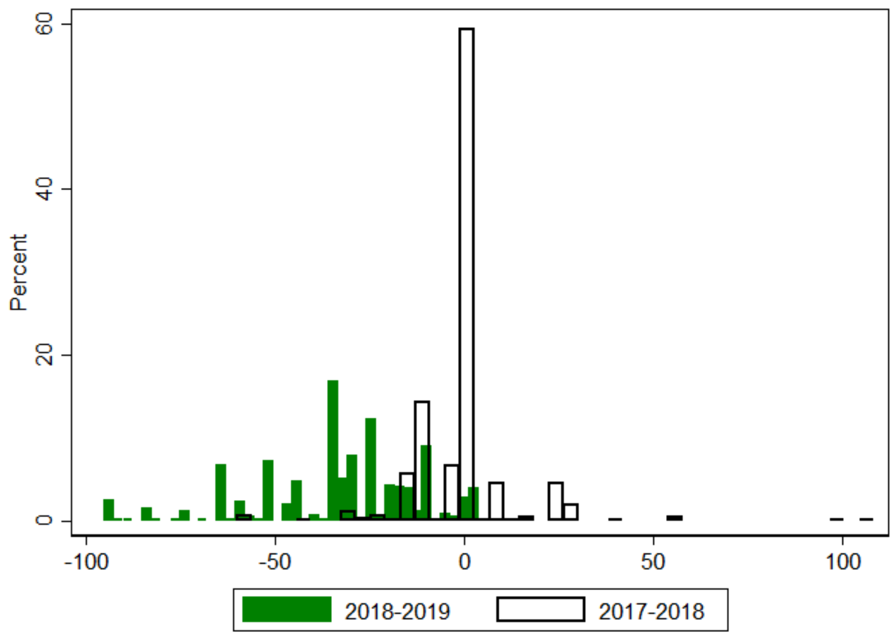
$$p_i = \beta^{RF}_{prices} c_{\tilde{q,f,t}} + \gamma_{q,j,f} + \tau_t + \varepsilon_i \qquad \text{if} \quad t = 2018, 2019 \tag{2}$$

Our identification strategy relies on the assumption that industries that will experience larger changes in $c_{\tilde{q,f,t}}$ in 2018-2019 did not report significantly different evolution in the outcome variable in previous years. This assumption can be tested using the following specification:

$$p_i = \beta^{E}_{prices} c_{\tilde{q,f,t}} + \beta^{PL}_{prices} c_{q,f,t+1} + \gamma_{q,j,f} + \tau_t + \varepsilon_i \quad \text{if} \quad t = 2017, 2018 \tag{3}$$

Where the placebo coefficient β^{PL}_{prices} should not be significantly different from zero. The coefficient β^{E}_{prices} reports instead the effect of changes in the maximum per-hour subsidy cap between 2017 and 2018, which are potentially endogenous as they are not imposed by the 2019 reform. Finally, for all our results we also include specifications controlling for Local Labor Market l fixed effects.

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



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

We will estimate both the first stage and the reduced form using an OLS regression, with training episode as unit of analysis, absorbing the relevant fixed effects. For inference, standard errors are clustered at training kind f level, to control for serial correlation in the outcomes.

Table 1 reports our baseline results. Column (1) reports the estimates of β^{FS} from the first stage specification (Equation 1), while column (2) reports the estimates of β^{RF}_{prices} from the reduced form specification (Equation 2). The first stage coefficient signals that a decrease in CPF maximum per-hour subsidy leads to a significant 18% decrease in the effective average per hour subsidy, gross of discretionary additions. In turn, this leads to a 9% decrease in the average price. The positive sign of the coefficient is consistent with our expectations that a reduction (resp. increase) in the per-hour subsidy leads to a decrease (resp. increase) in the price. The ratio of the reduced form to the first stage coefficients yields our estimate of ρ, and hence the pass-through to consumers of a change in the subsidy, $1 - \rho = 1 - \frac{\beta^{RF}_{prices}}{\beta^{FS}}$. Such pass-through is slightly less than 50%, suggesting that slightly more than half of the incidence of the subsidy falls on training producers, while the rest benefits consumers. To confirm our estimation, we obtain ρ using IV in Table 7 in the Appendix, obtaining estimates that are virtually identical to the ones obtained by dividing the reduced form for the first stage, and extremely significant.

Column (3), reports instead the reduced form estimate of the relationship between changes in per-hour subsidy caps and prices in 2017-2018 and the placebo test as in Equation 3. Note that the relationship between maximum per-hour subsidies and prices in 2017-2018 doesn't arise from an exogenous policy shock and might be in part endogenous, for example due to reverse causality if subsidies would increase because price increase. The estimated β^{E}_{prices} signals that the relation between prices and subsidy caps in 2017-2018 is stronger than the one in 2018-2019. This might suggest a potential endogeneity of changes in subsidy caps in 2017-2018 might. Most importantly, the placebo estimate signals no anticipation of our identifying shock, as the effect of changes in conversion rates in 2018-2019 on prices in 2017-2018 is insignificant and close to zero. Finally, in columns (4)-(6) we replicate the results controlling for local labor market fixed effects. The coefficients of both reduced form and first stage are virtually unchanged.

Table 1: Relationship between CPF Subsidy Caps, CPF Effective Subsidy and Prices, and Implied Pass-Through to Consumers

VARIABLES	(1) c_t	(2) p_t	(3) p_t	(4) c_t	(5) p_t	(6) p_t
$\tilde{c_t}$	0.177***	0.0926***	0.123***	0.178***	0.0929***	0.123***
	(0.0228)	(0.0265)	(0.0390)	(0.0226)	(0.0267)	(0.0394)
$c_{\tilde{t+1}}$			-0.0287			-0.0295
			(0.0200)			(0.0195)
Observations	527,180	527,180	164,285	526,975	526,975	164,285
R-squared	0.745	0.770	0.742	0.746	0.770	0.744
Years	2018-2019	2018-2019	2017-2018	2018-2019	2018-2019	2017-2018
add LL Mkt FE				X	X	X
$1-\rho$		.477			.48	

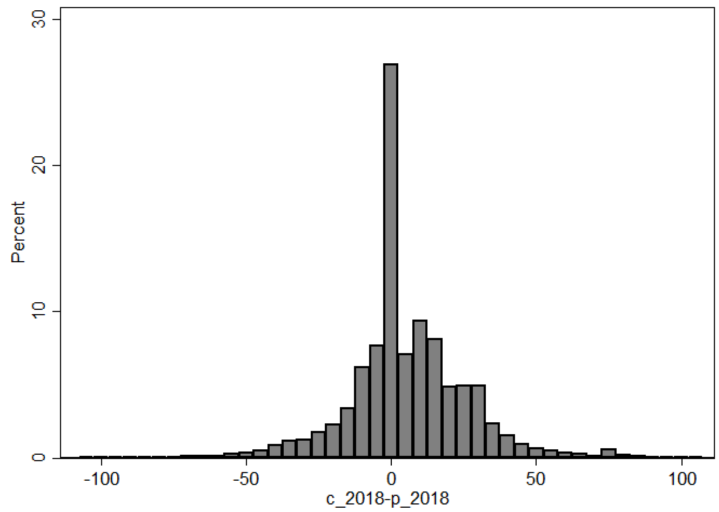
Notes: The table reports in columns (1) and (4) the first stage regression of total subsidy per-hour on the per-hour CPF subsidy; in columns (2) and (5) the reduced form estimate; in column (3) and (6) the reduced form estimate of the relationship between (endogenous) changes in per-hour CPF subsidy caps, the lead of the subsidy cap as placebo and prices in 2017-2018. All regressions include year fixed effects and fixed effects for training kind (training title +online/in presence) plus training firm and industry financing center FE, and year FE. Regressions in columns (4)-(6) also include fixed effects for local labor market. Standard errors are clustered at the training kind category plus industry financing center (the level of variation in the treatment). The final line reports the estimated pass-through of the subsidy to consumers, i.e. $1-\frac{\beta^{RF}_{prices}}{\beta^{FS}}$.

3.2 A Model-Based Heterogeneity

In Table 1, we estimated the average pass-through of a cut in the per-hour subsidy $c_{\tilde{q,f,t}}$ to prices. Usually, this pass-through parameter can be interpreted as a result of underlying structural characteristic of the market, such as the elasticity of demand and supply and degree of competition. In fact, in a market where demand ad supply are monotonic and smooth, market clearing wound always make sure that prices are at least equal to $c_{\tilde{q,f,t}}$, so that no subsidy is left on the table. In such case, if the statutory incidence is on consumers, a cut in $c_{\tilde{q,f,t}}$ will always "bite", i.e. generates a cut in the effective subsidy C_i (to which discretionary additions A_i are then added). Hence, under market clearing, the pass-through of a cut in the subsidy would also offer insights on the structural underlying parameters characterizing the market (e.g. the elasticities of demand and supply, the degree of competitiveness).

However, market clearing (which implies $p_i \geq c_{\tilde{q,f,t}}$) doesn't seem to be confirmed by the data. Figure 6 reports the distribution of the difference between maximum subsidy rates fixed by industry-specific training financing centers and prices, $c_{\tilde{q,f,t}} - p_i$. Not only there are indeed negative values, when $p_i < c_{\tilde{q,f,t}}$ and some of the subsidy is left on the table, but these cases are not so rare, as the distribution is fairly symmetric. This casts doubts on the possibility of interpreting the pass-through rate derived in the previous section in terms of underlying elasticities of demand and supply and competition in the market.

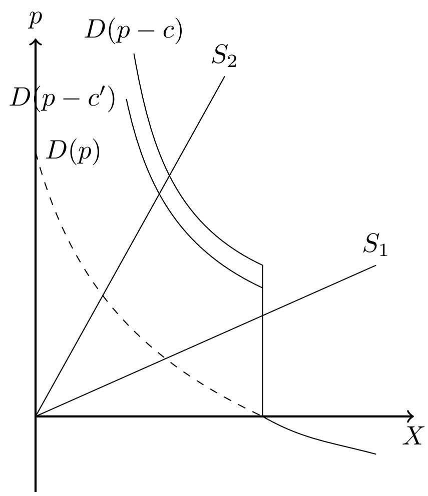
Figure 6: Distribution of the difference between maximum subsidy rate and prices



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

Why do markets not clear and how can per-unit prices remain below per-unit subsidy? In Section B in the Appendix we show how this can happen whenever aggregate demand becomes perfectly inelastic due to the subsidy. This instance can be not so uncommon in the training market, and it's indeed what emerges from modelling the effect of CPF on the training market under a variety of assumptions. As a baseline, we can model the choice to train under the assumption that it is discrete (given that training course duration is often constant), with individuals being heterogeneous according to their non-monetary cost of training. Furthermore, suppose aggregate demand for training without CPF subsidy is low, with some individuals unwilling to train even at zero monetary cost. This is what we realistically observe in the data, as training participation is low compared to the whole workforce even when generous training subsidies are guaranteed (Bassanini et al., 2005). When CPF is introduced demand shifts up only for those individuals who were already willing to pay some monetary costs to train, as in Figure 7. Those consumer who were unwilling to pay any price to train, possibly due to zero returns or high opportunity cost, remain in fact unwilling to train even if the subsidy covers the whole monetary cost. Hence, demand becomes kinked and perfectly inelastic at the total quantity demanded by consumers who were already willing to pay at least some prices to train without the subsidy.

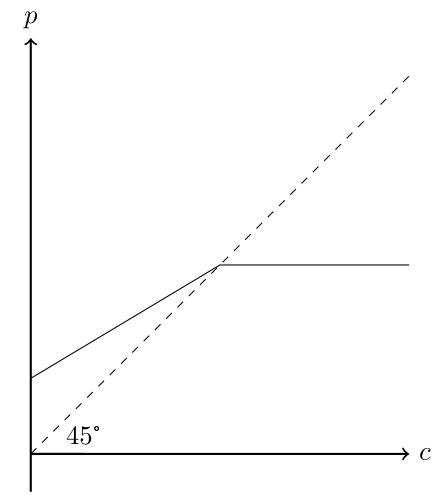
Figure 7: Equilibrium with training as discrete choice and some individuals not willing to pay any monetary cost



What is relevant for our analysis is that, in equilibrium, locally inelastic demand will result in a kinked and concave relationship between prices and the subsidy cap. In particular, prices will tend to react to changes in the per-unit subsidy only when it "bites", i.e. when the subsidy is lower than the price. For example, when subsidies are reduced from c to c', and demand lowers from $D(p-c)$ to $D(p-c')$, if supply is like S_2 and equilibrium prices were above the subsidy rate the cut will "bite" and lower price and quantity according to the elasticities of demand and supply. Conversely, when the per-unit subsidy is higher than the price, we can say that *the subsidy hits the zero-lower-bound*: the cut in the subsidy doesn't bite, and the reaction of prices in equilibrium is null. In the Figure above, equilibrium prices and quantities are unchanged if per-unit subsidy rate is reduced from c to c' and supply is like S_1.

Figure 8 illustrates the kind of kinked and concave relationship between subsidy rates and supply arising in this situation. The precise kinked-linear relationship pictured in Figure 8 arises under perfect competition and with linear supply (derivation in the Appendix), but a kinked (non linear) and concave shape arises also with log-linear supply and demand, as well as with imperfect competition.

Figure 8: Equilibrium prices as a function of per-hour value of the subsidy, with training as a discrete choice

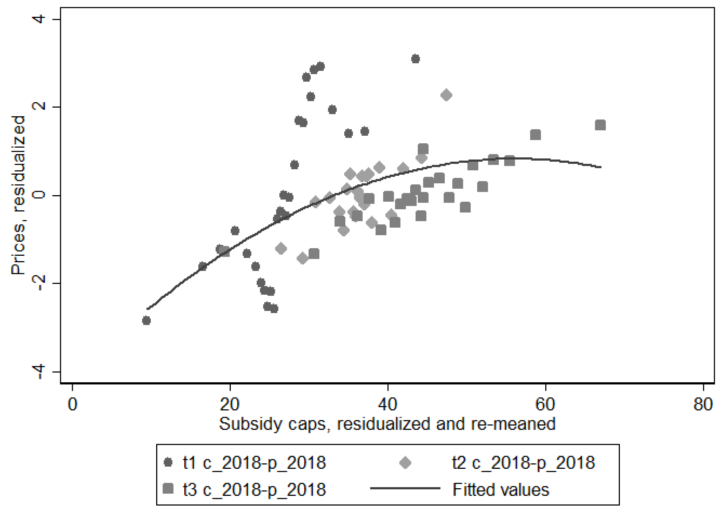


Such a locally-inelastic demand and convex relationship between prices and subsidy rates might not be limited to the case of CPF. For example, it can be obtained also when considering a model with continuous choice, if there is a cap to the maximum subsidy that could be used or to the quantity of training one can consume[11]. Eventually, a similar situation should arise whenever a subsidy is defined on a per-unit basis and some constraints to demand prevent market clearing, for example if the subsidized good has a discrete nature and high non-monetary cost, or there is a cap to the maximum amount subsidizable.

We thus go back to our analysis of the incidence of CPF and, in light of our theoretical analysis, we explore the hypothesis of a concave relationship between prices and subsidy rates. As a first piece of graphical evidence, we can create binned scatterplots of the relationship between residualized prices and residualized subsidy caps, where residualized implies taking the residuals of a regression of the outcome on time and training kind/producer/industry fixed effects. For Frish-Waugh-Lovell theorem, this should give us back the shape of our reduced-form relationship between prices and subsidy caps given fixed effects as in Equation 2. We create these scatter plots separately for cells belonging to different terciles of $c_{2018} - p_{2018}$, i.e. when prices are initially above subsidy rates (first tercile), around or precisely equal to the subsidy rate (second tercile) or below the subsidy rate (third tercile). We re-mean the independent variable according to the mean subsidy cap at baseline, and overlay the graphs in Figure 9. There is a clear similarity between our empirical estimates in Figure 9 with our theoretical predictions in Figure 8, as training kinds with larger subsidy caps exhibit a flatter relationship between residualized prices and residualized subsidies.

[11]In Appendix Section B we also consider the case that the amount of training undertaken is a continuous choice of a representative individual, and that the number of hours of training which can be financed by the subsidy is limited by the maximum amount of hours available in a CPF account. In such a case, aggregate demand is kinked at the maximum quantity subsidizable $\overline{x^{CPF}}$ and perfectly inelastic (Figure 19 in the Appendix). What happens is that, with generous CPF and low monetary cost of training paid out-of-pocket, consumers would individually demand much more hours of training, but the total amount hits the maximum amount of CPF available.

Figure 9: Residualized prices on residualized subsidy caps, re-meaned by tercile of $c_{2018} - p_{2018}$



Notes. the figure overlays three binscatter for different teciles of the difference between subsidy rate and hourly price of training in 2018, before the reform of 2019. Each binscatter creates create a binned scatterplot with 33 bins of the relationship between residualized prices and residualized subsidy caps, where residualized implies taking the residuals of a regression of training prices on time and training kind/producer/industry fixed effects. In the graph we trim top and bottom centiles, and fit a quadratic trend.

Next, we can re-estimate the relationship between prices and subsidies in Equation 2 piecewise, separating the dependent variable according to different terciles of $c_{2018} - p_{2018}$. In the first tercile, we will identify the true pass-through rate implied by structural paramenters. In the last tercile, the estimate will likely be a mix a null reaction until subsidy rates are above prices and don't bite, and the reaction associated to the true structural relationship, as the harmonized subsidy rate a €15 in 2019 is below the hourly price of most training programs. In other words, training providers who were initially charging prices below the subsidy (in the left side of Figure 8 will likely shift to the left of Figure 8 end up charging prices above the new subsidy rate of 15 Euros, hence moving first along the flat part then along the positive sloped one of Figure 8. For the mid tercile, things might be more complicated as it looks like a part of suppliers is able to exactly charge a price equal to the CPF subsidy. Hence, the relationship might be confunded by price-discrimination dynamics.

Table 2 reports the results. Column (1) and (3) report the first stage, where all coefficients remain strongly positive and significant, and the relationship between our instrument and the endogenous variable weakens when prices are well above initial subsidies (possibly as discretionary additions play a bigger role). The reduced form coefficients in columns (2) and (4) strikingly confirm the insights of our model. The relationship between changes in subsidy caps and in prices is much stronger for lower levels of the subsidy, where the cut of the subsidy is more likely to bite. In fact, the prices react to changes in the subsidy rate almost one-to-one in the bottom tercile, and the pass-through is close to zero, revealing that producers might actually capture almost all of the effective training subsidy when the subsidy rate bites. Conversely, in the top tercile the reduced form coefficient is less than one third lower compared to the first tercile, and always insignificant.

Table 2: Heterogeneity according to the difference between prices and subsidy cap in 2018

VARIABLES	(1) c_t	(2) p_t	(3) c_t	(4) p_t
$\tilde{c_t} * \mathbb{1}(p_{2018} - \tilde{c_{2018}} \leq p33)$	0.272***	0.259***	0.275***	0.261***
	(0.0897)	(0.0665)	(0.0882)	(0.0661)
$\tilde{c_t} * \mathbb{1}(p33 < p_{2018} - \tilde{c_{2018}} \leq p66)$	0.280***	0.175***	0.282***	0.177***
	(0.0817)	(0.0654)	(0.0809)	(0.0652)
$\tilde{c_t} * \mathbb{1}(p_{2018} - \tilde{c_{2018}} > p66)$	0.152**	0.0731	0.153**	0.0741
	(0.0609)	(0.0490)	(0.0603)	(0.0489)
Observations	527,180	527,180	526,975	526,975
R-squared	0.746	0.771	0.747	0.772
Years	2018-2019	2018-2019	2018-2019	2018-2019
add LL Mkt FE			X	X
$1 - \rho$ if $p_{2018} - \tilde{c_{2018}} \leq p33$		.045		.05
$1 - \rho$ if $p33 < p_{2018} - \tilde{c_{2018}} \leq p66$		.374		.375
$1 - \rho$ if $p_{2018} - \tilde{c_{2018}} > p66$		.519		.517

Notes: The table reports the reduced form estimate of our model by different terciles the difference between prices and subsidy cap in 2018. All regressions include year fixed effects and fixed effects for training kind (training title +online/in presence) plus training firm and industry financing center FE, and year FE. Regressions in columns (3) and (4) also include fixed effects for local labor market. Standard errors are clustered at the training kind category plus industry financing center (the level of variation in the treatment). The final lines report the estimated pass-through of the subsidy to consumers, i.e. $1 - \frac{\beta^{RF}_{prices}}{\beta^{FS}}$, in the different terciles.

4 The Impact of CPF on the Quantity of Training Undertaken and on Welfare

4.1 Impact of CPF on Quantities of Training in Each Industry

A question which is tightly related to the effect of CPF on prices is if the change in the subsidy led to a change in the quantity of training consumed. From a policy standpoint, this question is almost the most important one, as we can imagine that the goal of training subsidies is to increase training take-up, aiming at compensating for under-provision of training due to externalities. In this section we thus estimate the impact of a change in the effective subsidy on the quantity of training taken-up, focusing on the total quantity of training of a specific kind q and from a specific training supplier j undertaken by workers in a specific industry f, $X_{q,j,f,t} = \sum_{i \in q,j,f,t} x_i$[12]. However, note that $\frac{dX_{q,j,f,t}}{d\tilde{c_{q,f,t}}}$ will not be normally distributed. We thus use as outcome the natural logarithm of $X_{q,j,f,t}$ and estimate the percentage change in the total amount of

[12]In fact, to estimate $\frac{dx_i}{d\tilde{c_{q,f,t}}}$ using x_i as outcome we face a measurement problem: for each training kind q, the realized consumption of training we observe in the data cannot be negative, and it is concentrated around the "typical" amount of hours needed for that training kind. For example, the vast majority of trainings for VAE certificates last 24 hours. Hence, a regression using the number of hours of training consumed x_i as outcome suffers from left and right censoring.

training undertaken in a cell for every unit change in our instrument:

$$\ln X_{q,j,f,t} = \beta^{RF}_{quantities} \tilde{c_{q,f,t}} + \gamma_{q,j,f} + \tau_t + \varepsilon_i \tag{4}$$

Where all the fixed effects are like Equation 2.

The results are reported in Table 3. The estimates in column (1) and (4) indicate a quite precisely estimated zero effect of changes in the subsidy cap on the quantity of training taken up. In fact, the coefficient of the regressions mean that for a one euro change in the subsidy, the total amount of hours decreases by 0.1% and it's not significant. Given that the mean decrease in the subsidy cap is €33 on average and below €55 in 90% of the cases (see Figure 5), we can expect that the average decrease in the total quantity of training demanded following the reform of 2019 will unlikely exceed 5%. Note also that the coefficient becomes even closer to zero when adding local labor market fixed effects in column (4). A large cut in the training subsidies thus doesn't look like generating a substantial decrease in training subsidies. Subsequently, one can check the identification with a placebo analogous to Equation 3. In column (2) we find that there is indeed a slightly significant anticipation, which is however fully annulled when fixed effects for local labor markets are included. Finally, in columns (3) and (6) we run regressions piecewise according to the value of maximum subsidy caps relative to prices in 2018, like we did in Section 3.2 for prices. The results confirm a zero and insignificant effect in all segments.

Table 3: Impact on average quantities demanded: baseline results

VARIABLES	(1) $\ln X_t$	(2) X_t	(3) $\ln X_t$	(4) $\ln X_t$	(5) X_t	(6) $\ln X_t$
$\tilde{c_t}$	0.00110	0.0103		-0.000726	0.00566	
	(0.00288)	(0.00652)		(0.00266)	(0.00608)	
$\tilde{c_{t+1}}$		-0.00513**			-0.00306	
		(0.00235)			(0.00253)	
$\tilde{c_t} * \mathbb{1}(p_{2018} - \tilde{c_{2018}} \leq p33)$			0.00181			0.000391
			(0.00349)			(0.00341)
$\tilde{c_t} * \mathbb{1}(p33 < p_{2018} - \tilde{c_{2018}} \leq p66)$			0.00313			0.000713
			(0.00386)			(0.00343)
$\tilde{c_t} * \mathbb{1}(p_{2018} - \tilde{c_{2018}} > p66)$			-0.000898			-0.00261
			(0.00302)			(0.00350)
Observations	49,162	22,204	49,162	51,114	20,518	51,114
R-squared	0.867	0.909	0.867	0.841	0.888	0.842
Years	2018-2019	2017-2018	2018-2019	2018-2019	2017-2018	2018-2019
add LL Mkt FE				X	X	X
$\frac{dW}{dc}$	-.008			.005		
$\frac{\Delta W}{\Delta c}$	-.005			.003		

Notes: In columns (1)-(3) data are collapsed at the level of training kind (training title +online/in presence) plus training firm plus industry and year, and regressions include include fixed effects for training kind (training title +online/in presence) plus training firm plus industry FE, and year FE. In columns (4)-(5) data are collapsed at the level of training kind (training title +online/in presence) plus industry plus local labor market and year, and regressions also include local labor market FE. Standard errors are clustered at the training kind category plus industry financing center (the level of variation in the treatment).

4.2 Estimating the Welfare Effect of CPF: a Sufficient Statistics Approach

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

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

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

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

The last two lines write down how to recover the change in aggregate welfare for one extra euro of CPF subsidy for each eligible training hour in the sample, which we can recover using estimates of the reaction of total quantities to changes in the maximum cap of the subsidy, as in Table 3, and the actual subsidy used by each individual and in each industry/financing center. Then, one can divide by the number of hours of training to to obtain $\frac{dW(c)}{dc} = \frac{dW(\boldsymbol{c})}{d\boldsymbol{c}} / \sum_{q,f} X_{q,f,t}$, the average change in aggregate welfare from an additional Euro spent in CPF. Such estimates of are thus reported in Table 3. Not surprisingly, as the reaction of quantities is close to zero, the estimated impact on welfare of an additional Euro of CPF subsidy is also low.

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

$$\frac{\Delta W(\boldsymbol{c})}{\Delta \boldsymbol{c}} \approx \sum_{q,f} \frac{d \ln X_{q,f,t}}{d\tilde{c_{q,f,t}}} X_{q,f,t} \Big\{ \frac{c_{q,f,t-1}}{p_{q,f,t-1}} + \frac{1}{2} \Big[\min(1, \frac{\tilde{c_{q,f,t}}}{p_{q,f,t}}) - \min(1, \frac{c_{q,f,t-1}}{p_{q,f,t-1}}) \Big] \Big\}$$
$$\cdot \left[\min(p_{q,f,t}, \tilde{c_{q,f,t}}) - \min(p_{q,f,t-1}, c_{q,f,t-1}) \right] \quad (5)$$

Since this quantities can all be estimated, in the last line of Table 3 we can report $\frac{\Delta W(c)}{\Delta c} = \frac{\Delta W(\boldsymbol{c})}{\Delta \boldsymbol{c}} / \sum_{q,f} X_{q,f,t}$, the average change in aggregate welfare from one euro more invested in CPF, which remains close to zero.

5 Estimating the distributional incidence of CPF using its impact on companies profits and labor share

Until now we ascertained that the incidence of CPF is mostly on producers. Yet, behind "producers" of training there is actually a number of production factors on which the final incidence can fall. This section studies how revenues, costs, profits, total wage bill and employment of training suppliers are affected by changes in the CPF training subsidy. To do so, we will focus on training centers j as unit of analysis, and collapse our dataset at this level. Hence, our identifying variation will be provided by $\bar{c}_{jt} = \sum_{i \in j} \frac{x_i p_{i,t_0}}{\sum_{i \in j} x_{i,t_0} p_{i,t_0}} \tilde{c}_{i \in (q,f),t}$, the average subsidy cap allowed for a supplier's customers, weighted by the share of CPF revenues that each training accounts for. Note that $\sum_{i \in j} x_{i,t_0} p_{i,t_0}$ includes only CPF training, while training centers might of course provide trainings also outside of CPF scope, which we don't see in our data. The variation in $\bar{c}_{jt}$ in the years of interest is reported in Figure 10.

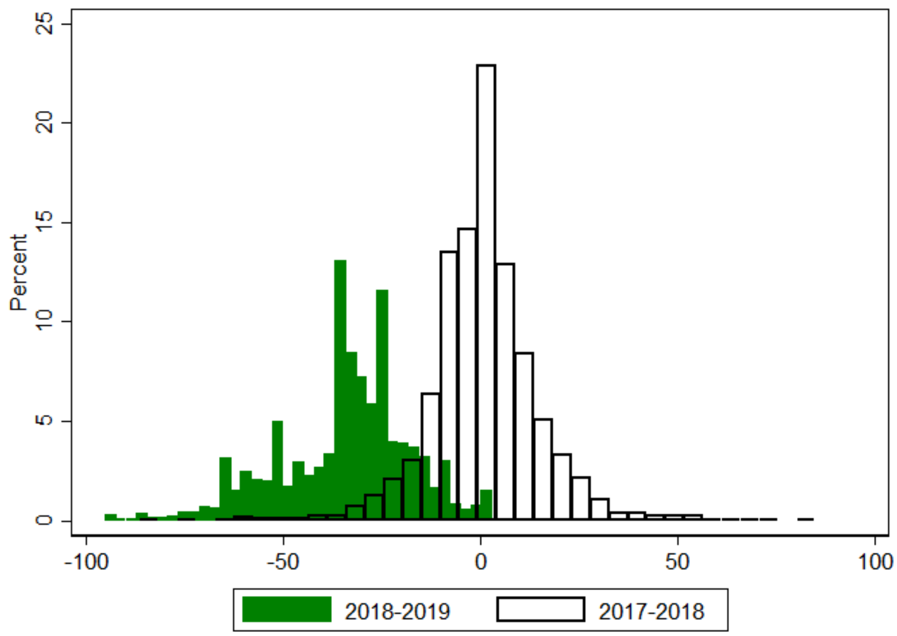
We estimate:

$$\ln y_{j,t} = \beta^{RF}_{REV} \bar{c}_{jt} + \gamma_j + \tau_t + \varepsilon_{j,t} \qquad \text{if} \quad t = 2018, 2019 \quad (6)$$

Where $y_{j,t}$ are different producer-level outcomes: revenues, costs, profits, labor costs, total labor. Like in the previous section, we took logs of dependent variables as they are not normally distributed, so that the coefficients of interests will have to be interpreted as percentage changes following a unitary change in the average subsidy guaranteed to a supplier's customers.

Table 4 reports the results. We estimate our results both using $\bar{c}_{jt}$ as a dependent variable, in the upper panel, and using a log transformation of $\bar{c}_{jt}$, in the lower panel, to correct for the skeness of $\bar{c}_{jt}$ and allow for a concave relationship between subsidies and prices. Note in fact that we cannot split suppliers in terciles of $c_{2018} - p_{2018}$ as suppliers often offer different training kinds. The estimates indicate a positive significant relationship between changes in the subsidy and changes in producers revenues, meaning that suppliers face a decrease in revenues when the average subsidy guaranteed to its customers decreases. The magnitude of the coefficients suggest that we observe a 0.13% decrease in revenues for a supplier for each 1 Euro decrease in the average subsidy allowed to their consumers (i.e., in the lower panel, a 1% reduction in the subsidy leads to a 0.06% decline in revenues). Conversely, the effect on costs is smaller and not significant, although still positive. Accordingly, we also find a small significant positive effect on profits: when subsidies decrease, profits decrease by a magnitude that roughly corresponds to the difference in reactions of costs and revenues. The zero effect on costs corresponds to a zero effect on labor costs and number of employees of the training center. Hence, the part of incidence of the subsidy which falls on producers seems to be shifted to producers, namely to owners of training centers.

Figure 10: Distribution of the average subsidy cap for trainings offered by training suppliers



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

Table 4: Impact of changes in CPF subsidy on producers' revenues, costs, profits, labor costs and number of teachers

	(1)	(2)	(3)	(4)	(5)
VARIABLES	$\ln REV_{jt}$	$\ln COST_{jt}$	$\ln \pi_{jt}$	$\ln L_{jt}$	$\ln N_{jt}$
$\bar{c}_{jt}$	0.00130***	0.000464	0.000800*	-0.000444	0.000160
	(0.000475)	(0.000636)	(0.000448)	(0.000668)	(0.000565)
Observations	11,470	10,824	10,756	10,290	10,896
R-squared	0.977	0.973	0.870	0.966	0.967
Years	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019

	(1)	(2)	(3)	(4)	(5)
VARIABLES	$\ln REV_{jt}$	$\ln COST_{jt}$	$\ln \pi_{jt}$	$\ln L_{jt}$	$\ln N_{jt}$
$\ln \bar{c}_{jt}$	0.0630***	0.0202	0.0401**	-0.0126	-0.00361
	(0.0206)	(0.0278)	(0.0204)	(0.0287)	(0.0253)
Observations	11,470	10,824	10,756	10,290	10,896
R-squared	0.977	0.973	0.870	0.966	0.967
Years	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019

The upper panel of the table reports the effect of an increase in the average subsidy allowed for a firms' customers on log revenues, costs, profits, labor costs and employment. All regressions include year and training firm fixed effects and are weighted by the total value of the firm revenues. Standard errors are clustered at the traning firm level. The lower panel uses as independent variable the log of the average subsidy allowed for a firms' customers.

Intuitively, the relationship between log revenues and the average subsidy cap is mediated by how much of a supplier's revenues is coming from CPF trainings. The share of revenues from CPF can vary across suppliers, as different training centers may target individuals with no CPF (like youth or self-employed) or as some trainings are simply not eligible for CPF. Table 5 reports estimates the effect of the 2019 cut in CPF on suppliers with different share of revenues coming from CPF. The estimates signal that, as expected, the effect of the decrease of the subsidy on profits increases with the share of revenues due to CPF. This is reassuring on the fact that the effect on revenues is actually due to policy changes in CPF, since significant effects materialize only for top two quartiles (which correspond to when CPF revenues are >20% of total revenues). A similar pattern emerges from regressions using profits as outcome.

Table 5: Impact of changes in CPF subsidy on producers' revenues: heterogeneity by importance of CPF revenues over total revenues

	(1)	(2)
VARIABLES	$\ln REV_{jt}$	$\ln \pi_{jt}$
$\bar{c}_t * \mathbb{1}(\frac{RevCPF}{TotRev_{jt_0}} < p20)$	-0.000373	0.000250
	(0.000482)	(0.000578)
$\bar{c}_t * \mathbb{1}(p20 < \frac{RevCPF}{TotRev_{jt_0}} \leq p40)$	0.000529	0.000231
	(0.000554)	(0.000602)
$\bar{c}_t * \mathbb{1}(p40 < \frac{RevCPF}{TotRev_{jt_0}} \leq p60)$	0.000995**	0.000478
	(0.000495)	(0.000648)
$\bar{c}_t * \mathbb{1}(p60 < \frac{RevCPF}{TotRev_{jt_0}} \leq p80)$	0.00137***	0.00139**
	(0.000490)	(0.000708)
Observations	11,470	10,756
R-squared	0.979	0.864
Years	2018-2019	2018-2019

Notes. The table reports the effect of an increase in the average subsidy allowed for a firms' customers on log revenues and profits by quartile of the share of revenues of a firm coming from CPF. All regressions include year and training firm fixed effects and are weighted by the total value of the firm revenues. Standard errors are clustered at the training firm level.

6 Mechanisms: Is the Training Market Competitive?

The effect of a subsidy on prices, quantities and producer surplus derives from the structural fundamentals of the market: how elastic are demand ad supply, and how competitive is the market. As a final piece of our analysis, in this section we discuss the implications of our results for the shape of the elasticities of demand and supply in the training market and its degree of competitiveness. Weyl and Fabinger (2013) show that with suppliers' market power, measured by a parameter θ ranging from zero (perfect competition) to one (monopoly), producers optimization requires that the pass-through of the subsidy results from a mix of elasticities and market power:

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

where $1 - \rho$ is the pass through we derived in Section 3. $\epsilon_d, \epsilon_s \in [0, 1]$ are the elasticities of demand and supply respectively, and ϵ_{ms} is the elasticity of the inverse marginal consumers' surplus. $\epsilon_{ms} \in [-\infty, +\infty]$ can be interpreted as the degree of convexity of the demand function, with $\epsilon_{ms} = 1$ when demand is linear, $\epsilon_{ms} > 1$ when it's concave, $\epsilon_{ms} < 1$ when it's convex and $\epsilon_{ms} < 0$ when it's log-convex. Instead, ϵ_θ is the elasticity of the competition parameter with respect to quantity. We can assume $\theta/\epsilon_\theta = 0$, as in Pless and van Benthem (2019), and as in Cournot's models and the Dixit-Stiglitz model of oligopoly. At this point, we can recall our empirical estimate of the pass-through rate:

$$1 - \rho = -\frac{d(p - c)}{dc} = 1 - \frac{\beta^{RF}_{prices}}{\beta^{FS}}$$

And note that we can recover the elasticity of demand from our estimates in Section 3 and 4[13]:

$$\frac{dx/x}{dc} = \frac{dx/x}{d(p-c)}\frac{d(p-c)}{dc} \qquad\qquad \Rightarrow \frac{dx/x}{d(p-c)/(p-c)} = -\epsilon_d = \frac{\beta^{RF}_{quantities}}{\beta^{RF}_{prices} - \beta^{FS}}(p-c)$$

Where the last equation is obtained since $\frac{dx/x}{dc}$ is the effect of a change in the subsidy on log quantities estimated in Section 4, $\frac{\beta^{RF}_{quantities}}{\beta^{FS}}$. Thus, we can derive an expression for the elasticity of supply ϵ_s which rationalizes our estimates, in terms of the degree of competition in the market θ and the parameter ϵ_{ms} measuring the concavity of the demand function.

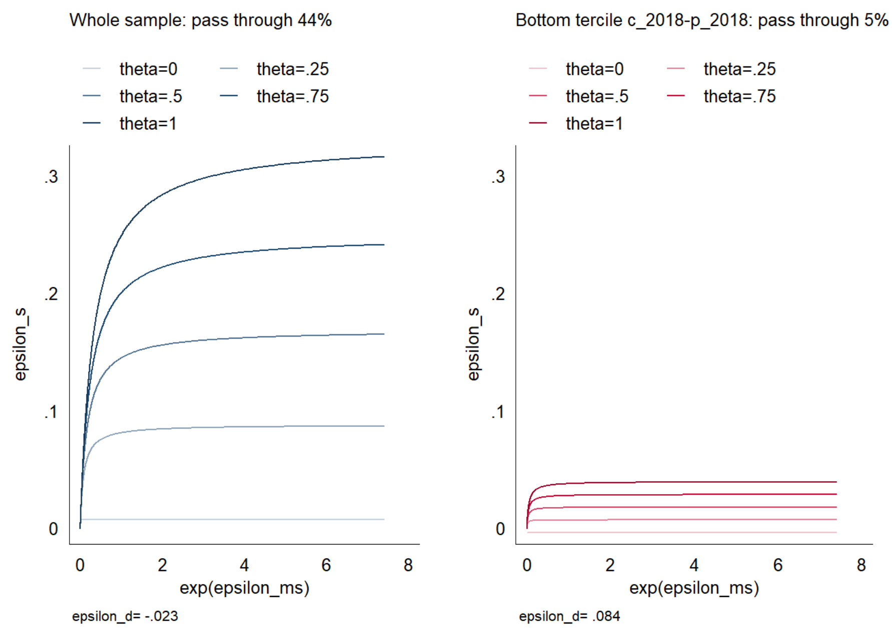
$$\epsilon_s = \frac{\theta - \frac{\beta^{RF}_{quantities}}{\beta^{FS} - \beta^{RF}_{prices}}(p-c)}{1 + \theta/\epsilon_{ms} + \frac{\beta^{FS}}{\beta^{FS} - \beta^{RF}{prices}}} \tag{7}$$

Figure 11 reports the values of ϵ_s estimated. The left panel uses the estimates of β^{FS}, β^{RF}_{prices} and $\beta^{RF}_{quantities}$ obtained using the whole sample, where pass-through $1-\rho$ is .44, and plugs them into Equation 7. Instead, the right panel considers the estimates when we focus only on training kind/industry pairs from the bottom tercile in the difference between the subsidy rate and the price in 2018, where the subsidy cut "bites", and pass-through is close to zero. In Section 3.2, we showed in fact that the pass-through is more informative of structural elasticities of supply and demand for lower values of the difference between the subsidy rate and the price in 2018. Hence, we tend to prefer the interpretation in the right panel.

---

[13] Note that we cannot also use $\frac{dx/x}{dc} = \frac{dx/x}{dp}\frac{dp}{dc} \Rightarrow \frac{dx/x}{dp/p} = \frac{\beta^{RF}_{quantities}}{\beta^{RF}_{prices}-1}(p-c) = \epsilon_s$ as it requires that prices are equal marginal costs.

Figure 11: Values of the estimated elasticity of the supply of training ϵ_s as a function of market power θ and the elasticity of consumers' marginal surplus ϵ_{ms}



Notes. The table reports the values of the elasticity of supply (epsilon_s) in terms of market power theta and elasticity of consumers' marginal surplus epsilon_ms (which measures the concavity of the demand function), obtained by substituting the estimates of the elasticity of demand and of pass-through from our data, in the equation of pass-through with market power derived by Weyl and Fabinger (2013). The left panel uses the estimates of pass-through considering the whole sample, from Table 1 column 5 and Table 3 column 4. The right panel uses estimates from Table 2 column 4 and Table 3 column 6,, focusing only on the bottom tercile, where prices are above subsidies and subsidy cut fully bites.

Figure 11 suggests that our results can be rationalized either with perfect competition and near-zero elasticity of supply of training or with imperfectly competitive training markets. In fact, with $\theta = 1$ (perfect competition), both elasticity of supply and demand are near zero. If instead one wants to allow supply to be moderately elastic, we need to introduce some degree of imperfect competition, up to assuming monopoly ($\theta = 0$). Especially when using only training from the bottom tercile of the difference between the subsidy rate and the price in 2018, as in the right panel of Figure 11, the level of market power needed to obtain elastic supply becomes quickly high, getting close to 1 (i.e. monopoly) for even mildly elastic supply curves.

Yet, both quantitative and qualitative reasons suggest that we should reject the perfect competition mechanism. Quantitatively, we showed how a reduction in the CPF subsidy leads to a substantial reduction in training prices gross of the subsidy. If prices were following marginal costs and markups were zero, this should be mirrored by a reduction in marginal costs, For example, one can think that unobserved time-varying conditions allowed producers to spend less to guarantee the same demand for training (e.g. if they can lower quality without consumers noticing/caring). However, Table 3 reports a zero effect of the reform on suppliers costs. In addition, the estimated effect of the reduction of CPF on revenues and profits of training suppliers can be seen as direct evidence of the presence of markups and market power. Although formally an industry can still be competitive and report profits as a form of remuneration for capital invested, such a significant fall in profits should lead to a substantial exit of marginal producers from the training market, which Table

8 in the Appendix seems to exclude. Finally, a near-perfectly inelastic supply of training is qualitatively implausible. Marginal costs of training are simply made of labor costs and the rental cost of classrooms or training locations and equipment, and none of them seems to be sufficiently inelastic. Indeed, Table 4 shows that workers capture no rents from the subsidy, hence are likely an elastic factor, and although there is some evidence of inelastic housing supply in France (Fack, 2006), no increase in the number of students per-course was observed.

Why is the market for training less than competitive? In the case of training, asymmetric information about training quality is clearly a significant concern, leading to the risk that the training market becomes a market for "lemons". In fact, DARES (2018) highlights that poor quality of the training was one of the most significant concerns of CPF users. Consumers might thus face high switching costs to ascertain the quality of a competitor. Moreover, French regulators intervened to tackle asymmetric information, for example requiring public certification to training centers to be eligible for public subsidies, or requiring the intermediation of industry financing centers. However, these remedies can turn into sources of market power for suppliers, because applying for CPF eligibility can be long and costly, and building a reputation with industry training financing centers can be difficult (end up in collusion of incumbent training suppliers).

7 Conclusions

In this paper we studied the incidence and welfare effects of training subsidies. Our empirical analysis studies a particular kind of training subsidies, the French CPF, and delivers four results. First, the change (mostly a decrease) in the per-hour CPF subsidy occurred in 2019 was passed-through to consumers only by 48%. Hence, we can infer that more than half of the incidence of the CPF training subsidy falls on training producers. However, we show that CPF can make demand for training locally inelastic, due to the fact that CPF is a per-unit subsidy and that the quantity of training to which the subsidy applies might be limited, either by regulation on the maximum amount of hours of CPF used or by non-monetary costs of training limiting demand. This locally-inelastic demand makes prices irreactive to a change in the subsidy, as the change in the subsidy rate doesn't reduce the effective subsidy (doesn't "bite"). When one focus on cases where prices are instead above the subsidy, then the incidence appears to be almost fully on producers, which constitutes our second result. Third, the amount of training undertaken is not significantly affected by subsidy changes, which is a sufficient statistic to highlight no effect on welfare of training subsidies. Fourth, we show that producers suffer a reduction of revenues and profits, with no effect on costs, including labor costs and employment of trainers.

Our paper offers is insightful for the literature studying the drivers of training demand demand and supply. Our results suggest a relatively small effect of the subsidy on the quantity of training consumed, in spite of the fact that the subsidy covers all monetary costs of training and can be used for either general or specific training. This result seems at odds with the claim that there is a large potential demand for training which is under-financed, an idea dating back to Becker (1964). Perhaps, what depresses demand for training is the presence of non-monetary costs, that make markets for training not clear and demand locally inelastic. Turning to the supply side, our estimates of a low pass-through to consumers imply either perfectly elastic supply or imperfect competition in the training market. This is an interesting case for the literature studying subsidies incidence when suppliers have market power. In comparison, for example, Turner (2012) finds that in the education market student aid doesn't increase tuitions (although institutions reduce their own grants). In the training market, marginal costs are likely comparable to the education market, while it is plausible that market power arises from asymmetric information, as training courses are less standardized and less recognizable by employers. Yet, more research is needed to study the drivers of demand and supply of training – including returns to training and non-monetary costs – as well as the sources of imperfect competition in the market for training – e.g. the role of asymmetric information.

Finally, this paper has relevant implications for human capital policy. First, we show how subsidies like CPF risk ending up in a transfer, mostly to producers, if supply is relatively inelastic or the market less than competitive. Policy makers who want to support human capital investment must – before subsidizing it – ensure that supply is sufficiently elastic and the market competitive. Importantly, regulators might face a tradeoff between the need to guarantee training quality (Acemoglu and Pischke, 1999; Rain, 2017) and the risk that certifications become an entry barrier, reducing competition. Second, our theoretical model highlights how Individual Learning Accounts training subsidies might be intrinsically unable to increase demand for long training, as they *hit the zero lower bound* (see Section 3.2), making demand perfectly inelastic. A solution could be to subsidize also non-monetary costs of training, and better target the subsidy to individuals with more elastic demand for training (e.g. workers with lower opportunity costs), as it was suggested by Cahuc and Zylberberg (2006)[14].

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[14] Another simple policy remedy in the case of CPF include to denominate these accounts directly in Euros, bypassing training centers. In the Appendix we show how if Individual Learning Accounts are denominated in Euros rather than hours, demand tilts on the right of the maximum amount of CPF available. Demand thus becomes steeper, but never perfectly inelastic, making it more likely that equilibrium quantities of training are actually larger.

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A Additional tables and figures

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

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

Table 7: IV estimates of pass-through

	(1)	(2)
VARIABLES	p_t	p_t
c_t	0.523***	0.522***
	(0.0991)	(0.0994)
Observations	527,180	526,975
R-squared	0.592	0.592
Years	2018-2019	2018-2019
add LL Mkt FE		X

Table 8: Effect on entry(/exit)

	(1)
VARIABLES	$\ln n_j$
$\tilde{c}_t$	-0.00162
	(0.00261)
Observations	162,150
R-squared	0.980
Years	2018-2019
Estimation method	OLS

Figure 12: Example of conversion table

Critères de prise en charge OPCA sur le CPF

Identification OPCA

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

I. Informations CPF sur site institutionnel de l'OPCA

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

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

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

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

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

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

Figure 13: Number of accounts by number of hours in the CPF account

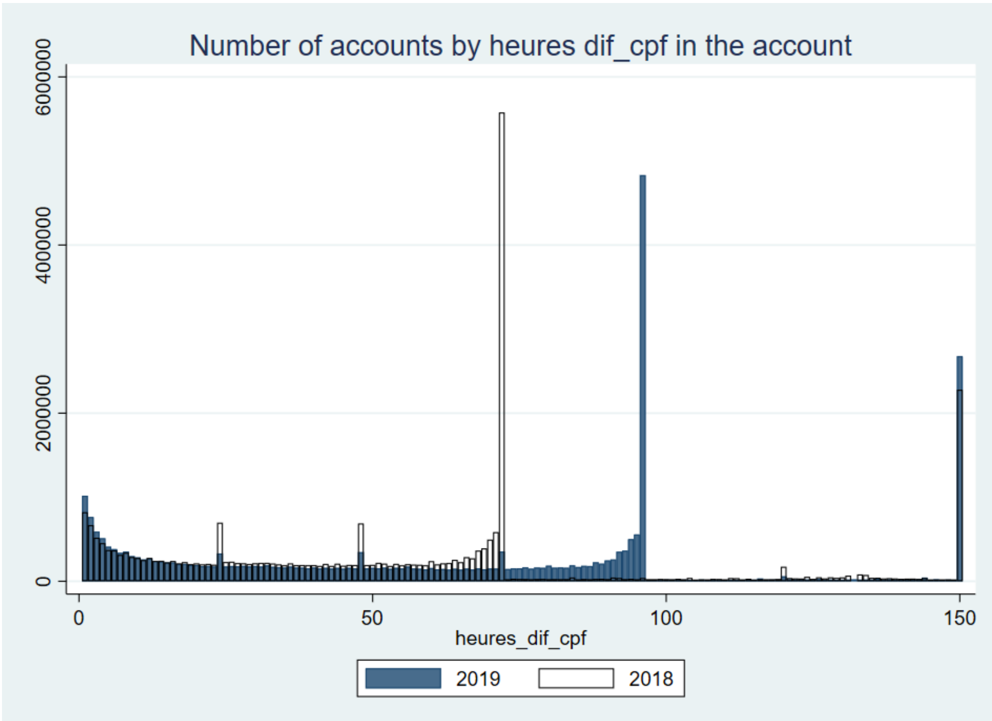


Figure 14: Time series of total cost of trainings undertaken and number of trainings started each week, in 2018 and 2019, breaking down 2019 into trainings validated by industry financing centers and those initiated through the centralized mobile app

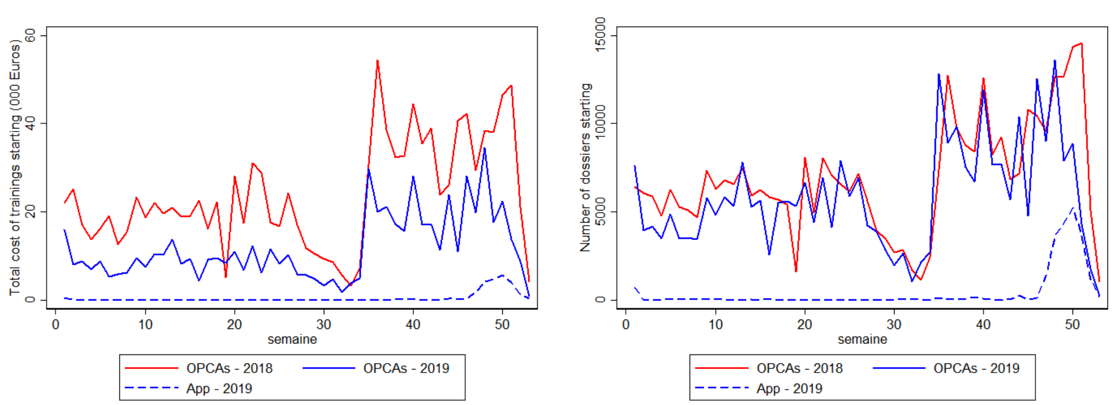


Figure 15: Time series of total number of trainings (training episodes), total hours of training and total cost of training for unemployed (*PRE*) and employees (*salaries*)

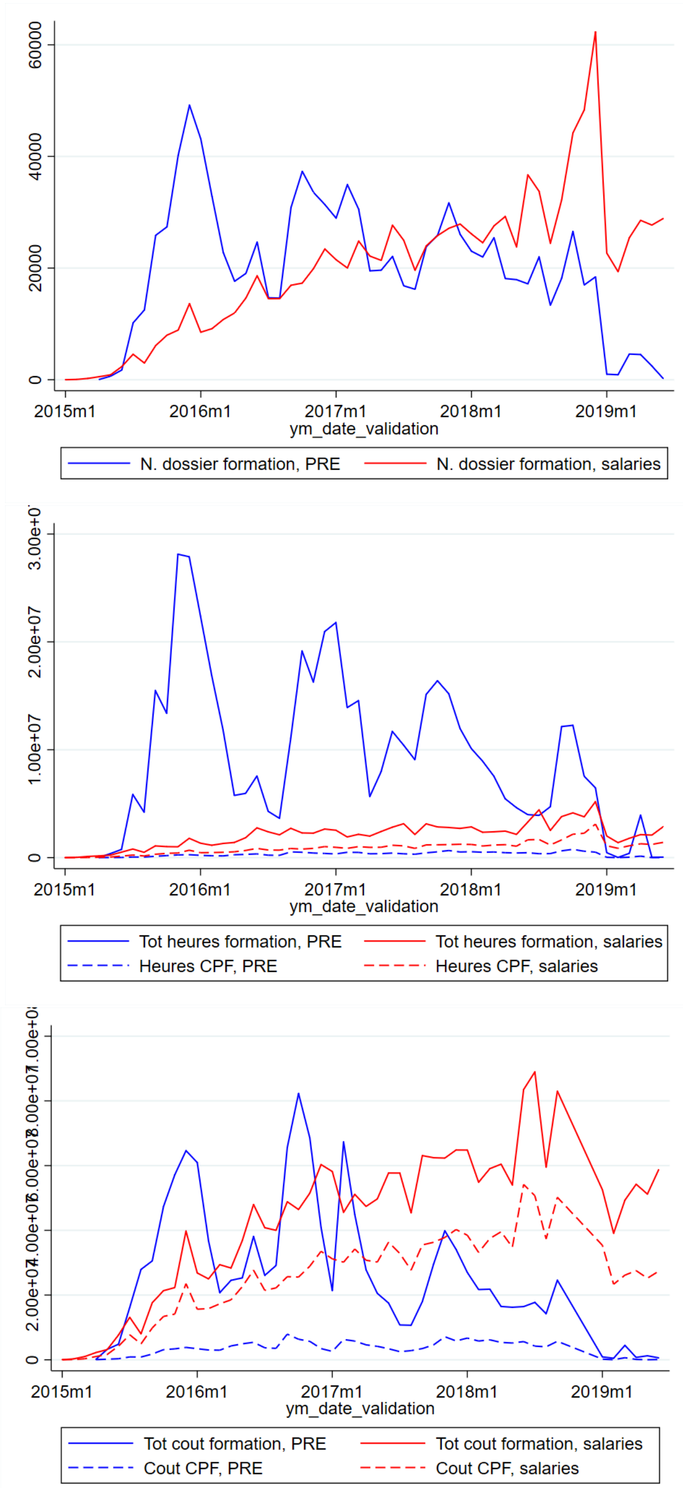


Figure 16: Link between agencies and their industry

Correspondence betwen the industry agency and industry

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

B What Can Make CPF Demand Locally Inelastic

B.1 CPF with training as a discrete choice

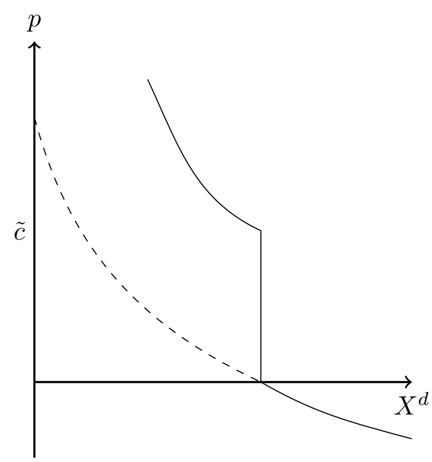
Let us assume training is discrete, i.e. consumers can either train for a fixed amount of hours $\bar{x} < \overline{x^{CPF}}$ or not train. Assume quasi-linear preferences with m_i as numeraire, and that consumers are heterogeneous in their utility from training $\phi_i(\bar{x}) = \phi(\bar{x}) + \eta_i$, where η_i can be interpreted as different benefits from training or different opportunity costs and is distributed as extreme values. Utilities from training and from not training are thus:

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

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

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

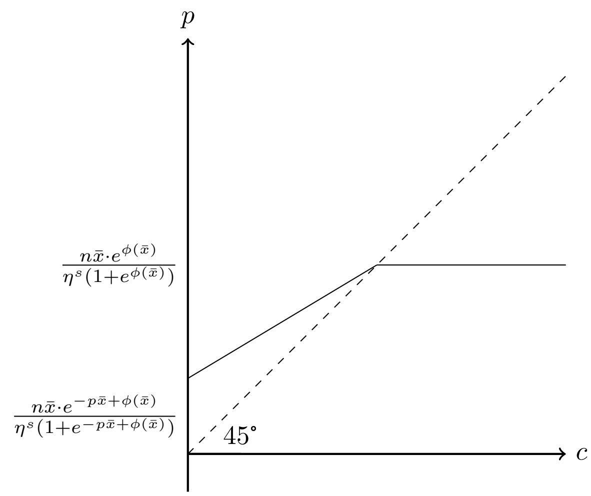
Figure 17: Aggregate demand with training as discrete choice and CPF in hours



With linear supply, in equilibrium:

- If $p > c$, then $\eta^s p = n\bar{x} \cdot e^{-p+c\cdot\bar{x}+\phi(\bar{x})}/(1 + e^{-p+c\cdot\bar{x}+\phi(\bar{x})})$
- If $p \leq c$, then $\eta^s p = n\bar{x} \cdot e^{\phi(\bar{x})}/(1 + e^{\phi(\bar{x})}) \quad \forall p \leq c$

Figure 18: Equilibrium prices as a function of per-hour value of the subsidy



B.2 CPF with training as a continuous choice

Let us assume quasi-linear preferences, for a representative consumer i, where m_i represents consumption of a numeraire good, x_i^{IND} is the consumption of training financed directly by the individual, at price p, and x_i^{CPF} is the amount of hours of training financed with ILA. Suppose there is a cap c on the amount of Euros of subsidy payable for each hour, so that the monetary cost for the consumer of each hour of x_i^{CPF} is either 0 or $p - c$. Together, $x_i^{IND} + x_i^{CPF} = x_i$, the total amount of training consumed. Utility of training is summarized by utility function $\phi(x_i)$, assumed twice differentiable, $\phi'(x_i) > 0, \phi''(x_i) \leq 0$, normalizing $\phi(0) = 0$. Each individual is endowed with monetary wealth ω, and with a total of $\overline{x^{CPF}}$ of CPF credit for training hours, given. With these assumptions, the consumer's problem is:

$$\max_{m_i, x_i^{IND}, x_i^{CPF}} [m_i + \phi(x_i^{IND} + x_i^{CPF})] \qquad s.t. \quad \begin{aligned} & m_i + p\, x_i^{IND} + \max(p-c,0)\cdot x_i^{CPF} \leq \omega \\ & x_i^{CPF} \leq \overline{x^{CPF}} \\ & x_i^{IND} \geq 0 \\ & x_i^{CPF} \geq 0 \end{aligned} \tag{8}$$

We are going to assume that $\omega > 0$, and that $m_i > 0$, so that the first constraint always holds with equality. We can thus re-write the problem as:

$$\max_{x_i^{IND}, x_i^{CPF}} \left[\omega - p\, x_i^{IND} - \max(p-c,0)\cdot x_i^{CPF} + \phi(x_i^{IND} + x_i^{CPF})\right] \qquad s.t. \quad \begin{aligned} & x_i^{IND} \geq 0 \\ & x_i^{CPF} \leq \overline{x^{CPF}} \\ & x_i^{CPF} \geq 0 \end{aligned}$$

1. If $p > c > 0$, the FOCs are:

$$\begin{array}{lll} [x_i^{CPF}]: & \phi'(x_i^{IND\star} + x_i^{CPF\star}) - (p-c) - \lambda \leq 0 & \text{with equality if } x_i^{CPF} > 0 \\ [x_i^{IND}]: & \phi'(x_i^{IND\star} + x_i^{CPF\star}) - p \leq 0 & \text{with equality if } x_i^{IND} > 0 \\ [\lambda]: & \lambda[x_i^{CPF\star} - \overline{x^{CPF}}] = 0 & \end{array}$$

   If $x_i^{CPF\star} = \overline{x^{CPF}}$, then $\lambda > 0$, for the last equality to hold. If $x_i^{IND\star} > 0$, then the second inequality holds with equality, $x_i^{IND\star} = \phi_i'^{-1}(p) - \overline{x^{CPF}}$, and $\lambda = c$ to satisfy the first equality. Note however that for $\phi_i'^{-1}(p) - \overline{x^{CPF}} > 0$ we need $p < \phi'(\overline{x^{CPF}})$. Else, if $x_i^{IND\star} = 0$, then the second inequality holds strictly, while the first holds with equality, so that $\phi'(\overline{x^{CPF}}) + c = p + \lambda > p > \phi'(\overline{x^{CPF}})$. If instead $x_i^{CPF\star} < \overline{x^{CPF}}$, $\lambda = 0$, then the second constraint cannot hold with equality, since if it was, the first cannot hold ever, so $x_i^{IND\star} = 0$. Hence, we can see from the first equality that if $x_i^{IND\star} = 0$ and $\lambda = 0$, then $x_i^{CPF\star} = \phi'^{-1}(p-c)$. Note that since $x_i^{CPF\star} < \overline{x^{CPF}}$, then $p > \phi'(\overline{x^{CPF}}) + c$.

2. If $c \geq p > 0$, the FOCs are:

$$\begin{array}{lll} [x_i^{CPF}]: & \phi'(x_i^{IND\star} + x_i^{CPF\star}) - \lambda \leq 0 & \text{with equality if } x_i^{ILA*} > 0 \\ [x_i^{IND}]: & \phi'(x_i^{IND\star} + x_i^{CPF\star}) - p \leq 0 & \text{with equality if } x_i^{IND*} > 0 \\ [\lambda]: & \lambda[x_i^{CPF\star} - \overline{x^{CPF}}] = 0 & \end{array}$$

   If $\lambda > 0$, then $x_i^{CPF\star} = \overline{x^{CPF}}$, $x_i^{IND\star} = \phi_i'^{-1}(p) - \overline{x^{CPF}}$. Then, if $p < \phi'(\overline{x^{CPF}})$, then $x_i^{IND\star} > 0$, and $\lambda = p$. Else, if $p \geq \phi'(\overline{x^{CPF}})$, $x_i^{IND\star} = 0$ for feasibility. Finally, if $\lambda = 0$ then the first constraint contradicts $\phi'(.) > 0$.

The resulting Walrasian demand for the representative consumer is perfectly inelastic at the maximum amount of hours available in the account:

- If $p \geq \phi'(\overline{x^{CPF}}) + c$, then $p = \phi'(x_i^{CPF\star}) + c$ and $x^\star = \phi'^{-1}(p-c)$
- If $\phi'(\overline{x^{CPF}}) + c > p > \phi'(\overline{x^{CPF}})$, then $x_i^\star = \overline{x^{CPF}}$
- If $p \leq \phi'(\overline{x^{CPF}})$, then $p = \phi'(x_i^{IND} + \overline{x^{CPF}})$ and $x_i^\star = \phi'^{-1}(p)$

Aggregate demand simply multiplies the amount demanded by the representative consumer by N. In equilibrium:

Figure 19: Equilibrium with training as continuous choice and CPF with maximum hours allowed $\overline{x^{CPF}}$

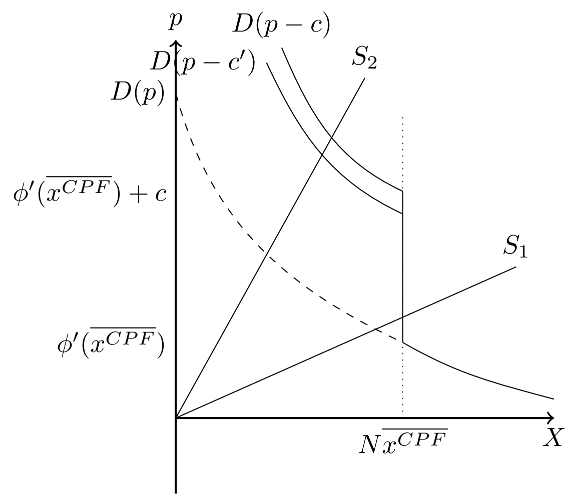


Figure 19 provides some intuition about the effect of subsidies capped in per-unit value and in total units. First, for any price which, with no subsidies, would yield a quantity demanded below $\overline{x^{CPF}}$ (the maximum number of units subsidized), demand shifts up by the per-hour value of the subsidy c. This means that for very costly trainings, in the upper right of Figure 19, since price exceeds the per-hour subsidy by more than the marginal utility of the last hour subsidizable plus the per-hour value of the subsidy, people will not use all their subsidy units(CPF hours in our case), as the extra price they have to pay on top of c tapers their demand. Conversely, for cheap trainings, individuals would be already demanding, without any subsidy, a quantity above the maximum amount of hours allowed by the subsidy, so that with the introduction of CPF in hours, nothing changes in terms of optimal quantity demanded. In fact, the marginal utility of the $(\overline{x^{CPF}}+1)$th hour is unchanged, the marginal utility of the numeraire m_i as well (as we assumed quasi-linear preferences), hence the quantity demanded is unchanged. Finally, when prices are above the marginal utility of the maximum amount of hours subsidizable $\phi'(\overline{x^{CPF}})$, but below $\phi'(\overline{x^{CPF}})+c$, people use all their CPF and don't add any training hours (yet, they may pay $(p-c)\cdot\overline{x^{CPF}}$ if $p>c$). This kinked demand differs from the standard case of a excise (per-unit) subsidy, where the subsidy pushes demand up by the per-unit value of the subsidy at any price level.

With linear supply[15]:

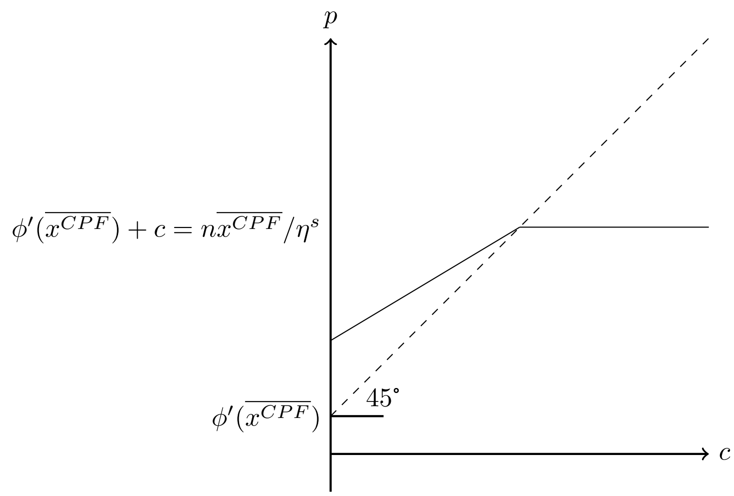
$$X^s = \eta^s p$$

In equilibrium, $X^d = X^s$, so that:

$$\begin{cases} \eta^s p = n\cdot\phi'^{-1}(p-c) & \text{if} \quad p>\phi'(\overline{x^{CPF}})+c \\ \eta^s p = n\cdot\overline{x^{CPF}} & \text{if} \quad \phi'(\overline{x^{CPF}})+c>p>\phi'(\overline{x^{CPF}}) \\ \eta^s p = n\cdot\phi'^{-1}(p) & \text{if} \quad p<\phi'(\overline{x^{CPF}}) \end{cases}$$

[15]The case of log-linear supply is analogous. Take the equilibrium condition for $\phi'(\overline{x^{CPF}})+c>p>\phi'(\overline{x^{CPF}})$, which is $\eta^s\ln p=\kappa-\eta^d\ln(p-c)$. One needs to implicitly differentiate for c to obtain $\frac{dp}{dc}=\frac{\frac{\partial x^d}{\partial c}}{\frac{\partial x^s}{\partial p}-\frac{\partial x^d}{\partial p}}$, and by rearranging $\frac{d\ln p}{d\ln c}=\frac{\frac{\partial x^d/x^d}{\partial c/c}}{\frac{\partial x^s/x^s}{\partial p/p}-\frac{\partial x^d/x^d}{\partial p/p}}$. This means that Figure 20 is the same but with logs on the axis.

Figure 20: Equilibrium prices as a function of per-hour value of the subsidy



B.3 Example of discrete variation with with linear demand

Building on the case of training as continuous choice in the previous section, in this one we show that reactions to discrete changes in subsidy rates will end up in different structural relationships between prices and subsidies. With linear demand, we are able to write down explicitly the equilibrium relationship between competitive prices and conversion rates:

$$p = R(\eta^d, \eta^s, \kappa, \overline{x^{CPF}}) \circ c = \begin{cases} p = \frac{\kappa}{\eta^s+\eta^d} + \frac{\eta^d}{\eta^s+\eta^d}c & \text{if} \quad c < p - \phi'(\overline{x^{CPF}}) \\ p = \overline{x^{CPF}}/\eta^s & \text{if} \quad c \geq p - \phi'(\overline{x^{CPF}}) \geq 0 \end{cases} \tag{9}$$

This equilibrium relationship $R(.) \circ c$ has a kink when $p = c$, as depicted in Figure 20.

Subsequently, let us introduce time subscript t and study the effect of a discrete variation in c_t, $\Delta c_t = c_t - c_{t-1}$, on prices $\Delta p_t = p_t - p_{t-1}$. Using Equation (9) to substitute p_t into Δp_t, one ends up with four cases:

1. if $c_t \geq \frac{\overline{x^{CPF}}}{\eta^s} + \frac{\overline{x^{CPF}}}{\eta^d} - \frac{k}{\eta^d}$ and $c_{t-1} \geq \frac{\overline{x^{CPF}}}{\eta^s} + \frac{\overline{x^{CPF}}}{\eta^d} - \frac{k}{\eta^d}$, then:
$$\Delta p_t = 0$$

2. if $c_t > \frac{\overline{x^{CPF}}}{\eta^s} + \frac{\overline{x^{CPF}}}{\eta^d} - \frac{k}{\eta^d} > c_{t-1}$, then
$$\Delta p_t = \frac{\overline{x^{CPF}}}{\eta^s} - \frac{\kappa}{\eta^s + \eta^d} - \frac{\eta^d}{\eta^s + \eta^d} c_{t-1}$$

3. if $c_t < \frac{\overline{x^{CPF}}}{\eta^s} + \frac{\overline{x^{CPF}}}{\eta^d} - \frac{k}{\eta^d} < c_{t-1}$, then
$$\Delta p_t = \frac{\kappa}{\eta^s + \eta^d} + \frac{\eta^d}{\eta^s + \eta^d} c_t - \frac{\overline{x^{CPF}}}{\eta^s}$$

4. if $c_t \leq \frac{\overline{x^{CPF}}}{\eta^s} + \frac{\overline{x^{CPF}}}{\eta^d} - \frac{k}{\eta^d}$ and $c_{t-1} \leq \frac{\overline{x^{CPF}}}{\eta^s} + \frac{\overline{x^{CPF}}}{\eta^d} - \frac{k}{\eta^d}$, then:
$$\Delta p_t = \frac{\eta^d}{\eta^s + \eta^d} \Delta c_t$$

Again, some intuition helps to steer the model. In case 1, both c_t and c_{t-1} are to the right of the kink in Figure 20, meaning that the per-hour value of the subsidy at both periods are above the critical value for which individuals use all of their CPF subsidy. In this case, the per-hour value of the subsidy is below equilibrium prices both at $t-1$ and t, so expected reaction of prices is zero. At the other extreme, in case 4, both c_t and c_{t-1} are binding, meaning that both at t and $t-1$ we have $p_t \geq c_t + \phi'(\overline{x^{CPF}})$: the equilibrium price is in any case so high, even with the subsidy, that the individual demands a quantity lower than the maximum amount that the CPF covers. Hence, the constraint of the maximum amount of hours available doesn't bind, and a change in c is akin to the standard case of a change in a excise subsidy. In Figure 20, this means that both levels of c lie left of the kink. In Figure **??**, this means that both equilibria lie in the up left part of the graph, where demand is downward sloped, and a decrease (resp. increase) in c just shifts demand and the equilibrium point down-left (resp. up-right). Case 2 and case 3 are symmetric cases where instead only one of the two caps c_t and c_{t-1} binds. In Figure 20, this means moving across the kink, from left to right (case 2) or from right to left (case 3).

Now, how can we estimate η^d, η^s, from $R(\eta^d, \eta^s, \kappa, \overline{x^{CPF}})$? By looking at the four cases just enumerated, one sees that first-differencing gets rid of $\overline{x^{CPF}}$ and κ only in case 4. Yet, whether or not one ends up in case 4 depends from c_t, c_{t-1}, $\overline{x^{CPF}}$, κ and unknown η^d, η^s. In theory, one could measure $\overline{x^{CPF}}$, make assumptions on κ, and estimate a threshold model of regime changes for the four cases (Potter, 1999). A more simple and agnostic approach is to approximate Equation (9) with a logaritmic function or with a piecewise-linear function. This would account for the fact that, due to peculiarities of ILA, shocks to high per-hour subsidies relative to prices should generate a lower reaction in prices than shocks to lower per-hour subsidies, within the same training. Note in fact that fitting a linear model regressing Δp on Δc would underestimate $\frac{\eta^d}{\eta^s+\eta^d}$. Then, one can assume that the derivative of the log or the slope of the piece-wise linear function around the median value of c_t approximates well $\frac{\eta^d}{\eta^s+\eta^d}$.

B.4 What changes with discretionary additions?

Often, at least in the case of the French CPF, training agencies or firms guarantee discretionary additions to the basic value of CPF hour credits. This doesn't affect the basic functioning of the model we just described, but makes the interpretation of the parameters different. Consider again the consumer (trainee) problem in (8). Any kind of discretionary addition to the basic CPF credits can be modeled as doing either one or both of two things: guaranteeing extra hours of CPF so that $x^{\tilde{CPF}} = \overline{x^{CPF}} + M$, and/or increasing the per-hour subsidy cap c by a fraction μ of the difference between prices and the per-hour value of the subsidy. To model this, define $c = c + \mu \cdot \max(p - c, 0)$, the actual cap to per-hour subsidy, gross of discretionary per-hour component. We can re-write the consumer problem as:

$$\max_{m_i, x_i^{IND}, x_i^{CPF}} [m_i + \phi(x_i^{IND} + x_i^{CPF})] \qquad s.t. \quad \begin{aligned} & m_i + p\, x_i^{IND} + \max(p - c, 0) \cdot x_i^{CPF} \leq \omega \\ & x_i^{CPF} \leq x^{\tilde{CPF}} \\ & x_i^{IND} \geq 0 \\ & x_i^{CPF} \geq 0 \end{aligned}$$

The handling of problem is analogous to the one without additions. First, we simply need to substitute $x^{\tilde{CPF}} = \overline{x^{CPF}} + M$. Integrating $c = c + \mu \cdot \max(p - c, 0)$ is more tricky, since while c is given, c is a function of prices, so that it is endogenous to competitive equilibrium. Hence, we need to solve again for competitive equilibrium, as in section 2.2, taking μ into account, obtaining:

$$p = \tilde{R}(\eta^d, \eta^s, \kappa, x^{\tilde{CPF}}, \mu, c) = \begin{cases} p = \frac{\kappa}{\eta^s+\eta^d} \frac{1}{1-\frac{\eta^d}{\eta^s+\eta^d}\mu} + \frac{\eta^d}{\eta^s+\eta^d} \frac{1-\mu}{1-\frac{\eta^d}{\eta^s+\eta^d}\mu} c & \text{if} \quad c < p - \frac{\phi'(x^{\tilde{CPF}})}{1-\mu} \\ p = x^{\tilde{CPF}}/\eta^s & \text{if} \quad c \geq p - \frac{\phi'(x^{\tilde{CPF}})}{1-\mu} \geq 0 \end{cases} \tag{10}$$

Finally, the four cases of reactions of prices to a discrete change the subsidy, according to the reaction function are:

1. if $c_t \geq \frac{x^{\tilde{CPF}}}{\eta^s} + \frac{x^{\tilde{CPF}}}{\eta^d(1-\mu)} - \frac{k}{\eta^d(1-\mu)}$ and $c_{t-1} \geq \frac{x^{\tilde{CPF}}}{\eta^s} + \frac{x^{\tilde{CPF}}}{\eta^d(1-\mu)} - \frac{k}{\eta^d(1-\mu)}$, then:

$$\Delta p_t = 0$$

2. if $c_t > \frac{x^{\tilde{CPF}}}{\eta^s} + \frac{x^{\tilde{CPF}}}{\eta^d(1-\mu)} - \frac{k}{\eta^d(1-\mu)} > c_{t-1}$, then

$$\Delta p_t = \frac{x^{\tilde{CPF}}}{\eta^s} - \frac{\kappa}{\eta^s + \eta^d} \frac{1}{1 - \frac{\eta^d}{\eta^s+\eta^d}\mu} + \frac{\eta^d}{\eta^s + \eta^d} \frac{1-\mu}{1 - \frac{\eta^d}{\eta^s+\eta^d}\mu} c_{t-1}$$

3. if $c_t < \frac{x^{\tilde{CPF}}}{\eta^s} + \frac{x^{\tilde{CPF}}}{\eta^d(1-\mu)} - \frac{k}{\eta^d(1-\mu)} < c_{t-1}$, then

$$\Delta p_t = \frac{\kappa}{\eta^s + \eta^d} \frac{1}{1 - \frac{\eta^d}{\eta^s+\eta^d}\mu} + \frac{\eta^d}{\eta^s + \eta^d} \frac{1-\mu}{1 - \frac{\eta^d}{\eta^s+\eta^d}\mu} c_t - \frac{x^{\tilde{CPF}}}{\eta^s}$$

4. if $c_t \leq \frac{x^{\tilde{CPF}}}{\eta^s} + \frac{x^{\tilde{CPF}}}{\eta^d(1-\mu)} - \frac{k}{\eta^d(1-\mu)}$ and $c_{t-1} \leq \frac{x^{\tilde{CPF}}}{\eta^s} + \frac{\overline{x^{CPF}}}{\eta^d(1-\mu)} - \frac{k}{\eta^d(1-\mu)}$, then:

$$\Delta p_t = \frac{\eta^d}{\eta^s + \eta^d} \frac{1-\mu}{1 - \frac{\eta^d}{\eta^s+\eta^d}\mu} \Delta c_t$$

To wrap up, even in case 4, in presence of discretionary additions the relationship between a change in the per-hour subsidy and prices depends not only on demand and supply elasticities, but also on the parameter μ, the generosity of the per-hour discretionary addition. To estimate this extra parameter note that if $p > c$ $c = c + \mu(p - c) = (1-\mu)c + \mu p$, and that consequently:

$$\Delta \tilde{c_t} = (1-\mu) \left[1 + \frac{\eta^d}{\eta^s + \eta^d} \frac{\mu}{1 - \frac{\eta^d}{\eta^s+\eta^d}\mu} \right] \Delta c_t \tag{11}$$

So, although μ represents an additional parameter to be estimated, one can rely on a "first-stage" relationship as in (11) to recover it.