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

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Abstract

This paper studies the incidence and welfare effects of a particular kind of training subsidies, Individual Learning Accounts (ILA). We exploit a natural experiment provided by the reform of a French ILA, the *Compte personnel de formation* (CPF). First, we theoretically model the impact of changing the per-hour subsidy rate on demand and supply for training, using a simple partial equilibrium model. Informed by this, we study the impact of a reform of 2019, which differentially lowered the per-hour value of the CPF subsidy across industries. We highlight three results. First, the supply of training is between 15% and 50% less elastic than demand, so that more than half of the benefit of the subsidy is captured by training producers. Second, total hours of training undertaken are not significantly affected by subsidy changes, leading to estimates of demand and supply elasticities which are close to zero. This makes CPF subsidy a simple transfer to producers and trainees. The silver lining is that, when studied through the lenses of a sufficient statistics framework, the efficiency cost of CPF is also low. Third, we use data on revenues and expenses of training to see that the reduction of the subsidy eventually translates in a reduction of producers' profits, with no effect on labor costs and employment of trainers.

Keywords: training, individual learning accounts, incidence, salience, entry barriers

JEL Codes: M53, H22, J24, J28

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1 Introduction

Adult learning is considered important 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 prescription. However, Microeconomic theory dating back to Harberger (1962) suggests that the welfare effects of subsidies depend on the reaction of equilibrium prices and quantities, hence on market characteristics summarized by the elasticities of demand and supply. As a general rule, the incidence of a tax/subsidy falls on the less elastic side of the market (Fullerton and Metcalf, 2002), so that if supply is relatively inelastic, the benefit of the subsidy is partially of fully captured by producers. This prediction is confirmed in several contexts: for example, in the housing market (Gibbons and Manning, 2006; Fack, 2006), or in the market for health insurance (Cabral et al., 2018). Conversely, in markets where suppliers have a lower market power the pass-through rate is minimal (e.g. in the education market, Turner, 2012). Notwithstanding these regularities, the empirical literature reports several cases where peculiarities of market conditions make the predictions of standard incidence theory fail (Sallee, 2011; Kirwan, 2009; Pless and van Benthem, 2019; Benzarti et al., 2020). Incidence questions remain therefore open, especially in contexts characterized by potential market failures or behavioral issues.

The market for training is likely not a perfectly competitive one, and the peculiarities of demand and supply are both crucial for the success of a training subsidy and hard to predict. On the demand side, private returns to training are widely uncertain, while spillovers are likely, both positive and negative (Bassanini et al., 2005). In particular, the so-called poaching externality may lead to under-financing of training by employers and workers, possibly justifying public support to investment in training (Becker, 1964; Acemoglu and Pischke, 1999). On the supply side, asymmetric information on training quality can create a market for "lemons", so that signaling devices like reputation or repeated interaction, as well as policy mechanisms such as certifications, play an important role. However, these could in turn build entry barriers and jeopardize competition, especially in the short run. If demand is relatively more elastic than supply, then subsidies might be more beneficial to training providers than to consumers. If either demand or supply are instead very inelastic, then the subsidy would not push up the quantity of training consumed as desired, and the policy will end up being just a transfer of resources to trainees and training suppliers.

This paper studies what is the incidence of training subsidies. We exploit a natural experiment provided by the 2019 reform of the French *Compte Personnel de Formation* (CPF), a national Individual Learning Account (ILA) in which each French worker accumulates training credits, proportionally to tenure, which workers can use to finance trainings by certified providers. This device represented a large investment for the French government, and was relatively welcomed by social parties. Only some scholars had voiced concerns, already before the introduction of CPF, about the risks arising from lack of competition and detrimental consequences on equity(Cahuc and Zylberberg, 2006).

The CPF was introduced in 2015, and reformed in 2019. Between 2015 and 2018 each industry was allowed to finance his own CPF, with richer industries offering more generous subsidies. The 2019 reform differentially lowered the per-hour value of the subsidy across industries, fixing a uniform subsidy of 15 Euros per-hour. Using administrative data from the operating system of CPF, we compare different industries across time within each training kind, studying the effect of a change in the subsidy on prices and quantities of training. In addition, we merge data on trainings with administrative data on training providers, including balance-sheet information and details on the workforce. This allows us to disentangle the final incidence of the subsidy on production factors, by measuring the effect of the policy change on profits and employment.

Our results show that, in terms of incidence, a reduction in the per-hour cap triggers a 19-20% reduction in total subsidies (discretionary additions by industry training agencies attenuate the cut of the subsidy), and a 10-12% decrease in prices. This points out how the incidence of CPF falls partially on suppliers of training, but also that supply of training is found to be relatively less elastic than demand. Equilibrium quantities, measured as total hours of training, are instead not significantly affected. This suggests that both demand and supply are inelastic enough to make the CPF 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 to see that the reduction of prices translated in a reduction of profits, not of costs. In particular, no effect is detected on labor costs and number of trainees. This can be seen as evidence of the presence of rents for capital invested in the training market, perhaps due to entry barriers or simply as risk premium.

Chiefly, our results speaks to literature on on-the-job training and training policy evaluation. This literature has often focused on the question of whether or not training is under-supplied/under-demanded (Bassanini et al., 2005), so as to justify (or not) subsidization policies, but ignored the risk that training subsidies might be ineffective in equilibrium. We are the first, to our knowledge, to study the incidence of training subsidies. Our results confirm that consumers demand for training is not much responsive to monetary incentives which relatively small in total value (Görlitz and Tamm, 2016). This supports the conclusions of Cahuc and Zylberberg (2006) who advocated for better targeting of training subsidies on weaker workers for longer trainings. In this low demand environment, our results highlight how low elasticity of supply can make training subsidies look like a transfer to producers and trainees, impacting only gross and net prices, not quantities of training.

Second, ours is the first paper that studies training in the form of ILA. Some experimental studies on the effect ILA were run administrating information treatments about small training vouchers programs Hidalgo et al. (2014); Van den Berg et al. (2020), finding insignificant effects on take up. This new device is on the rise in European policy environments. Yet, we highlight how it's intrinsically unable to increase demand of long trainings, making demand perfectly inelastic around the maximum amount of hours subsidizable and unchanged for for longer hours. Simple policy remedies in the case of ILA include to denominate these accounts in Euros, and to better target weaker workers. More generally in the case of training subsidies policy makers should better consider the reasons why demand and supply of training might be inelastic. We discuss some hypothesis briefly in the conclusions.

Finally, our study is relevant for the literature on subsidies incidence and competition, which bridges Public Economics and Industrial Organization. Our results are fairly consistent with the traditional model of subsidies incidence, showing how the training subsidy affects prices. The effect on training providers' profits suggests however the presence of entry barriers in the training market, which allow short-run rents to capital invested in training centers.

The rest of this article is structured as follows. Section 2 introduces a model of Individual Learning Accounts which we use to interpret the effect of a change in CPF training subsidies on prices. Section 3 presents our empirical setting: the institutional context, the data and measurement we use, and descriptives of the policy shock. Section 4 presents the results of our study on the effect of a change in the CPF subsidy on prices. Section 5 presents the results concerning the effect on quantities, which in a sufficient statistics framework yield insights on the efficiency cost of the CPF subsidy. Section 6 looks at the effect of the subsidy cut on suppliers of training, particularly on revenues, costs, profits and employment. Section 7 discusses possible interpretations of the results and concludes.

2 A model of a particular kind of training subsidies: Individual learning accounts (ILAs)

According to OECD (2019), Individual Learning Accounts (ILAs) are defined as "virtual, individual accounts in which training rights are accumulated over time". They are virtual in the sense that resources are only mobilised if training is actually undertaken, and lost otherwise[1]. They are individual in the sense that such accounts are attached to individuals, rather than to a specific employer or employment status, and remain at their disposal to undertake training along their working lives and at their own initiative. An example of ILA is the French *Compte Personnel de Formation* (CPF), considered in international comparison as a paradigm of a fully-fledged, nation-wide ILA. Yet, several similar schemes exist[2], and more are on the rise: versions of national ILAs have been discussed in Italy and Germany, and an Initiative on Individual Learning Accounts is included in the European Skills Agenda of 2020.

In this section we propose a simple partial equilibrium model to study the impact on demand and supply of ILAs when the ILA is denominated in hours. This corresponds to a setting where individuals have the right to a specific amount of *hours* of training, subsidized up to a per-hour cap to the monetary value of the subsidy. This is the case of the French CPF before 2019 reform and in the transition period of 2019, which will be the setting of our empirical section. In the following passages, we will use our theoretical model to interpret the change in prices and quantity following a shock to the per-hour value of the subsidy. In the next section, we will see how this example corresponds to the case of French CPF in January 2019. In the Appendix, we also study ILAs denominated in money, where individuals have right to training subsidies up to a total monetary amount, independently from hours, and accumulate training credits in local currency (we will from now on refer to them as credits in "Euros"). This second case is instead the case of CPF after November 2019 and, although interesting, it is out of the scope of our empirical part.

[1] This distinguishes them from Individual Saving Accounts such as learn$ave in Canada and the Lifelong Learning Accounts in the United States.

[2] A similar scheme to ILA are training vouchers. These are more diffused. Examples of voucher 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). These programs are often concentrated at regional or sectoral level, and our model is applicable to them as well, as long as these subsidies are denominated in hours with a cap to total per-hour subsidy, or fully denominated in Euros. The difference between ILA and vouchers is that ILA are accumulated over time, while vouchers are more often contingent on some specific condition of the worker or of the training undertaken, or they are in force for limited time windows. This difference is not relevant for our simple static model, in which the individual does not choose strategically between the possibility of using training subsidies today or wait to accumulate more (in the case of ILA).

2.1 Demand for training with ILA in hours and limit to per-hour subsidy (CPF pre-reform case)

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^{ILA} 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^{ILA} is either 0 or $p - c$. Together, $x_i^{IND} + x_i^{ILA} = x_i$, 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_i, and with a total of $\overline{x^{ILA}}$ ILA hours, given. With these assumptions, the consumer's problem is:

$$\max_{m_i, x_i^{IND}, x_i^{ILA}} [m_i + \phi(x_i^{IND} + x_i^{ILA})] \qquad s.t. \quad \begin{aligned} & m_i + p\, x_i^{IND} + \max(p-c, 0) \cdot x_i^{ILA} \leq \omega_i \\ & x_i^{ILA} \leq \overline{x^{ILA}} \\ & x_i^{IND} \geq 0 \\ & x_i^{ILA} \geq 0 \end{aligned} \tag{1}$$

We are going to assume that $\omega_i > 0$, and that $m_i > 0$, so that the first constraint always holds with equality. Solving the problem (in the Appendix), the resulting Walrasian demand for the representative consumer is:

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

Which can be plotted in Figure 1.

Figure 1: Demand with ILA in hours

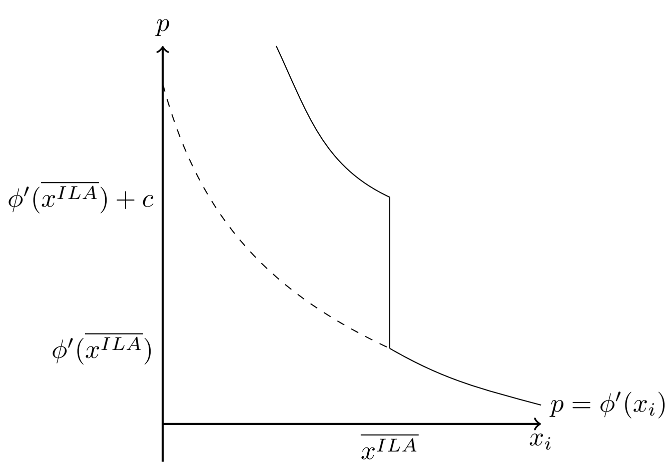


Figure 1 lends itself to some intuition on the effect of training subsidies in the form of ILA on the demand for training. First, for any price which, with no subsidies, would yield a quantity demanded below $\overline{x^{ILA}}$ (the maximum number of hours subsidized by the ILA account), demand shifts up by the per-hour value of the subsidy c. This means that for very costly trainings, in the upper right of Figure 1, 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 ILA hours (the extra price they have to pay on top of c limits their demand). Conversely, for cheap trainings, individuals would be already demanding, without any ILA subsidy, a quantity above the maximum amount of hours allowed by the subsidy, so that with the introduction of ILA in hours, nothing changes in terms of optimal quantity demanded. In fact, the marginal utility of the $(\overline{x^{ILA}}+1)$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 $\phi'(\overline{x^{ILA}})$, but below $\phi'(\overline{x^{ILA}})+c$, people use all their ILA and don't add any training hours (yet, they may pay $(p-c)\cdot\overline{x^{ILA}}$ if $p>c$).

To make the difference clearer, it is useful to compare the demand effect of subsidies in the form of Individual Learning Accounts and the standard case of a excise (per-unit) subsidy. In the latter, the subsidy pushes demand up by the per-unit value of the subsidy at any price level. In the case of ILA, when ILA is denominated in hours, this is true only up to the maximum amount of hours available in the account. This difference corresponds to a more complex reaction of equilibrium prices/quantities, in the ILA case, to shocks to the amount of the subsidy, as discussed in the next section.

2.2 Competitive equilibrium in hours-denominated ILA and effect of a change in the per-hour value of the subsidy

We now analyze the competitive equilibrium in the case of hours-denominated ILA with a per-hour subsidy c. Subsequently, we study what happens if a change occurs in the per-hour subsidy c. Let us consider a training market characterized by a set of representative training centers who supply x^s of training, and suppose that a standard supplier's problem delivers linear supply:

$$x^s = \eta^s p$$

Suppose also that a representative worker in each industry demands a total of x^d hours of training, according to Walrasian demand derived in section 2.1, with $\phi'^{-1}(p) = \kappa - \eta^d \cdot p$. i.e. linear demand[3]. In equilibrium, $x^d_f = x^s$, so that:

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

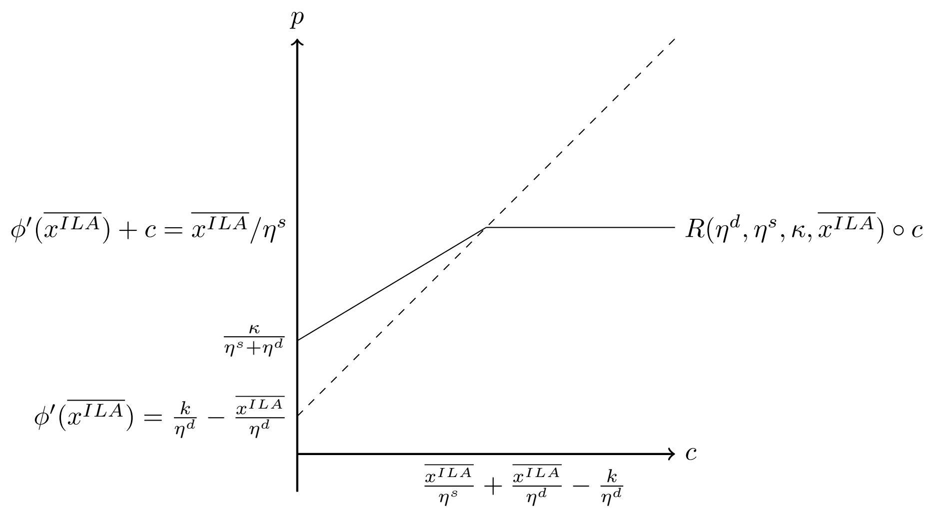
With linear demand, we are able to write down explicitly the equilibrium relationship between competitive prices and conversion rates:

$$p = R(\eta^d, \eta^s, \kappa, \overline{x^{ILA}}) \cdot c = \begin{cases} p = \frac{\kappa}{\eta^s+\eta^d} + \frac{\eta^d}{\eta^s+\eta^d} c & \text{if} \quad c < p - \phi'(\overline{x^{ILA}}) \\ p = \overline{x^{ILA}}/\eta^s & \text{if} \quad c \geq p - \phi'(\overline{x^{ILA}}) \geq 0 \end{cases} \tag{2}$$

[3]The case of log-linear elasticities is analogous. Take the equilibrium condition for $\phi'(\overline{x^{ILA}}) + c > p > \phi'(\overline{x^{ILA}})$, 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 $\frac{d \ln p}{d \ln c} = \frac{\frac{\partial x^d/x^d}{\partial c/c}}{\frac{\partial x^s/x^s}{\partial p/p} - \frac{\partial x^d/x^d}{\partial p/p}}$. This means that Figure 2 is the same but with logs on the axis.

This reaction function $R(.) \circ c$ has a kink when $p = c$, as depicted in Figure 2.

Figure 2: Reaction function $R(\eta^d, \eta^s, \kappa, \overline{x^{ILA}}) \circ c$: equilibrium prices as a function of per-hour value of the subsidy



Let us now introduce time subscript t, and suppose now one wants to study the effect on prices $\Delta p_t = p_t - p_{t-1}$ of a discrete variation in c_t, $\Delta c_t = c_t - c_{t-1}$. Using Equation (2) to substitute p_t into Δp_t, one ends up with four cases:

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

$$\Delta p_t = 0$$

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

$$\Delta p_t = \frac{\overline{x^{ILA}}}{\eta^s} - \frac{\kappa}{\eta^s + \eta^d} - \frac{\eta^d}{\eta^s + \eta^d} c_{t-1}$$

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

$$\Delta p_t = \frac{\kappa}{\eta^s + \eta^d} + \frac{\eta^d}{\eta^s + \eta^d} c_t - \frac{\overline{x^{ILA}}}{\eta^s}$$

4. if $c_t \leq \frac{\overline{x^{ILA}}}{\eta^s} + \frac{\overline{x^{ILA}}}{\eta^d} - \frac{k}{\eta^d}$ and $c_{t-1} \leq \frac{\overline{x^{ILA}}}{\eta^s} + \frac{\overline{x^{ILA}}}{\eta^d} - \frac{k}{\eta^d}$, 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 2, meaning that the per-hour value of the subsidy at both periods are above the critical value for which individuals use all of their ILA subsidy (i.e. when in Figure 1, supply intersects demand at $\overline{x^{ILA}}$, where demand is perfectly inelastic, or to the right of $\overline{x^{ILA}}$, where demand is unchanged). 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 $p_t \geq c_t + \phi'(\overline{x^{ILA}})$: 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 ILA 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 2, this means that both levels of c lie left of the kink. In Figure 1, 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 2, 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 $R(\eta^d, \eta^s, \kappa, \overline{x^{ILA}})$? By looking at the four cases just enumerated, one sees that first-differencing gets rid of $\overline{x^{ILA}}$ and κ only in case 4. Yet, whether or not one ends up in case 4 depends from c_t, c_{t-1}, $\overline{x^{ILA}}$, κ and unknown η^d, η^s. In theory, one could measure $\overline{x^{ILA}}$, 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 (2) 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 $\frac{\eta^d}{\eta^s+\eta^d}$.

Finally, what is the meaning of η^d, η^s? Note that we assumed linear demand and supply, so that these paramenteres are to be interpreted as slopes rather than elasticities.

2.3 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 ILA 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 (1). Any kind of discretionary addition to the basic ILA credits can be modeled as doing either one or both of two things: guaranteeing extra hours of ILA so that $x^{\tilde{ILA}} = \overline{x^{ILA}} + M$, 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 $\tilde{c} = c + \mu \cdot \max(p-c, 0)$, the actual cap to per-hour subsidy, gross of discretionary per-hour component. We can re-write the consumer problem as:

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

The handling of problem is analogous to the one without additions. First, we simply need to substitute $x^{\tilde{ILA}} = \overline{x^{ILA}} + M$. Integrating $\tilde{c} = c + \mu \cdot \max(p-c, 0)$ is more tricky, since while c is given, $\tilde{c}$ 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:

$$p = \tilde{R}(\eta^d, \eta^s, \kappa, x^{\tilde{ILA}}, \mu, c) = \begin{cases} p = \frac{\kappa}{\eta^s+\eta^d} \frac{1}{1-\frac{\eta^d}{\eta^s+\eta^d}\mu} + \frac{\eta^d}{\eta^s+\eta^d} \frac{1-\mu}{1-\frac{\eta^d}{\eta^s+\eta^d}\mu} c & \text{if} \quad c < p - \frac{\phi'(x^{\tilde{ILA}})}{1-\mu} \\ p = x^{\tilde{ILA}}/\eta^s & \text{if} \quad c \geq p - \frac{\phi'(x^{\tilde{ILA}})}{1-\mu} \geq 0 \end{cases} \tag{3}$$

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

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

$$\Delta p_t = 0$$

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

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

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

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

4. if $c_t \leq \frac{x^{\tilde{ILA}}}{\eta^s} + \frac{x^{\tilde{ILA}}}{\eta^d(1-\mu)} - \frac{k}{\eta^d(1-\mu)}$ and $c_{t-1} \leq \frac{x^{\tilde{ILA}}}{\eta^s} + \frac{\overline{x^{ILA}}}{\eta^d(1-\mu)} - \frac{k}{\eta^d(1-\mu)}$, 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 $p > c$ $\tilde{c} = c + \mu(p - c) = (1 - \mu)c + \mu p$, and that consequently:

$$\Delta \tilde{c}_t = (1 - \mu) \left[1 + \frac{\eta^d}{\eta^s + \eta^d} \frac{\mu}{1 - \frac{\eta^d}{\eta^s+\eta^d}\mu} \right] \Delta c_t \tag{4}$$

So, although μ represents an additional parameter to be estimated, one can rely on a “first-stage” relationship as in (4) to recover it.

3 An example of ILA: the French CPF and its reforms

We will study the functioning of ILAs basing on the French *Compte Personnel de Formation* (CPF), which is considered as the most complete example of a nationally available ILA. We will in particular exploit the reform to CPF introduced in January 2019. In this section, we describe the institutional context of the CPF system, the characteristics of the reform in 2019, the administrative dataset we use, and we present some introductory descriptives of the reform under study.

3.1 Functioning of the French CPF

Introduced in 2015, the CPF replaced a previous device (*Droit Individuel de Formation – DIF*), which was non-portable, meaning that the worker could not transfer training credits from one employer to the other. Initially, CPF provided training credits only for employees of the private sector, while workers of the public sector were added to the program from 2017, and self-employed workers from 2019. The principle of CPF is that each worker owns a CPF account, in which he accumulates credits depending on its working experience and personal characteristics[4]. Some additional credits can be added by employers. Workers can then spend credits at their will on training programs they choose. Importantly, these trainings can come only from a list of eligible providers.

CPF underwent a significant reform in January 2019. Before the reform, between 2015 and 2018, CPF credits were denominated 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 applications for funding to the training agency of their industry, (named *organisme paritaire collecteur agréé – OPCA*), and the training agency was reimbursing the training provider of the training costs incurred. The credit and debit of training hours was then recorded on the online platform. This pre-reform institutional context is summarized in Panel A of Figure 3.

Importantly, not every hour of CPF credit was worth any price for any training. Industry-specific training agencies were fixing different caps to per-hour subsidies[5], which noted down the amount of Euros payable for each hour of different kinds of training. This system was thus centered on industry-specific training agencies: companies were paying mandatory contributions (1% of the wage bill for firms above 10 employees) to industry financing centers, of which 0,2% was mandatorily allocated to a CPF financing line. Industry training agencies had discretion over the value of the subsidy, but were obliged to maintain an accounting system for their workers' CPF separately from other training devices managed by the agencies, so that CPF contributions were to be used exclusively to finance CPF on the basis of per-hour subsidy caps. If contributions exceeded the cost of trainings undertaken by workers, the excess funding was assigned to an inter-industry organization for being used to finance other kinds of training, including CPF for the unemployed. As a result, industry-specific financing centers had the incentive to spend as much of this CPF pot as possible, fixing high caps to per-hour subsidy, in order to keep the money within the industry, not losing them in favor of inter-industry financing. Several French regulators confirmed this mechanism[6].

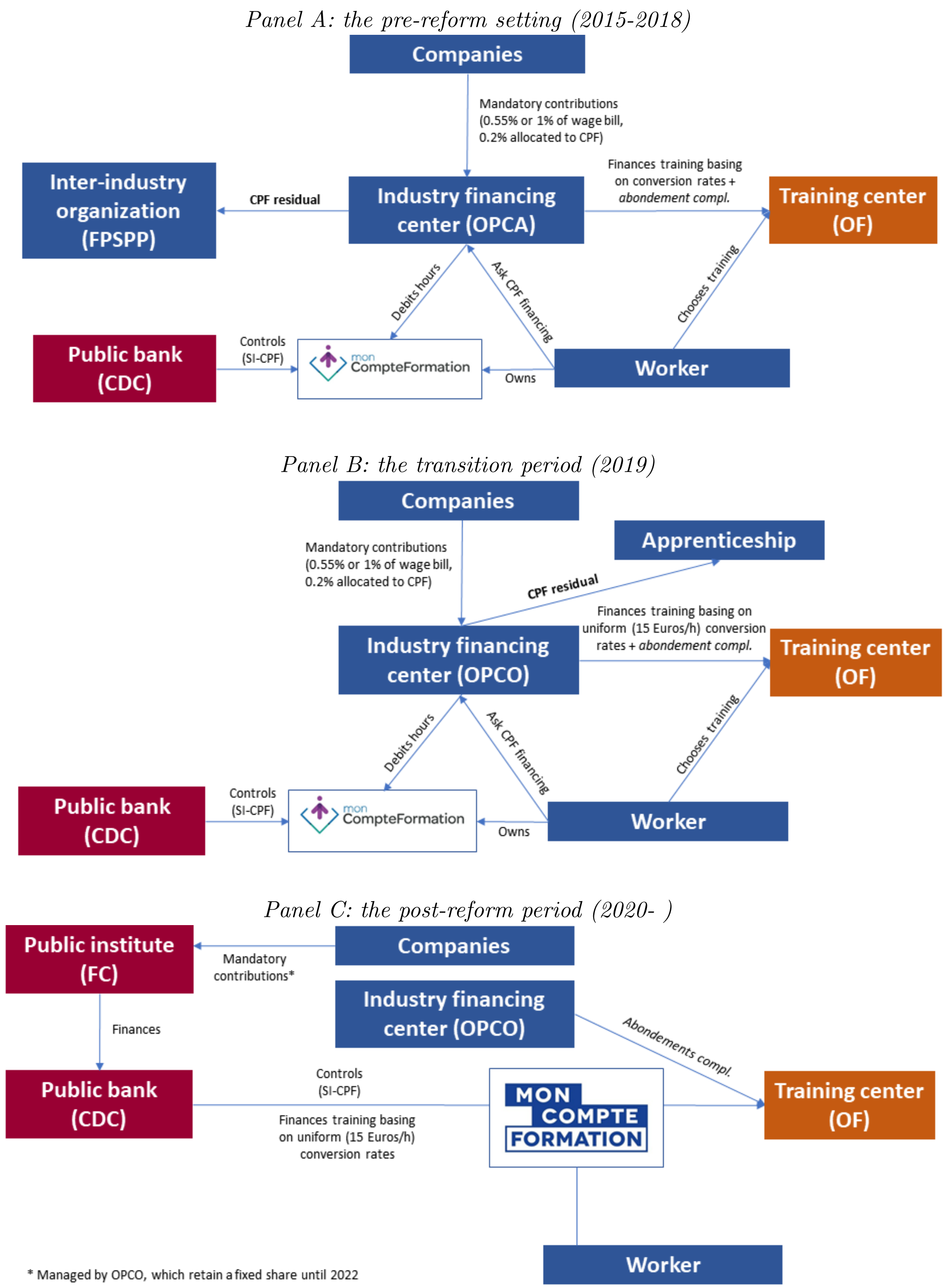
If the CPF hour credits were not sufficient to pay for the whole training, additional discretionary subsidies called *abondements* could be offered by the training agency or the employer. This was not mandatory, subject to discretion of the center, and its financing was not linked to the CPF financing line. The worker could also finance part of the training himself. Before 2018, CPF was quite generous in terms of per-hour value, especially in richer industries, so that discretionary additions mostly covered cases where the amount of *hours* was not sufficient, guaranteeing extra hours. Finally, it is worth noting that CPF was underused in 2018: individuals tended to accumulate credits without using them (Figure 12 in the Appendix), so that most individual actually reached the maximum amount of hours which could be accumulated in the account.

[4]Disabled workers and low qualified workers are granted more credits than others.

[5]An example of the tables reporting per-hour caps is reported in Figure 11 in the Appendix.

[6]We quote one: "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".

Figure 3: Schematization of the CPF institutional infrastructure. From top to bottom: the pre-reform setting (2015-2018), the transition period (2019), the post-reform period (2020-).



The main change of reform that came into force in January 2019[7] was the so-called "monetization" of the CPF: 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, became uniformly worth 15 Euros. Accordingly, a secondary change concerns the accrual of hours. From 2019 full-time workers benefit from 500 Euros yearly (up to 5000 Euros), low qualified and disabled workers obtain 800 Euros each year (up to 8000 Euros). A third goal of the reform was to completely centralize CPF management, through a unique mobile app on which workers could ask financing without passing through industry financing centers (called *opérateurs de compétences – OPCO* after the reform), managed by a public bank (*Caisse des dépôts et consignations – CDC*) jointly with a public authority (*France Compétences*)[8]. Panel C of Figure 3 describes the post-reform scenario at which the policy aimed.

Yet, between January and November 2019 a transition period was enacted, which in practice affected almost all trainings of 2019[9]. In the transition period, the monetization of CPF was applied by uniforming the value of the hour credits, and the accumulation of credits switched to the new system, but centralization was not implemented. In practice, workers still submitted applications for funding to the training agency of their industry, and the agency payed the training provider, but the value of the subsidy was determined as the amount of hours available on the CPF account converted at the uniform 15 Euros rate. Discretionary additions (*abondements*) were still possible, from the training agency, the employer, or the worker himself, if the CPF subsidy was not enough to cover the cost of training. In fact, since the subsidy cap dropped dramatically in some industries, some OPCAs started using discretionary additions to increase the per-hour value of their workers' CPF (rather than the total amount of hours, as was happening before). However, training agencies were not incentivized to do so: from the reform, training agencies were not anymore forced to redistribute the excess money in the CPF financing line, but were allowed to keep it and convert it to funds for financing apprenticeship, a much more popular tool among employers. Panel B of Figure 3 describes the institutional setting of the transition period.

3.2 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 of CPF pre-reform and fully in charge of CPF financing after the reform. The SI-CPF is also used by French authorities to build official statistics on the device. Between 2015 and November 2019, the public bank received information by employers to calculate CPF credits and from financing centers to calculate CPF consumption. From December 2019, the public bank used the SI-CPF directly to manage CPF and pay training centers. The dataset contains:

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

[8] 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 13 in the Appendix suggests only a small bunching of CPF-subsidized trainings at the end of 2018.

[9] As Figure 13 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.

Table 1: Initial sample selection

			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	
	2016	**2017**	**2018**	**2019**
sample broken down by year	176 983	251 032	359 990	310 483

personal characteristics of beneficiaries (sex, age, working status, diploma, CPF stock, etc.); data on the training (duration, specialty, name, training center, etc.); and financial data (cost, financing center, amount financed by each financing center, etc.).

The scope of the SI-CPF is larger than what needed for this study, so Table 1 describes the different stage of sample selection. 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 14 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[10].

After the first selection, outlier treatments were applied. In the pre-2019 period, 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)[11].

We then define the variables we will use from SI-CPF. The dataset provides information at the level of

[10]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.

[11]Moreover, some financing centers rarely finance CPF training to employees: employers (8 000 training episodes), regions (100 training episodes), and employed individuals financed by the unemployment agency *Pôle emploi* (30 training episodes). They all are exclude from the analysis (1.2% of the observations). Our analysis then focuses only on training episodes financed by the 20 industry training agencies.

training episode (also called training episodes). We will index this by i, which corresponded to individuals in our model in Section 2, since 79% of individuals correspond to only one dossier (95% correspond to at most 2 dossiers), 87% of individuals undertake one training in a year, and more than half the remaining simply takes twice the same training (probably corresponding to two different phases or levels). We have information on the number of hours subsidized by CPF, x_i^{ILA}, and on their value in terms of Euros, which in terms of our model in Section 2 is equal to the product of hours and per-hour subsidy $V_i = x_i^{ILA} \cdot \min(c, p)$. Moreover, we have information on the discretionary additional transfer, $A_i = \tilde{x}_i^{ILA} \cdot \tilde{c}$. In addition, we have information on the total duration x_i and on the total cost of the training $P_i = x_i \cdot p_i$. Hence, although our dataset doesn't provide information on hourly prices, we can indirectly measure them as $p_i = \frac{P_i}{x_i}$. We will collapse our dataset by cells corresponding to the level of variation of the treatment and to the level of meaningful aggregation of prices. For defining cells, we have information on what we call "training kind", indexed by q, as the combination of the title of the training and weather it is run online or in person. Industry financing center is indexed by f. Time t is the year when the training occurs (which was reported as the relevant date for accounting in the SI-CPF by the public bank managing the system). Finally, training provider, indexed by j, is reported basing on the firm identifier (SIREN) of the provider, and local labor markets (indexed by l) are defined basing on reported municipality and postal code of the training establishment and on correspondance tables for commuting zones by INSEE.

Our second source is official documentation on the per-hour value of the CPF subsidy allowed by training agencies. We construct a small database from documentation of the inter-industry organization (FPSPP), of the national training council (CNEFOP) and of the training agencies. We also interviewed training agencies to complete the dataset and insure a better understanding of the process. The final dataset records 224 different per-hour subsidy caps $c_{q,f,t}$ according to the industry financing agency f, the (group of) kind of training q[12], and the year t (2016 to 2019).

We merge this new dataset on conversion policy with SI-CPF basing on the financing center, the year of the source, and the training kind for which the source is valid. 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. Yet, 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).

Our final source is called BPF (*bilans pédagogiques et financiers*), which provides balance-sheet information for training centers. This source is an administrative dataset coming from mandatory declarations for any training provider which uses public subsidies (not only CPF). It's collected by the Ministry of Labor (DGEFP), and it's used for official statistics as well as supervision by the French government. The advan-

[12] 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.

tage 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 centers (employees wages, teacher wages, external consultant wages) and information on the staff (number of teachers, external consultants). These information do not only concern CPF but the total of trainings undertaken at the training center, including unsubsidized trainings or trainings subsidized by other devices. We use the version as of the beginning of 2021, which reliably covers until fiscal year 2019. We merge BPF with SI-CPF basing on firm identifier SIREN. The merge is quite satisfying: 93,3% in 2018 and 95,1% in 2019 of SI-CPF training episodes found a match filled in the BPF. The data report outliers, so that we trim our variables of interest – revenues, costs, profits, and revenues from CPF – to the 1-99th percentile.

3.3 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 4 displays the per-hour subsidy cap applied in 2018 as reported in official documentation and from interviews with industry financing centers, for the industry financing centers who finance at least 100 dossiers of that training, for the 9 most diffused groups of training kind[13]. The graph also reports mean, mode and IQR of the CPF per hour, V_i/x_i^{ILA}, actually observed in the data. This set of figures points out two starting considerations. First, our data gathering on per-hour subsidy caps looks accurate: with few exceptions, the per-hour value of the CPF subsidy is below the per-hour subsidy cap. Interestingly, 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 often binding. The IQR of the CPF/hour is also very close to the value of the cap to per-hour subsidy, especially for lower values of the cap. Trainings for enterprise creation and machine conduction represent an interesting exception. 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 5, 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 importance of CPF: while before the reform for almost 80% of the training episodes reported in the SI-CPF the full cost was covered with CPF credits, 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 6 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 heterogeneity remains wide. This suggests the importance to treat different financing centers as different markets in a diff-in-diff context, since different financing centers may

[13]The graph for training "Cléa" is reported in Figure 15 in the Appendix, for graphical purposes and since it's the least diffused training, concentrated only in some industries.

Figure 4: Per-hour subsidy caps ($c_{q,f,t}$), and V_i/x_i^{ILA} (average, mode, and IQR), according to training type q

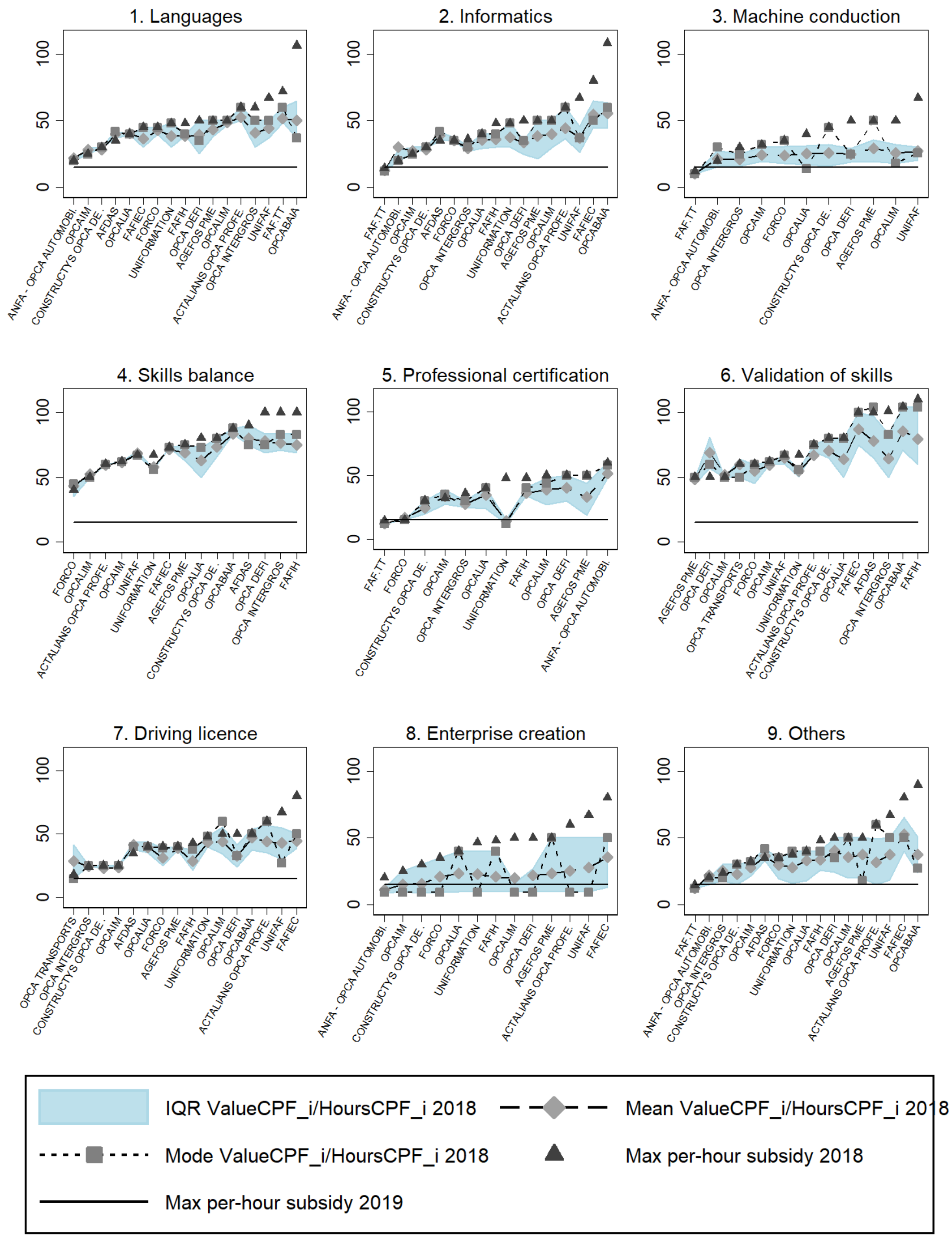
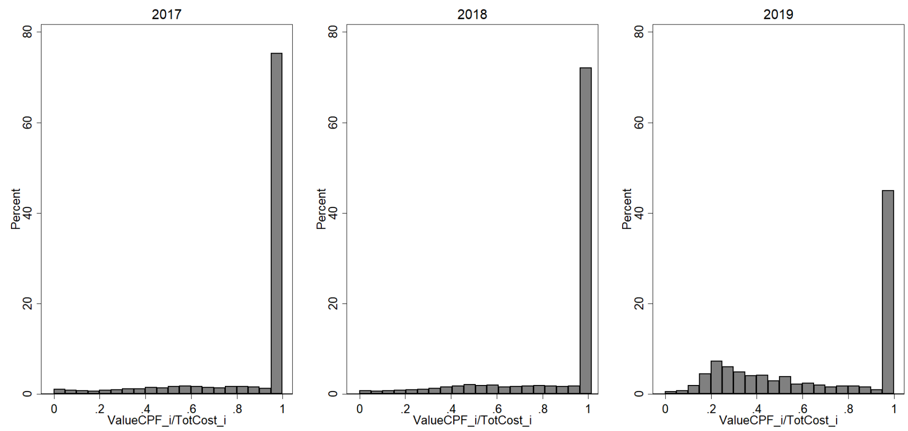


Figure 5: Percentage of total training cost covered by CPF subsidy, $V_i/(x_i * p_i)$



face structurally different prices (e.g. different areas, different level of qualification, ...). Note however that this is not true for all kinds of trainings: in the case of lifeguard certificate, instead, prices converge to a much more similar level after equalization of the subsidy. This is possibly due to differences in the market structure of both training kinds.

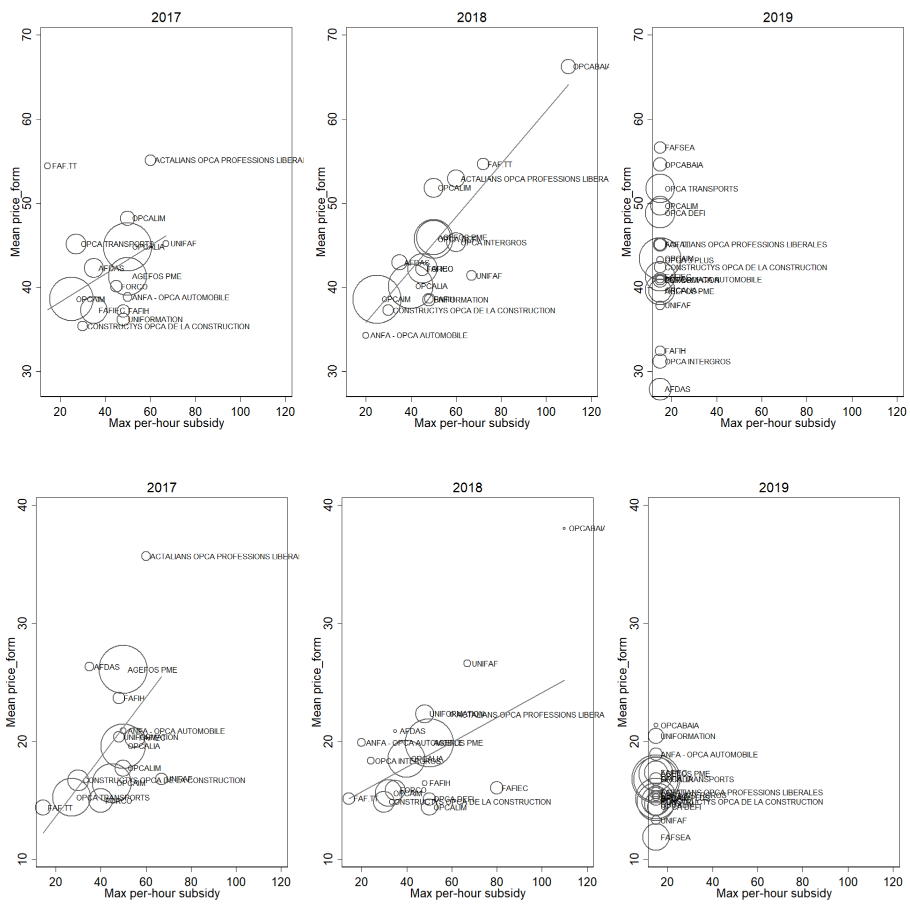
4 Estimating the incidence of CPF using its impact on training prices

The goal of this section is to understand how we can use the reaction of prices to changes in the CPF subsidy, $\frac{\Delta p}{\Delta c}$, to obtain estimates of the relative slopes of training demand and supply, η^d/η^s . We will exploit the shock detailed in the previous Section. Before January 2019 each industry financing center was allowing different amount of CPF subsidy for each kind of training. On January 2019 for the whole transition period, the same system centered on industry financing centers remained in place, but the per-hour value of CPF was unified at 15 Euros per hour.

4.1 Baseline identification strategy

Formally, recall our model in Section 2 and let the per-hour subsidy cap be different for industries f: $c := c_f$. the first challenge is to determine the unit of analysis, i.e. the appropriate level at which prices p are determined. We will consider two different levels of aggregation. The preferred option is to use as unit of analysis each training kind (i.e. the title of the training reported in the data and if it is online or in presence) plus training provider combination. Alternatively, we use training kind plus local labor market. Furthermore, suppose by now that the market for a specific training kind is segmented across different industries f. This may arise, for example, with “perfect discrimination” between workers coming from different industries, if each supplier specializes in an industry, or if training courses are specific to an industry. It turns out that this situation is quite close to reality: 40% of training episodes come from the most important industry f in

Figure 6: 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)



a training kinds/training firm pairs q, j, and 65% from the three most important [14]. Even then, graphical evidence of how prices can differ across industries for the same training kind in the pre-reform period is provided by Figure 6. We anyway relax this assumption in Section 4.4, and the results are very close to our baseline. We will then conduct the analysis at the training kind q+training supplier j+industry f level, and at the training kind q+local labor market l+industry f level. Finally, time is indexed by t. In the following lines we will thus use pedex q, j, f, t to indicate the values in the cells of our panel (for the panel with q, l, f, t cells all derivations are equivalent). If markets for training for each industry are separated, suppliers charge different competitive prices to every f so that supply becomes $x^s_{q,j,f,t} = \eta^s p_{q,j,f,t}$ and each industry behaves as a separate market with a separate price p_f. This way, the shock to the per-hour subsidy cap $c_{q,f,t}$ directly translates into prices, so that $\Delta p_{q,j,f,t} = R(.) \circ \Delta c_{q,f,t}$.

Yet, $R(.)$ is an unknown function, possibly non-linear and concave as in Equation 2. We will tackle this problem indirectly, obtaining different approximations of our parameters of interest. First, we will estimate a simple linear relationship between Δp and Δc, as if we are in case 4 of section 2.2. Intuitively, due to concavity this would be a lower bound of our relationship of interest in the left side of our graph in Figure 2. Second, we will estimate the relationship between changes in the log c and changes in p. Third, we will estimate $R(.) \circ c$ at different "points" of the range of c. Concentrating on lower cs will yield estimates closer to case 4, and we expect the magniude of $R(.) \circ c$ to decline as c gets larger.

A second difficulty to recover η^d/η^s is that, in our empirical setting, we will need to allow for discretionary additions. Discretionary additions represent in fact a threat to identification and a potential attenuator of our variation of interest, $\Delta c_{q,f,t}$. On the one hand, discretionary additions only intervene when CPF subsidies are not enough to cover the whole cost of training, and are thus endogenous to the magnitude of the cut in the CPF subsidy for each industry given a specific training. We will solve this by imposing the cap gross of additions $\hat{c}$ to be a linear function of the difference between price and caps if price exceeds the subsidy cap, leading to Equation 4. On the other hand, since the reform tended to lower the value of CPF (per-hour subsidy caps were generally above 15 Euros per hour, Figure 4) in general across industries, after January 2019 the discretionary addition was more likely to be needed, and we assume that. If additions always compensate for the lowering of CPF per-hour subsidy, it would fully annul our identifying identifying variation.

Given the assumption on discretionary additions, from Section 2.3 one can see that estimates of the reduced form yield a parameter that is a mix of elasticities and the share of discretionary subsidy, $\Delta p = R(\eta^d, \eta^s, \mu) \cdot \Delta c$. Thus, our two-stage strategy will need to estimate two relationships: the reduced form relationship between c and prices, and the first stage relationship in Equation 4. Let a reduced form estimand be the reaction function as in case 4 of Section 2.3, i.e. $\beta^{RF}_{prices} := \frac{\eta^d}{\eta^s+\eta^d} \frac{1-\mu}{1-\frac{\eta^d}{\eta^s+\eta^d}\mu}$, and let the first-stage estimator be $\beta^{FS} = \Delta\tilde{c}/\Delta c$. Note that one can re-write Equation 4 as:

$$\Delta \tilde{c_t} = (1 - \mu + \mu \beta^{RF}_{prices}) \Delta c_t \tag{5}$$
$$\Rightarrow \mu = \frac{1 - \beta^{FS}}{1 - \beta^{RF}_{prices}}$$

Then:

$$\eta^d/\eta^s = \frac{\beta^{RF}_{prices}}{\beta^{FS} - \beta^{RF}_{prices}} \tag{6}$$

[14] The figure is 28% and 53% for training kinds/local labor markets pairs q, l.

To estimate $\beta^{RF}_{prices}, \beta^{FS}$, we use two-way fixed effects regressions. One can see this approach as akin to a diff-in-diff approach where treatment varies according to training kind-industry financing center pairs. As already mentioned, we collapse our data, since our level of variation occurs at the q, f, t level and prices might be defined either at a level of firm j or at a level of market l. In our preferred specification, the unit of analysis is the group of trainings belonging to a particular training program (training kind q+training provider j), coming from a specific financing center f at year t, so that the first stage model is:

$$\tilde{c}_{q,j,f,t} = \beta^{FS} c_{q,f,t} + \gamma_{q,j,f} + \tau_t + \varepsilon_{q,j,f,t} \qquad \text{if} \quad t = 2018, 2019 \tag{7}$$

Where τ_t and $\gamma_{q,j,f}$ are respectively time FE and program plus financing center FE. The reduced form is obtained by replacing our instrument in the structural equation of interest:

$$p_{q,j,f,t} = \beta^{RF}_{prices} c_{q,f,t} + \gamma_{q,j,f} + \tau_t + \varepsilon_{q,j,f,t} \qquad \text{if} \quad t = 2018, 2019 \tag{8}$$

Where $y_{q,j,f,t}$ is our outcome of interest at the training program level: average price of the training program, total amount of hours undertaken in the year, and as robustness average duration of the training and average total cost of the training. All regressions are estimated at the unit of analysis level q, j, f, t, weighted by number of trainings i in each cell[15]. Following Bertrand et al. (2004) standard errors are clustered at training program q and financing center f level. Note that we estimate reduced form (years 2018-2019) and placebo (years 2017-2018) separately. This is due to the fact that the kind of training q is quite volatile, so that to obtain a balanced panel from 2017 to 2019 we would need to drop more than half of the sample. Also, we ignore 2016, since it is considered no reliable, as CPF was mostly used for unemployed and the control system is not reliable.

$c_{q,f,t}$ is our policy instrument, which is exogenously changed between 2018 and 2019. The distribution of such a change is reported in green in Figure 7. Identification stems from the fact 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. Yet, changes to $c_{q,f,t}$ occurred, in some industries, also in 2017-2018. These changes are clearly endogenous, and the estimate $\hat{\beta^E}$ does not identify any meaningful parameter, but could still provide an interesting insight into the mechanisms driving the definition of pre-reform per-hour values of the subsidy.

$$p_{q,j,f,t} = \beta^{E}_{prices} c_{q,f,t} + \gamma_{q,j,f} + \tau_t + \varepsilon_{q,j,f,t} \qquad \text{if} \quad t = 2017, 2018 \tag{9}$$

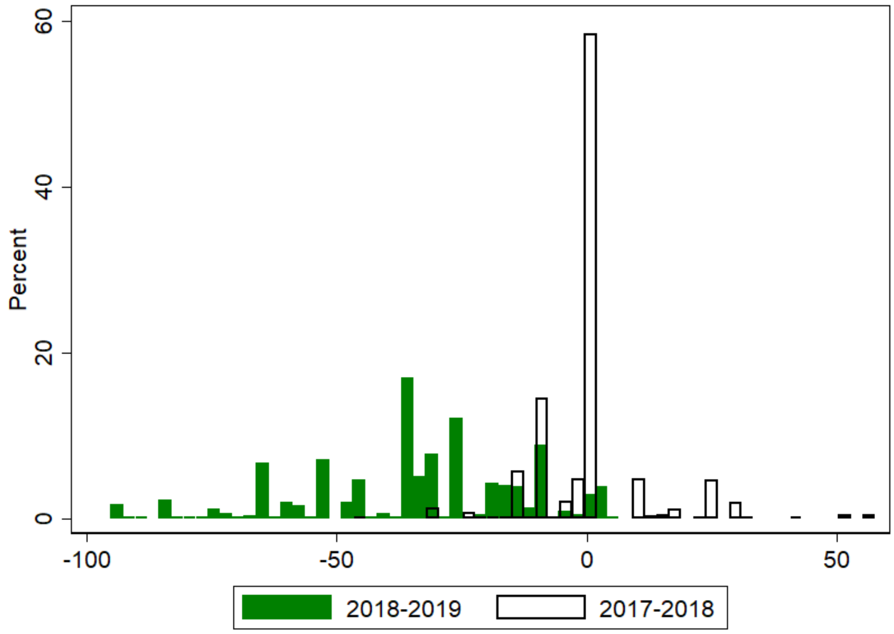
Finally, among standard identifying assumptions behind our diff-in-diff in 2018-2019, a relevant one is that our potential outcomes when untreated, for the variables of interest (training prices charged to individuals coming from different financing agencies, training duration, total cost and total hours undertaken in a year), were not different in different groups. This hypothesis implies the testable prediction that future treatment status will not affect today's ones. We will thus include a placebo test specified as:

$$p_{q,j,f,t} = \beta^{E}_{prices} c_{q,f,t} + \beta^{P}_{prices} c_{q,j,f,t+1} + \gamma_{q,j,f} + \tau_t + \varepsilon_{q,j,f,t} \quad \text{if} \quad t = 2017, 2018 \tag{10}$$

For all our results, we also include in the tables a second panel replicating the results with regressions where the unit of analysis is training kind p+ Local Labor Market l (instead of training firm j). These specifications are exactly the same as Equations (7)-(10), just substituting j with l. Finally, in the Appendix we run regressions at the dossier i level, including fixed effects for training program. In these specifications the number of observations is higher, but the noise and the presence of outliers might affect power. It turns out that the first effect prevails, and these estimates are eventually more powerful, yet very close to our baseline estimates.

[15] This is thus equivalent to estimating them at the individual training level

Figure 7: Distribution of $\Delta c_{q,f,t}$



4.2 Baseline Results

Table 2 reports the results for our preferred specification, in panel A using training kind and firm as unit of analysis and in panel B using training kind and local labor markets. In both panels, column (1) reports the estimates of β^{FS} from the first stage specification (Equation 7), while column (2) reports the estimates of β^{RF}_{prices} from the reduced form specification (Equation 8). The first stage coefficient signals that a decrease in CPF credit per-hour net subsidy leads to a significant 19%-20% decrease in the average per hour subsidy gross of discretionary additions. In turn, this leads to a 11% decrease in the average price. Both coefficients are very significant. 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.

Finally, we report in column 3 the reduced form estimate of the relationship between (endogenous) changes in per-hour ILA subsidy caps and prices in 2017-2018, as in Equation 9; and in column 4 the estimates of the placebo equation (10). The endogenous coefficient signals that the endogenous relation is stronger, though not much more than the identified one. this might suggest that the reverse causality story – for which in 2017-2018 subsidies would increase because price increase – might not be so strong. The placebo signals no anticipation, as the effect of changes in conversion rates in 2018-2019 on prices in 2017-2018 is insignificant and close to zero.

What does this effect suggest in terms of relative slopes of demand and supply? If one looks only at the reduced form, a reaction of .11/.12 in prices seems to suggest a relatively elastic supply. Yet, one should account for attenuation by discretionary additions, as we do at the end of column (2), reporting the estimate of η^d/η^s according to Equation 6. These estimates suggest that once accounting for attenuation by discretionary additions consumers' quantity demanded is relatively more elastic compared to suppliers. Yet, the numbers are not so far, being the slope of demand between 78% and 85% of supply slope. The two elasticities come even closer if one runs a specification at the individual level, controlling for both local labor market and firm fixed effects (Table 8 in the Appendix).

Finally, the incidence on suppliers is given by the variation in the gross price relative to the variation of the actual spending in the subsidy $\frac{dp}{d\tilde{c}} = \frac{dp/dc}{d\tilde{c}/dc}$, the ratio of reduced form to first stage coefficients. This means that such an incidence falls between 55% and 58% on suppliers, the more inelastic factor.

Table 2: Baseline results

Panel A: Training kind + training firm as unit of analysis

	(1)	(2)	(3)	(4)
VARIABLES	$\tilde{c}_t$	p_t	p_t	p_t
c_t	0.188***	0.104***	0.139***	0.142***
	(0.0176)	(0.0165)	(0.0192)	(0.0258)
c_{t+1}				-0.00236
				(0.00914)
Observations	52,953	52,953	44,691	23,597
R-squared	0.888	0.908	0.958	0.965
Years	2018-2019	2018-2019	2017-2018	2017-2018
η^d/η^s		1.22		

Panel B: training kind + Local labor market as unit of analysis

	(1)	(2)	(3)	(4)
VARIABLES	$\tilde{c}_t$	p_t	p_t	p_t
c_t	0.205***	0.119***	0.150***	0.141***
	(0.0255)	(0.0258)	(0.0260)	(0.0351)
c_{t+1}				-0.0131
				(0.0108)
Observations	48,665	48,665	40,937	24,347
R-squared	0.889	0.906	0.951	0.958
Years	2018-2019	2018-2019	2017-2018	2017-2018
η^d/η^s		1.37		

Notes: In Panel A data are collapsed at the level of training kind (training title +online/in presence) plus training firm, industry and year. Regressions in panel A thus include include fixed effects for training kind (training title +online/in presence) plus training firm FE plus industry, and year FE. In Panel B data are collapsed at the level of training kind (training title +online/in presence) plus local labor market, industry and year. Regressions in panel B thus include fixed effects for training kind (training title +online/in presence) plus local labor market plus industry FE, and year FE. Standard errors are clustered at the training kind (training title +online/in presence) plus training firm in Panel A, and at the training kind (training title +online/in presence) plus local labor market in Panel B. Both panels report in column 1 the first stage regression of total subsidy per-hour on the per-hour ILA subsidy (controlling for price levels); in column 2 the reduced form estimate (also includes the estimate of implied elasticities according to (6); in column 3 the reduced form estimate of the relationship between (endogenous) changes in per-hour ILA subsidy caps and prices in 2017-2018; and in column 4 the estimates of the placebo equation (10).

4.3 Results using different functional forms

Our model in Section 2 suggests however that the relationship between changes in CPF per-hour subsidy and prices might be concave. This is confirmed by visual inspection of the data: in Figure 8 we plot prices on per-hour subsidies after having residualized both variables with respect to unit and time FE. The positive relationship appears to flatten for higher values of the independent variable. To assess this non-linearity, we fit two alternative specifications. First, a regression similar to Equation 8, but with $\ln c_{qft}$ as the independent variable of interest. Second, we estimate the relationship pointwise by quartile of c_{2018}. Columns (1) and (2) of Table 3 report the results for the first strategy.

Clearly, the coefficient of the reduced form with the log-transformed instrument is much larger. Yet, we can estimate the slope of the curve around critical points of c_t, such as its median. The slope indicates that the ratio between elasticity of demand and supply is now around 1.1, lower than with the linear specification. This is consistent with the hypothesis that the linear specification is underestimating the reaction of prices. The specification estimated quartile-by-quartile also confirms that the relationship between subsidies and prices is decreasing over c_t. In the top quartile, the coefficient is almost halved with respect to the bottom one. Estimates of the first stage offer insights about μ. The estimates in column (3) are relatively stable, actually slightly decreasing over baseline c_t. This happens while reduced form estimates are significantly decreasing, and should drive the first stage coefficient down (see Equation 6). The estimates of μ indeed decrease slightly in Panel B, signaling that discretionary additions are less able to compensate for the decrease in CPF when the values of c_t were higher before the reform, but the implied μ range between 1 and .9, so not an extremely large fall.

Figure 8: Binned scatterplot of residuals of prices p_{qjft} on c_{qjft} absorbing year and training kind-training supplier FE, with quadratic fit.

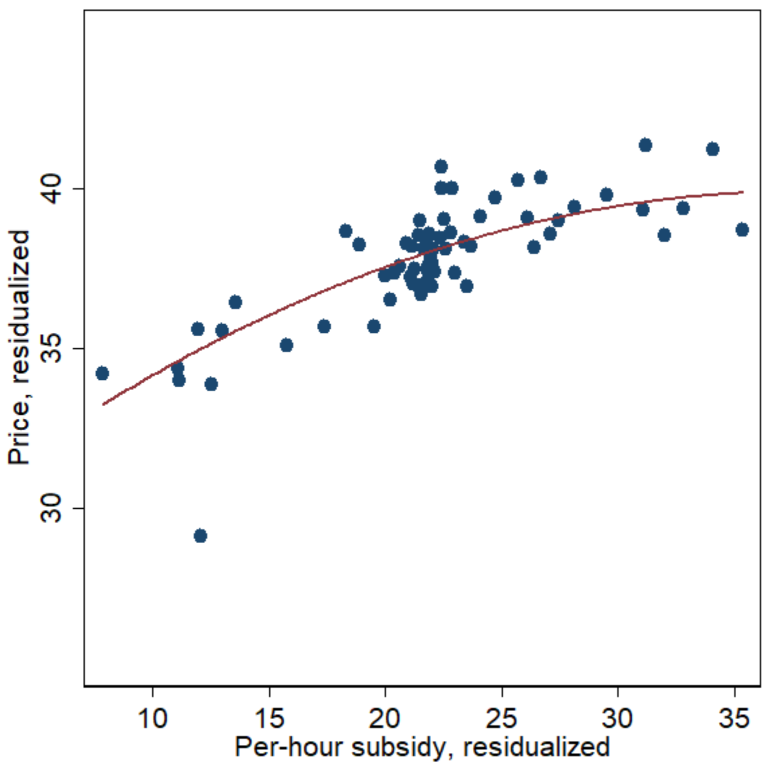


Table 3: Results using different functional forms

Panel A: Training kind + training firm as unit of analysis

VARIABLES	(1) $\tilde{c_t}$	(2) p_t	(3) $\tilde{c_t}$	(4) p_t
c_t	0.188***		0.208***	0.210***
	(0.0176)		(0.0356)	(0.0298)
$\ln(c_t)$		4.073***		
		(0.504)		
$c_t * \mathbb{1}(p25 < c_{2018} \leq p50)$			0.0307	-0.0524*
			(0.0291)	(0.0280)
$c_t * \mathbb{1}(p50 < c_{2018} \leq p75)$			0.0338	-0.0520**
			(0.0282)	(0.0250)
$c_t * \mathbb{1}(c_{2018} > p75)$			-0.0219	-0.0959***
			(0.0284)	(0.0236)
Observations	52,953	52,953	50,272	50,272
R-squared	0.888	0.908	0.879	0.901
Years	2018-2019	2018-2019	2018-2019	2018-2019
η^d/η^s at median		2.31		1.87

Panel B: training kind + local labor market as unit of analysis

VARIABLES	(1) $\tilde{c_t}$	(2) p_t	(3) $\tilde{c_t}$	(4) p_t
c_t	0.205***		0.265***	0.250***
	(0.0255)		(0.0380)	(0.0336)
$\ln(c_t)$		4.568***		
		(0.843)		
$c_t * \mathbb{1}(p25 < c_{2018} \leq p50)$			-0.0106	-0.0970***
			(0.0311)	(0.0313)
$c_t * \mathbb{1}(p50 < c_{2018} \leq p75)$			-0.0147	-0.0895***
			(0.0315)	(0.0289)
$c_t * \mathbb{1}(c_{2018} > p75)$			-0.0540	-0.114***
			(0.0331)	(0.0298)
Observations	48,665	48,665	45,462	45,462
R-squared	0.889	0.905	0.882	0.899
Years	2018-2019	2018-2019	2018-2019	2018-2019
η^d/η^s at median		2.54		1.57

Notes: In Panel A data are collapsed at the level of training kind (training title +online/in presence), training firm, industry and year. Regressions in panel A thus include include fixed effects for training kind (training title +online/in presence) plus training firm plus industry FE, and year FE. In Panel B data are collapsed at the level of training kind (training title +online/in presence), local labor market, industry and year. Regressions in panel B thus include include fixed effects for training kind (training title +online/in presence) plus local labor market FE plus industry, and year FE. Standard errors are clustered at the training kind (training title +online/in presence) plus training firm in Panel A, and at the training kind (training title +online/in presence) plus local labor market in Panel B. Both panels report in column 1 the first stage regression of the log of total subsidy per-hour on the log of per-hour ILA subsidy (controlling for log prices); and in column 2 the reduced form estimate (also includes the estimate of implied elasticities according to (6). In column 3 and 4 we report first stage and reduced form estimated pointwise. (10).

5 Estimating the impact on quantities and the welfare effect of CPF

5.1 Impact on average quantities demanded by each individual

The previous section highlighted a positive significant relationship between changes in the subsidy cap and prices for a specific industry/training cell. The magnitude of the coefficient indicates that supply is more inelastic than demand, although the difference between the two elasticities is not huge especially in baseline specifications. Estimating the reaction of quantities to changes in the subsidy can complement the analysis, delivering us an estimate of the elasticities in absolute terms. Consider:

$$\eta^s = \frac{dx_i^s}{dp_{q,f,t}} = \frac{dx_i^s}{dc_{q,f,t}}\frac{1}{R(.)}.$$

$\frac{1}{R(.)}$ is estimated by $1/\beta^{RF}_{prices}$, the inverse of the coefficient obtained using Equation 8 with prices as an outcome. However, to estimate $\frac{dx_i^d}{dc_i}$, where x_i^d is the amount of training demanded by each individual, we face a measurement problem: for each training kind q, the distribution of realized consumption of training we observe in the data x_i 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 of the mean number of hours consumed of a training consumed $1/n \cdot \sum_{i\in q,j,f,t} x_i$, where n is the number of training episodes for a specific training, on $p_{q,j,f,t}$, suffers from left and right censoring in the outcome variable. A solution is to sum over all N individuals in the population, including the ones who don't train, both sides of the equation. On the right hand, we end up having the sum of the hours consumed for each training-kind, training firm, and financing center cell $X_{q,j,f,t} = \sum_{i\in q,j,f,t} x_i$. Hence:

$$N_{q,j,f,t}\eta^s = \frac{d\sum_{i\in q,j,f,t} x_i^d}{dp_{q,f,t}} = \frac{dX_{q,j,f,t}}{dc_{q,f,t}}\frac{1}{R(.)}$$
$$\eta^s = \frac{d\bar{x}_{q,j,f,t}}{dc_{q,f,t}}\frac{1}{R(.)} = \frac{\beta^{RF}_{quantities}}{\beta^{RF}_{prices}}$$

where $\bar{x}_{q,j,f,t} = \frac{X_{q,j,f,t}}{N_{q,j,f,t}}$ is the avrage number of hours per private sector employee in a q,j,f,t cell, β^{RF}_{prices} is the reduced form effect on prices discussed in the previous section, and $\beta^{RF}_{quantities}$ can be estimated through:

$$\bar{x}_{q,j,f,t} = \beta^{RF}_{quantities}c_{q,f,t} + \gamma_{q,j,f} + \tau_t + \varepsilon_{q,j,f,t} \tag{11}$$

Where all the fixed effects are like Equation 8. However, note that $\frac{d\bar{x}_{q,j,f,t}}{dc_{q,f,t}}$ cannot be estimated with OLS, since it's not normally distributed, but with Poisson regression[16].

The results are reported in Table 4. The results indicate a quite precisely estimated zero effect of changes in subsidy on training demand. In fact, the coefficient of the Poisson regressions mean that for a one euro change in the subsidy, the difference in the logs of expected counts is tiny and insignificant. This is true especially in the specification with training kind+training provider as unit of analysis (Panel A). Hence, one

[16] Alternatively, we can divide by $X_{q,j,f,t}$, which is equivalent to log-transform our dependent variable.

$$\eta^d = -\frac{dX_{q,j,f,t}/X_{q,j,f,t}}{dc_{q,f,t}}\frac{X_{q,j,f,t}/n}{R(.)}$$

Yet, this leaves an $X_{q,j,f,t}$.

obtains estimates of η^d and η^s from Equation 6 and 12. Results with log subsidies in columns (3) and (4) confirm the ones obtained in columns (1) and (2).

Subsequently, one can check the identification with a placebo analogous to Equation 10. We do so in column (2), finding that there is indeed a small but significant anticipation: where the subsidies will decrease more, training demand is higher the year before. This small anticipation suggests we should interpret the result in column (1) with caution: while demand doesn't decrease in 2019 when subsidies are lowered, it might be that the marginal consumer anticipated his consumption to 2018, to enjoy higher subsidies. This happened in spite of the fact that the reform was made public quite last minute, in late 2018. Demand might thus be more elastic than what we find by looking at column (1). On the other hand, the fact that an anticipation effect exists might reassure that our shock matters and is salient. One final interesting fact, which is partially reassuring, is that anticipation seems to be concentrated on specific groups of training kind: driving licenses and languages (Table **??** in the Appendix). There are many reasons why consumers might be more responsive and tending to anticipate the shock in these sectors. By now, we believe it is just important to point out how demand elasticity might vary a lot by sub-groups of consumers. This is an important insight if one wants to better target training subsidies to more elastic groups of consumers (Cahuc and Zylberberg, 2006)).

Table 4: Impact on average quantities demanded: baseline results

Panel A: Training kind + training firm as unit of analysis

VARIABLES	(1) $\bar{x}_t$	(2) $\bar{x}_t$	(3) $\bar{x}_t$	(4) $\bar{x}_t$
c_t	0.00391	0.0364		
	(0.00576)	(0.0238)		
c_{t+1}		-0.0174*		
		(0.00922)		
$\ln(c_t)$			0.177	1.668*
			(0.243)	(0.968)
$\ln(c_{t+1})$				-0.544*
				(0.306)
Observations	50,272	22,100	50,272	22,100
Number of training_program_financeur	25,136	11,050	25,136	11,050
Years	2018-2019	2017-2018	2018-2019	2017-2018
η^d	.047		.102	
η^s	.038		.044	
$\frac{\Delta W}{\Delta c}/N$	-.013		-.028	

Panel B: training kind + Local labor market as unit of analysis

VARIABLES	(1) $\bar{x}_t$	(2) $\bar{x}_t$	(3) $\bar{x}_t$	(4) $\bar{x}_t$
c_t	0.00257	0.0395***		
	(0.00493)	(0.0146)		
c_{t+1}		-0.00692		
		(0.00660)		
$\ln(c_t)$			0.227	1.835***
			(0.242)	(0.615)
$\ln(c_{t+1})$				-0.283
				(0.212)
Observations	45,462	22,862	45,462	22,862
Number of training_kind_financeur	22,731	11,431	22,731	11,431
Years	2018-2019	2017-2018	2018-2019	2017-2018
η^d	.03		.127	
η^s	.022		.05	
$\frac{\Delta W}{\Delta c}/N$	-.01		-.043	

Notes: In Panel A data are collapsed at the level of training kind (training title +online/in presence) plus training firm and year. Regressions in panel A thus include include fixed effects for training kind (training title +online/in presence) plus training firm FE, and year FE. In Panel B data are collapsed at the level of training kind (training title +online/in presence) plus local labor market and year. Regressions in panel B thus include include fixed effects for training kind (training title +online/in presence) plus local labor market FE, and year FE. Standard errors are clustered at the training kind (training title +online/in presence) plus training firm in Panel A, and at the training kind (training title +online/in presence) plus local labor market in Panel B. Both panels report in column 1 the first stage regression of total subsidy per-hour on the maximum ILA subsidy per hour (controlling for price levels); in column 2 the reduced form estimate (also includes the estimate of implied elasticities according to (6); in column 3 the reduced form estimate of the relationship between (endogenous) changes in maximum subsidies and prices in 2017-2018; and in column 4 the estimates of the placebo equation (10).

5.2 Calculating welfare effect: 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 elasticities rather than deep primitives, and 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 how the efficiency cost of small tax changes can be estimated using a simple elasticity-based formula.

As a first step, we can adapt Harberger's approach to ILA subsidies. Using the model derived in Section 2, total welfare is defined as the sum of individuals welfare[17]:

$$
\begin{aligned}
W(\boldsymbol{c}) &= \sum_i \max_{x_i}[\phi'^{-1}(x_i) + m + \min(p_{q,f,t}, c_{q,f,t})x_i - p_{q,f,t}x_i)] + \max_{x_i}[p_{q,f,t}x_i - COST(x_i)] - \min(p_{q,f,t}, c_{q,f,t})x_i \\
&= \begin{cases} \sum_i \max_{x_i}[\phi'^{-1}(x_i) + m + c_{q,f,t}x_i - COST(x)] - c_{q,f,t}x_i & \text{if} \quad p_{q,f,t} \geq c_{q,f,t} \\ \sum_i \max_{x_i}[\phi'^{-1}(x_i) + m + p_{q,f,t}x_i - COST(x)] - p_{q,f,t}x_i & \text{if} \quad p_{q,f,t} < c_{q,f,t} \end{cases} \\
\frac{dW(\boldsymbol{c})}{d\boldsymbol{c}} &= \begin{cases} \sum_{q,f} \sum_{i \in q,f,t} -x_i + x_i - c_{q,f,t} \cdot \frac{dx_i}{dc_{q,f,t}} & \text{if} \quad p_{q,f,t} \geq c_{q,f,t} \\ \sum_{q,f} \sum_{i \in q,f,t} -R(.) \circ x_i + R(.) \circ x_i - p_{q,f,t} \cdot \frac{dx_i}{dc_{q,f,t}} & \text{if} \quad p_{q,f,t} < c_{q,f,t} \end{cases} \\
&= \sum_{q,f} N_{q,f} \eta^d \min(p_{q,f,t}, c_{q,f,t})
\end{aligned}
$$

The last two lines write down the change in aggregate welfare for one extra euro of CPF subsidy for each individual. It suggests that in the case of ILA, to estimate the change in aggregate welfare one should simply estimate the reaction of quantities to changes in the maximum cap of the subsidy, multiply them by the actual subsidy erogated for each individual and in each industry/financing center and sum up over the whole population. 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. Kleven (2020)'s formula adapted to our case looks like[18]:

[17] Few individuals have multiple training episodes at a given time

[18] Suppose we are in case 4 of Section 2.3, let us approximate demand-weighted average Hicksian elasticity with η^d, and the tax wedge with c/p. Then:

$$\frac{\Delta W(c)}{\Delta c} \approx \eta^d \frac{c}{p} \Delta c + \frac{1}{2} \left[\eta^d \Delta \frac{c}{p} + \Delta \eta^d \frac{c}{p} + \Delta \eta^d \Delta \frac{c}{p} \right]$$

This formula highlights how changes in elasticities and changes in the tax wedge following the policy change. Of course, if utilities (hence demand, since the model is quasi-linear) are iso-elastic, as in our case, the problem simplifies.

$$\frac{\Delta W(c)}{\Delta c} \approx \eta^d \frac{c}{p} \Delta c + \frac{1}{2} \left[\eta^d \Delta \frac{c}{p} \right]$$

Now, one needs to separate the four cases and obtains the result.

$$\frac{\Delta W(\boldsymbol{c})}{\Delta \boldsymbol{c}} \approx \sum_{q,f} N_{q,f}\eta^d \Big\{ \frac{c_{q,f,t-1}}{p_{q,f,t-1}} \left[\min(p_{q,f,t}, c_{q,f,t}) - \min(p_{q,f,t-1}, c_{q,f,t-1})\right]$$
$$+ \frac{1}{2}\left[\min(1, \frac{c_{q,f,t}}{p_{q,f,t}}) - \min(1, \frac{c_{q,f,t-1}}{p_{q,f,t-1}})\right] \Big\} \tag{12}$$

Since this quantities can all be estimated, in the last line of Table 4 we can report the efficiency cost of CPF using elasticities obtained with different specifications. Note that we report such cost relative to the total number of private sector employees N. The figure can then be interpreted as the average change in aggregate welfare from one euro more of CPF. Since all our estimates of η^d are close to zero, it is not surprising that the impact on welfare is estimated very small.

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

Section 4 suggests that the incidence of CPF subsidy falls slightly more on producers than on consumers. However, "producers" of training are not a final entity, and the incidence on producers is actually shared between production factors determining the supply of training (Harberger, 1962). This section exploits our CPF reform and data on the balance sheet and labor force of training suppliers to show which factor eventually bears the final incidence of the subsidy, meaning how the share of incidence falling on suppliers is passed through to labor of capital invested in training production. We will check this in a direct way by regressing the change in revenues, costs, profits, total wage bill and employment on the average change in the subsidy faced by each supplier.

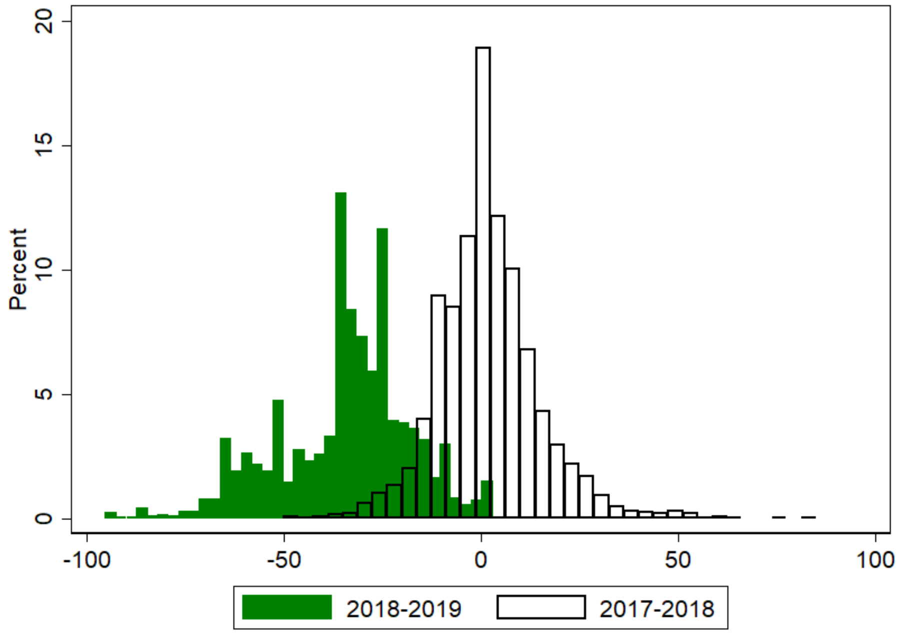
First, note that CPF trainings are not the totality of trainings for suppliers reported in our dataset. Let total training produced be the sum of hours in CPF training episodes x_i plus total hours of training out of CPF x^{OTH}: $x_j^{TOT} = \sum_{i \in j} x_i + x^{OTH}$. We assume that the prices charged on CPF and non-CPF trainings are independent. This is both convenient - otherwise one has to model how the two markets affect each other - and not irrealistic, since several episodes of price discrimination between CPF and non-CPF trainings are reported. Define total revenues:

$$REV_j = \sum_{i \in j} x_i p_i + x^{OTH} p^{OTH}$$
$$REV_j = \sum_{i \in j} \eta^s p_i^2 + x^{OTH} p^{OTH}$$
$$\frac{dREV_j}{dc_i} = 2\eta^s \sum_{i \in j} \frac{dp_i}{dc_i} p_i$$
$$\frac{dREV_j}{dc_i} = 2R(.) \sum_{i \in j} x_i$$

Note however that both REV_j and $\sum_{i \in j} p_i$ are not normally distributed. We can re-arrange:

$$\frac{dREV_j}{REV_{j,t_0}} = 2R(.) \frac{\sum_{i \in j} x_{i,t_0} p_{i,t_0}}{REV_{j,t_0}} / p_{i,t_0} d\bar{c}_{jt} \tag{13}$$

Figure 9: Distribution of $\Delta \sum_{i \in j} \frac{x_i p_{i,t_0}}{\sum_{i \in j} x_{i,t_0} p_{i,t_0}} c_i$



where $\frac{dREV_j}{REV_{j,t_0}}$ approximates the % change in revenues, and $\bar{c}_{jt} = \sum_{i \in j} \frac{x_i p_{i,t_0}}{\sum_{i \in j} x_{i,t_0} p_{i,t_0}} c_i$ is the average conversion rate faced by a supplier, weighted by the share of CPF revenues that each training accounts for. The variation of this right-hand side independent variable is reported in Figure 9.

We can thus estimate $\beta^{RF}_{REV} = \frac{dREV_j / REV_{j,t_0}}{d\bar{c}_{jt}}$ in Equation 13 with the regression:

$$\ln y_{j,t} = \beta^{RF}_{REV} \bar{c}_{jt} + \gamma_j + \tau_t + \varepsilon_{j,t} \qquad \text{if} \quad t = 2018, 2019 \tag{14}$$

Where $y_{j,t}$ are different producer-level outcomes: revenues, costs, profits, labor costs, total labor. Analogously, we obtain equations for total costs $COST_j$, profits π_j, labor costs L_j and total labor N_j (measured as number of teachers). Finally, recall that $R(.)$ in Equation 13 has a concave non-linear shape (Equation 2). Hence, we will also estimate a specification with log-transformation of the independent variable $\bar{c}_{jt}$.

Table 5 reports the results. There seems to be a positive significant relationship between changes in the subsidy and changes in producers revenues, meaning that a larger decrease in the average subsidy allowed to a supplier's consumers leads to a larger decrease in revenues. The magnitude of the coefficients suggest that we observe a .1% decrease in profits 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 .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 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 teachers. Hence, the part of incidence of the subsidy which falls on producers seems to be shifted to producers. This is consistent with the idea that in the short run labor is less elastic than capital, perhaps due to labor market regulation.

Note that the relationship in Equation 13 is mediated by $\frac{\sum_{i \in j} x_{i,t_0} p_{i,t_0}}{REV_{j,t_0}}$, the share of revenues coming from

Table 5: Impact of changes in CPF subsidy on producers' revenues, costs, profits, labor costs and number of teachers

VARIABLES	(1) $\ln REV_{jt}$	(2) $\ln COST_{jt}$	(3) $\ln \pi_{jt}$	(4) $\ln L_{jt}$	(5) $\ln N_{jt}$
$\bar{c}_{jt}$	0.00127**	0.000406	0.000834*	-0.000470	0.000120
	(0.000593)	(0.000679)	(0.000476)	(0.000641)	(0.000646)
Observations	11,496	10,847	10,779	10,312	10,922
R-squared	0.977	0.973	0.870	0.966	0.967
Years	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019

VARIABLES	(1) $\ln REV_{jt}$	(2) $\ln COST_{jt}$	(3) $\ln \pi_{jt}$	(4) $\ln L_{jt}$	(5) $\ln N_{jt}$
$\ln \bar{c}_{jt}$	0.0616***	0.0177	0.0411***	-0.0148	-0.00574
	(0.0170)	(0.0199)	(0.0141)	(0.0213)	(0.0203)
Observations	11,496	10,847	10,779	10,312	10,922
R-squared	0.977	0.973	0.870	0.966	0.967
Years	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019

CPF at baseline. In the case of revenues we can actually estimate this quantity for each firm j (while for the share of costs, profits, labor costs and labor we cannot, as we can't define what is the cost and labor dedicated to CPF). Table 6 reports this heterogeneity. 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 only for top two quintiles (which correspond to when CPF revenues are >20% of total revenues). It also allows us to obtain another estimate of $R(.)$, by dividing the coefficients by twice the average revenue share and multiplying by the average price. These estimates vary substantially, but are consistently below 1, and surprisingly close to β^{RF}_{prices} for the upper two quintiles (the ones where the coefficient is significant).

7 Conclusions

In this paper we studied the incidence and welfare effects of a particular kind of training subsidies, Individual Learning Accounts (ILA). In the first part of the paper, our theoretical model highlights how ILAs training subsidies might be intrinsically unable to increase demand for long trainings, making demand perfectly inelastic around the maximum amount of hours subsidizable and unchanged for for longer hours. A simple policy remedies in the case of ILA include to denominate these accounts in Euros, and to better target weaker workers. In the Appendix we show how if ILAs are denominated in Euros rather than hours, demand tilts on the right of the maximum amount of ILA available. Demand thus becomes steeper, but never perfectly inelastic, making it more likely that equilibrium quantities of training are actually larger.

Our empirical analysis delivers three results. First, the supply of training is between 15% and 50% less elastic

Table 6: Impact of changes in CPF subsidy on producers' revenues: heterogeneity by importance of CPF revenues over total revenues

VARIABLES	(1) $\ln REV_{jt}$	VARIABLES	(1) $\ln REV_{jt}$
$c_t * \mathbb{1}(\frac{RevCPF}{TotRev_{jt_0}} < p20)$	-0.000383	$\ln c_t * \mathbb{1}(\frac{RevCPF}{TotRev_{jt_0}} < p20)$	-0.00643
	(0.000561)		(0.0232)
$c_t * \mathbb{1}(p20 < \frac{RevCPF}{TotRev_{jt_0}} \leq p40)$	3.51e-05	$\ln c_t * \mathbb{1}(p20 < \frac{RevCPF}{TotRev_{jt_0}} \leq p40)$	0.00985
	(0.000668)		(0.0258)
$c_t * \mathbb{1}(p40 < \frac{RevCPF}{TotRev_{jt_0}} \leq p60)$	0.000922	$\ln c_t * \mathbb{1}(p40 < \frac{RevCPF}{TotRev_{jt_0}} \leq p60)$	0.0320
	(0.000586)		(0.0234)
$c_t * \mathbb{1}(p60 < \frac{RevCPF}{TotRev_{jt_0}} \leq p80)$	0.00117***	$\ln c_t * \mathbb{1}(p60 < \frac{RevCPF}{TotRev_{jt_0}} \leq p80)$	0.0415**
	(0.000434)		(0.0196)
$c_t * \mathbb{1}(\frac{RevCPF}{TotRev_{jt_0}} > p80)$	0.00146**	$\ln c_t * \mathbb{1}(\frac{RevCPF}{TotRev_{jt_0}} > p80)$	0.0554**
	(0.000612)		(0.0239)
Observations	11,496	Observations	11,496
R-squared	0.978	R-squared	0.978
Years	2018-2019	Years	2018-2019
dp/dc quintile #1	-1.062	$dp/d\ln c$ quintile #1	-17.817
dp/dc quintile #2	.023	$dp/d\ln c$ quintile #2	6.518
dp/dc quintile #3	.238	$dp/d\ln c$ quintile #3	8.241
dp/dc quintile #4	.128	$dp/d\ln c$ quintile #4	4.543
dp/dc quintile #5	.056	$dp/d\ln c$ quintile #5	2.128

than demand, so that more than half of the benefit of the subsidy is captured by training producers. Second, total hours of training undertaken are not significantly affected by subsidy changes, leading to estimates of demand and supply elasticities which are close to zero. This makes CPF subsidy a simple transfer to producers and trainees. The silver lining is that, when studied through the lenses of a sufficient statistics framework, the efficiency cost of CPF is also low. Third, we use data on revenues and expenses of training to see 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 policy relevance of our result is evident: if demand and supply for training are inelastic, subsidies like CPF risk ending up in a transfer to producers and trainers. Policy makers who want to support training investment must - before subsidizing training - either find ways to make supply and demand more elastic or better target the subsidy on potentially more elastic sub-markets. Our results confirm the intuition by Cahuc and Zylberberg (2006). On the demand side, one might want to focus on individuals with more elastic demand for training (e.g. workers with lower opportuity costs), and in any case avoid quantity caps to the subsidy. On the other side, training supply seems very inelastic at least in the short run, possibly due to institutional rigidities making it difficult to expand the supply of training. An example of these frictions could be eligibility requirments and quality certifications, which we know are in place for CPF. Interestingly, in this case policy makers might face a tradeoff between the need to guarantee quality (Acemoglu and Pischke, 1999; Rain, 2017) and the risk that certifications become an entry barrier. In any case, we argue that more research is needed on the reasons why demand and supply for training are found to be so inelastic, a fact that makes it difficult for policy to promote workforce training and lifelong investment in skills.

References

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

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

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

Youssef Benzarti, Dorian Carloni, Jarkko Harju, and Tuomas Kosonen. What goes up may not come down: asymmetric incidence of value-added taxes. *Journal of Political Economy*, 128(12):4438–4474, 2020.

Marianne Bertrand, Esther Duflo, and Sendhil Mullainathan. How much should we trust differences-in-differences estimates? *The Quarterly journal of economics*, 119(1):249–275, 2004.

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

Pierre Cahuc and André Zylberberg. La formation professionnelle des adultes: un système à la dérive. *rapport au COE de la CCIP*, 2006.

Raj Chetty. Sufficient statistics for welfare analysis: A bridge between structural and reduced-form methods. *Annu. Rev. Econ.*, 1(1):451–488, 2009.

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

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

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

Katja Görlitz and Marcus Tamm. The returns to voucher-financed training on wages, employment and job tasks. *Economics of Education Review*, 52:51–62, 2016.

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

Arnold C Harberger. The measurement of waste. *The American Economic Review*, 54(3):58–76, 1964.

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

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

Henrik Kleven. Sufficient statistics revisited. *National Bureau of Economic Research Working Paper Series*, (w27242), 2020.

OECD. *Individual Learning Accounts*. 2019. doi: https://doi.org/https://doi.org/10.1787/203b21a8-en. URL `https://www.oecd-ilibrary.org/content/publication/203b21a8-en`.

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

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

Simon Potter. Nonlinear time series modelling: An introduction. *Journal of Economic Surveys*, 13(5): 505–528, 1999.

Audrey Rain. *Trois essais empiriques en économie de l'éducation et de la formation*. PhD thesis, Paris 2, 2017.

James M Sallee. The surprising incidence of tax credits for the toyota prius. *American Economic Journal: Economic Policy*, 3(2):189–219, 2011.

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

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

A Appendix

A.1 Proof of Section 2.1

We can thus re-write the problem as:

$$\max_{x_i^{IND}, x_i^{ILA}} \left[\omega_i - p\, x_i^{IND} - \max(p-c,0)\cdot x_i^{ILA} + \phi(x_i^{IND} + x_i^{ILA})\right] \qquad s.t. \quad x_i^{IND} \geq 0$$

$$x_i^{ILA} \leq \overline{x^{ILA}}$$

$$x_i^{ILA} \geq 0$$

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

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

   If $x_i^{ILA\star} = \overline{x^{ILA}}$, then $\lambda > 0$, for the last equality to hold. If $x_i^{IND\star} > 0$, then the second inequality holds with equality, $x_i^{IND\star} = \phi_i'^{-1}(p) - \overline{x^{ILA}}$, and $\lambda = c$ to satisfy the first equality. Note however that for $\phi_i'^{-1}(p) - \overline{x^{ILA}} > 0$ we need $p < \phi'(\overline{x^{ILA}})$. Else, if $x_i^{IND\star} = 0$, then the second inequality holds strictly, while the first holds with equality, so that $\phi'(\overline{x^{ILA}}) + c = p + \lambda > p > \phi'(\overline{x^{ILA}})$. If instead $x_i^{ILA\star} < \overline{x^{ILA}}$, $\lambda = 0$, 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 $x_i^{ILA\star} = \phi'^{-1}(p-c)$. Note that since $x_i^{ILA\star} < \overline{x^{ILA}}$, then $p > \phi'(\overline{x^{ILA}}) + c$.

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

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

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

A.2 Demand for training with ILA in money (CPF post-reform and general case)

With the same assumptions as the previous section, let the consumer's problem be:

$$\max_{m_i, x_i^{IND}, x_i^{ILA}} [m_i + \phi(x_i^{IND} + x_i^{ILA})] \qquad s.t. \quad m_i + p\, x_i^{IND} \leq \omega_i$$

$$x_i^{IND} \geq 0$$

$$p \cdot x_i^{ILA} \leq \overline{ILA}$$

$$x_i^{ILA} \geq 0$$

The FOCs are:

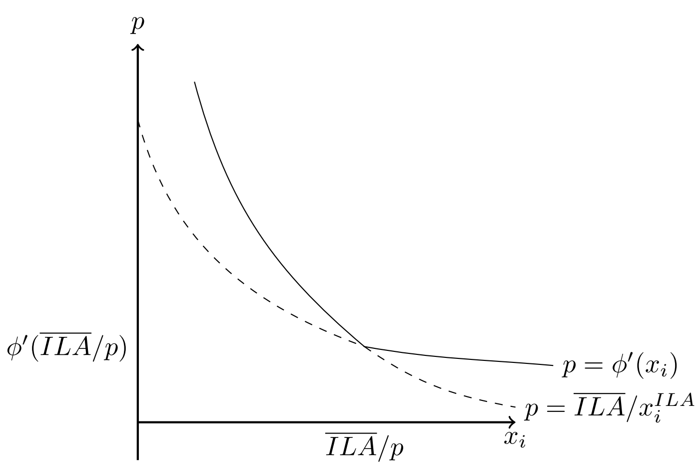
$$
\begin{aligned}
&[x_i^{ILA}]: && \phi'(x_i^{IND\star}+x_i^{ILA\star})-\lambda p \leq 0 && \text{with equality if } x_i^{ILA*}>0\\
&[x_i^{IND}]: && \phi'(x_i^{IND\star}+x_i^{ILA\star})-p \leq 0 && \text{with equality if } x_i^{IND*}>0\\
&[\lambda]: && \lambda[p\cdot x_i^{ILA\star}-\overline{ILA}]=0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

If $\lambda > 0$, then $x_i^{ILA\star} = \overline{ILA}/p$ for the last equality to hold. If $x_i^{IND\star} > 0$, then the second inequality holds with equality, $x_i^{IND\star} = \phi_i'^{-1}(p) - \overline{ILA}/p$, and $\lambda = 1$ to satisfy the first equality. Note that for $x_i^{IND\star} = \phi_i'^{-1}(p) - \overline{ILA}/p > 0$ we need $p < \phi'(\overline{ILA}/p)$. Else, if $x_i^{IND\star} = 0$, then the second inequality is $\phi'(\overline{ILA}/p) \leq p$, while the first holds with equality, so that $\phi'(\overline{ILA}/p) = \lambda \cdot p$. If instead $\lambda = 0$, then the first constraint contradicts $\phi'(.) > 0$.

The resulting walrasian demand for the representative consumer is:

- If $p \leq \phi'(\overline{ILA}/p)$, $x_i^\star = \phi_i'^{-1}(p)$
- If $p > \phi'(\overline{ILA}/p)$, $x_i^\star = \overline{ILA}/p$

Figure 10: Demand with ILA in Euros



A.3 What changes with no price discrimination?

Suppose that instead of $p_{q,j,f,t} = R(.) \circ c_{q,f,t}$ we have $p_{q,j,t} = R(.) \circ \sum_f \frac{n_{q,j,f,t}}{N_{q,j,t}} c_{q,f,t}$. Less-than perfect market segmentation across different industries f underestimate the impact of changes in the subsidy on prices. This can be seen focusing on a simple case of two industries: $f \in \{f^1, f^2\}$ with $n_{q,j,f^1,t} = n_{q,j,f^2,t}$, $\Delta c_{q,j,f^1,t} = 0$ and $\Delta c_{q,j,f^2,t} = \upsilon$. Then $\Delta p_{q,j,t} = R(.) \circ \frac{1}{2}\upsilon$. Note also that in the regression at the υ level we would observe the following two observations (in terms of differences): $(\Delta c_{q,j,f^1,t} = 0, \Delta p_{q,j,f^2,t} = R(.) \circ \frac{1}{2}\upsilon)$, $(\Delta c_{q,j,f^2,t} = \upsilon, \Delta p_{q,j,f^2,t} = R(.) \circ \frac{1}{2}\upsilon)$.

To understand the magnitude of this treat, we replicate the regressions at the q, j, t and q, l, t level. Regression

8 becomes:

$$p_{q,j,t} = \beta^{RF}_{prices} \sum_{f} \frac{n_{q,j,f,t}}{N_{q,j,t}} c_{q,f,t} + \gamma_{q,j} + \tau_t + \varepsilon_{q,jt} \qquad \text{if} \quad t = 2018, 2019$$

The results are reported in the table below, and although they tend to estimate a relatively more inelastic supply, they are quite comparable to our baseline estimates:

Table 7: Results without assuming market segmentation

Panel A: Training kind + training firm as unit of analysis

	(1)	(2)	(3)	(4)
VARIABLES	$\tilde{c}_t$	p_t	p_t	p_t
c_t	0.152***	0.0897***	0.121***	0.120***
	(0.0169)	(0.0138)	(0.0227)	(0.0294)
c_{t+1}				-0.00438
				(0.0122)
Observations	33,920	33,920	31,160	20,077
R-squared	0.928	0.942	0.955	0.961
Years	2018-2019	2018-2019	2017-2018	2017-2018
η^d/η^s		1.44		

Panel B: training kind + Local labor market as unit of analysis

	(1)	(2)	(3)	(4)
VARIABLES	$\tilde{c}_t$	p_t	p_t	p_t
c_t	0.138***	0.0836***	0.0776***	0.0589**
	(0.0165)	(0.0179)	(0.0215)	(0.0279)
c_{t+1}				-0.0119
				(0.0159)
Observations	28,021	28,021	26,368	17,968
R-squared	0.939	0.949	0.953	0.960
Years	2018-2019	2018-2019	2017-2018	2017-2018
η^d/η^s		1.54		

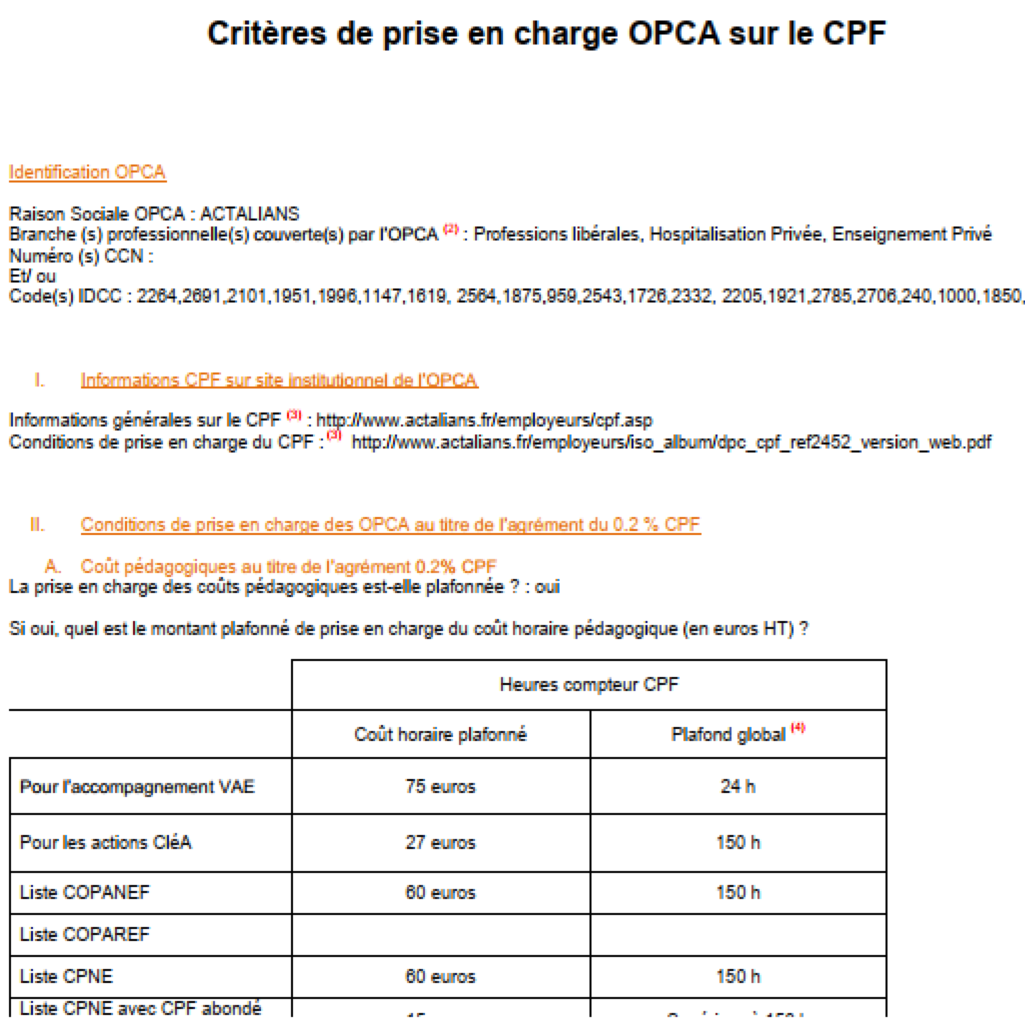
Notes: In Panel A data are collapsed at the level of training kind (training title +online/in presence) plus training firm and year. Regressions in panel A thus include include fixed effects for training kind (training title +online/in presence) plus training firm FE, and year FE. In Panel B data are collapsed at the level of training kind (training title +online/in presence) plus local labor market and year. Regressions in panel B thus include fixed effects for training kind (training title +online/in presence) plus local labor market FE, and year FE. Standard errors are clustered at the training kind (training title +online/in presence) plus training firm in Panel A, and at the training kind (training title +online/in presence) plus local labor market in Panel B. Both panels report in column 1 the first stage regression of total subsidy per-hour on the per-hour ILA subsidy (controlling for price levels); in column 2 the reduced form estimate (also includes the estimate of implied elasticities according to (6); in column 3 the reduced form estimate of the relationship between (endogenous) changes in per-hour ILA subsidy caps and prices in 2017-2018; and in column 4 the estimates of the placebo equation.

Table 8: Baseline Regressions at the individual level

VARIABLES	(1) $\tilde{c_t}$	(2) p_t	(3) p_t	(4) $\tilde{c_t}$	(5) p_t	(6) p_t	(7) $\tilde{c_t}$	(8) p_t
c_t	0.205***	0.119***	0.143***	0.188***	0.104***	0.154***	0.186***	0.0992***
	(0.0193)	(0.0194)	(0.0245)	(0.0138)	(0.0129)	(0.0206)	(0.0209)	(0.0207)
c_{t+1}			-0.0128*			-0.00110		
			(0.00756)			(0.00677)		
Observations	607,858	607,858	293,920	607,858	607,858	238,881	508,680	508,680
R-squared	0.704	0.718	0.662	0.786	0.807	0.770	0.773	0.794
Years	2018-2019	2018-2019	2017-2018	2018-2019	2018-2019	2017-2018	2018-2019	2018-2019
Tr. kind/LL Mkt FE	YES	YES	YES	NO	NO	NO	YES	YES
Tr. kind/Tr. firm FE	NO	NO	NO	YES	YES	YES	YES	YES
η^d/η^s		1.38			1.227			1.14

A.4 Additional figures

Figure 11: 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 12: Number of accounts by number of hours in the CPF account

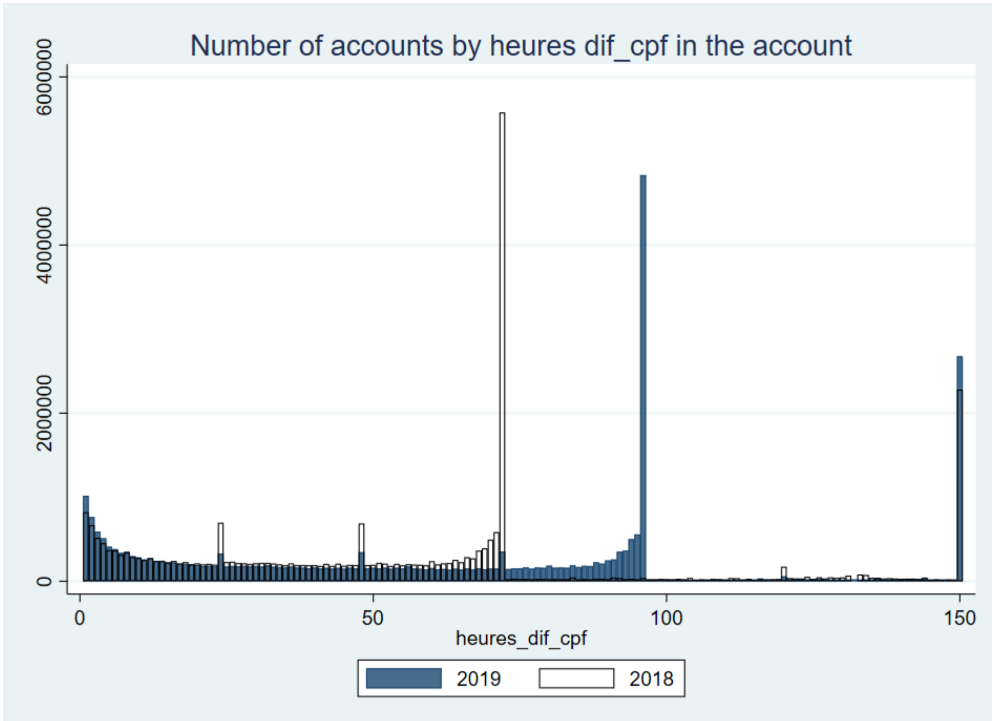


Figure 13: Time series of total cost of trainings undertaken and number of trainings started each week, in 2018 and 2019, breaking down 2019 into trainings validated by industry financing centers and those initiated through the centralized mobile app

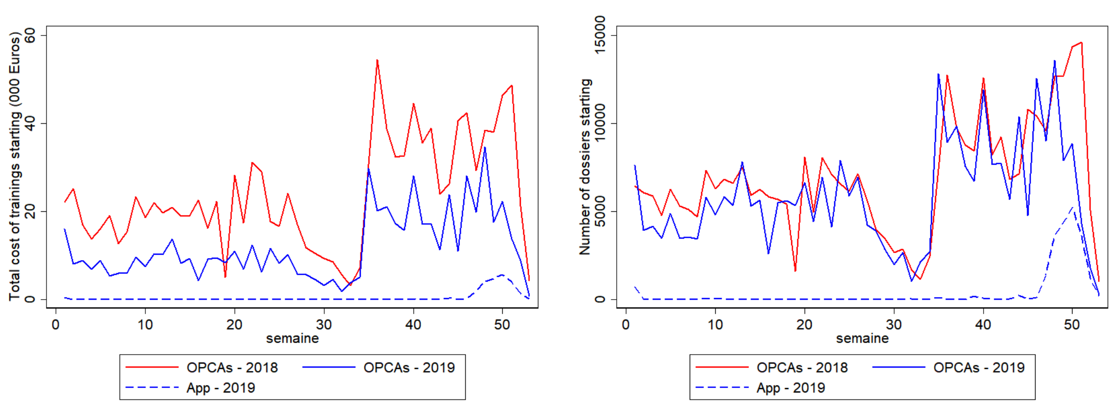


Figure 14: Time series of total number of trainings (training episodes), total hours of training and total cost of training for unemployed (*PRE*) and employees (*salaries*)

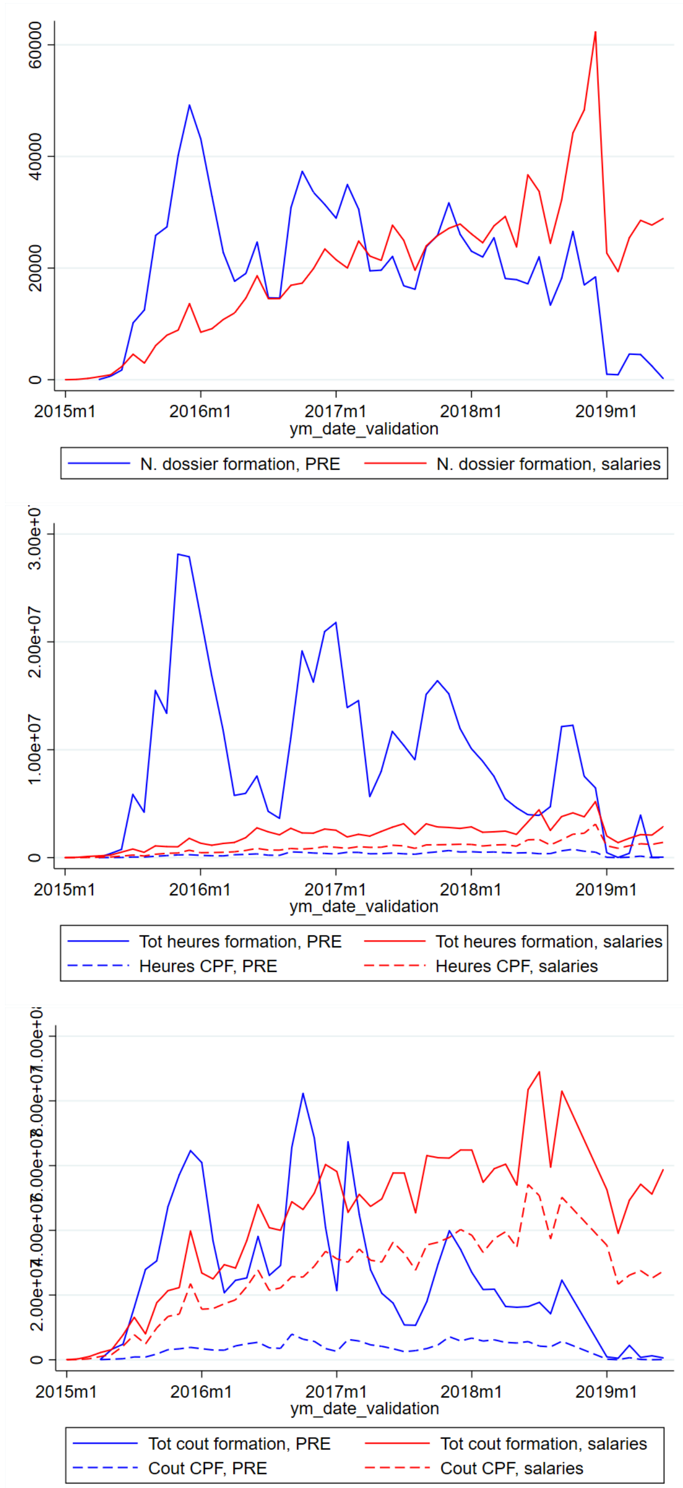


Figure 15: Per-hour value of the CPF subsidy ($\overline{ConvRate}_{q,f,t}$), and observed ratio of $CPF_i/HoursCPF_i$ (average, mode, and IQR), for $p \in$ CléA

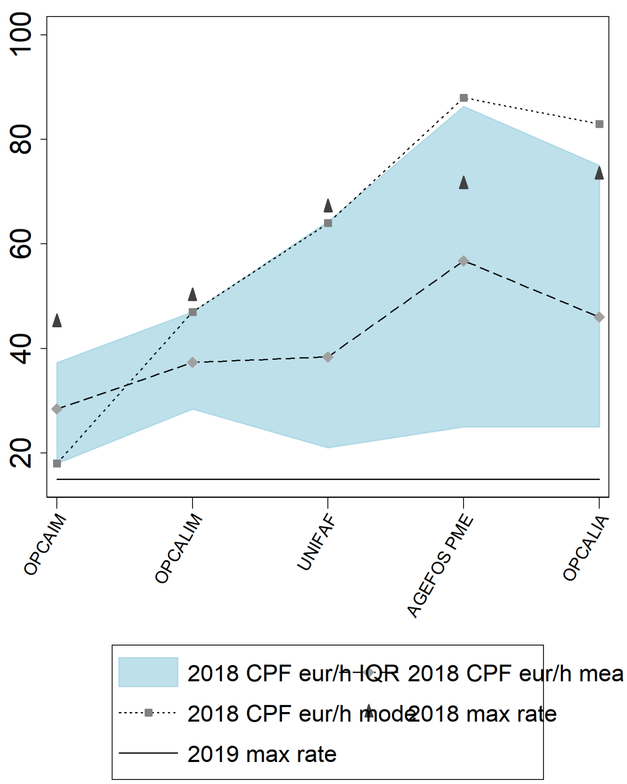


Figure 16: Link between agencies and their industry

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

Table 10: Effect on entry(/exit)

VARIABLES	(1) n_j	(2) $\ln n_j$	(3) p_t
(mean) max_conv	-0.000910*	0.000420	0.128***
	(0.000546)	(0.00338)	(0.0383)
c_concentrated			0.0186
			(0.0252)
Observations	26,360	55,695	61,142
R-squared		0.930	0.919
Number of training_kind_financeur	13,180		
Years	2018-2019	2018-2019	2018-2019
Estimation method	Poisson	OLS	
Unit of analysis			Tr. kind+LLM

Table 9: Placebos of robusness checks' regressions

VARIABLES	(1) p_t	(2) p_t	(3) p_t
$\ln(c_t)$	6.367***	6.117***	6.779***
	(1.682)	(1.294)	(1.243)
$\ln(c_{t+1})$	-0.260	0.154	0.223
	(0.438)	(0.351)	(0.278)
Observations	24,347	23,597	276,251
R-squared	0.958	0.965	0.787
Years	2017-2018	2017-2018	2017-2018
Unit of anal.	T.kind/LLMkt	T.kind/T.firm	
Tr. kind/LL Mkt FE			YES
Tr. kind/Tr. firm FE			YES

Table 11: Heterogeneity according to training kind in placebo of hours

Panel A: Training kind + training firm as unit of analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	Total hours	Total hours	Total hours	Total hours	Total hours	Total hours	Total hours	Total hours	Total hours	Total hours
(mean) max_conv	0.0136***	0.0134***	0.0129***	0.0137***	0.00838**	0.0137***	0.0137***	0.0133***	0.0121***	0.0136***
	(0.00336)	(0.00338)	(0.00326)	(0.00319)	(0.00341)	(0.00323)	(0.00321)	(0.00321)	(0.00404)	(0.00328)
max_conv_lead	-0.00536***	-0.00426**	-0.00526***	-0.00490***	-0.00646***	-0.00464***	-0.00548***	-0.00482***	-0.00353***	-0.00459***
	(0.00193)	(0.00206)	(0.00176)	(0.00171)	(0.00187)	(0.00172)	(0.00175)	(0.00172)	(0.00132)	(0.00177)
Observations	18,566	19,424	21,806	22,076	15,184	21,014	20,916	21,286	18,272	20,356
Number of training_program_financeur	9,283	9,712	10,903	11,038	7,592	10,507	10,458	10,643	9,136	10,178
Years	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019
Training kind	Bilan de compet	CACES	CQP	CleA	Langues	Permis B	VAE	creation d'entr	everything else	informatique

Panel A: Training kind + Local labor market

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	Total hours	Total hours	Total hours	Total hours	Total hours	Total hours	Total hours	Total hours	Total hours	Total hours
(mean) max_conv	0.0106***	0.0101***	0.0102***	0.0100***	0.00608**	0.0105***	0.0103***	0.00991***	0.00714***	0.0103***
	(0.00248)	(0.00239)	(0.00229)	(0.00232)	(0.00309)	(0.00236)	(0.00236)	(0.00233)	(0.00254)	(0.00240)
max_conv_lead	-0.00368***	-0.00246*	-0.00323***	-0.00349***	-0.00463***	-0.00297**	-0.00415***	-0.00334***	-0.00340***	-0.00363***
	(0.00139)	(0.00136)	(0.00122)	(0.00121)	(0.00164)	(0.00122)	(0.00127)	(0.00122)	(0.00110)	(0.00126)
Observations	20,324	19,426	22,552	22,802	16,070	21,886	21,270	22,034	18,564	20,830
Number of training_kind_financeur	10,162	9,713	11,276	11,401	8,035	10,943	10,635	11,017	9,282	10,415
Years	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019
Training kind	Bilan de compet	CACES	CQP	CleA	Langues	Permis B	VAE	creation d'entr	everything else	informatique

Table 12: Heterogeneity according to training kind

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	p_t	p_t	p_t	p_t	p_t	p_t
c_t	0.107***	0.124***	0.119***	0.0866***	0.107***	0.101**
	(0.0284)	(0.0463)	(0.0382)	(0.0330)	(0.0308)	(0.0417)
$c_t \cdot \mathbb{1}(q = \text{Bilan de compet})$	0.0436			0.0612*		
	(0.0691)			(0.0355)		
$c_t \cdot \mathbb{1}(q = \text{CACES})$	-0.0116			0.000679		
	(0.0308)			(0.0342)		
$c_t \cdot \mathbb{1}(q = \text{CQP})$	-0.0623			-0.0566		
	(0.0767)			(0.0869)		
$c_t \cdot \mathbb{1}(q = \text{CleA})$	-0.0621			-0.0254		
	(0.182)			(0.243)		
$c_t \cdot \mathbb{1}(q = \text{Langues})$	-0.00513			-0.00340		
	(0.0363)			(0.0453)		
$c_t \cdot \mathbb{1}(q = \text{Permis B})$	0.00583			0.0149		
	(0.0462)			(0.0365)		
$c_t \cdot \mathbb{1}(q = \text{VAE})$	-0.0430			-0.0511		
	(0.0389)			(0.0539)		
$c_t \cdot \mathbb{1}(q = \text{creation d'entr})$	0.0292			0.0467		
	(0.0523)			(0.0472)		
$c_t \cdot \mathbb{1}(q = \text{informatique})$	-0.00668			0.00255		
	(0.0331)			(0.0387)		
$c_t \cdot \mathbb{1}(q \in \{\text{online training}\})$		-0.0304			-0.0216	
		(0.0328)			(0.0343)	
$c_t \cdot \mathbb{1}(q \in \{\text{higher level certif.}\})$			0.000296			0.00401
			(0.0330)			(0.0267)
Observations	132,753	132,753	132,753	163,271	163,271	163,271
R-squared	0.942	0.942	0.942	0.951	0.951	0.951
Years	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019	2018-2019
Unit of analysis	Tr. kind+LLM	Tr. kind+LLM	Tr. kind+LLM	Tr. kind+firm	Tr. kind+firm	Tr. kind+firm