

Fixed-term contracts and wages: Rent-sharing and compensating differentials

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Abstract

The effect of fixed-term contracts on wages is theoretically ambiguous. I introduce a simple monopsonistic model which incorporates segmented fixed-term and open-ended contracts markets, differential rent-sharing and compensating wage differentials for job security. Using exhaustive French administrative data, I then confirm several predictions of the model, documenting novel empirical facts about FTCs and wages. While the overall average wage gap between the contract types is estimated to be a precise zero, wages vary differentially between both contract types, resulting in a wage premium for low productivity firms and a wage penalty for high productivity firms. I then further illustrate the differential rent-sharing mechanism by documenting that firms only extend about half of the wage premium of open-ended contract workers to fixed-term contract workers. Finally, I show that the degree of rent-sharing varies with local labor market concentration for OECs but not for FTCs.

Keywords : fixed-term contracts, temporary contracts, wages, labor market duality, France

JEL Codes: E24, J08, J31, J41, J42

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1 Introduction

A central topic in European labor market policy debates in the past three decades has been about determining the appropriate level of employment protection legislation, with a particular focus on the regulation of fixed-term contracts (FTCs) and open-ended contracts (OECs). While academic discussions have primarily revolved around employment and labor market flows, as well as the productivity effects of FTCs, less attention has been given to their impact on the wage structure.¹

The theoretical effect of FTCs on wages is ambiguous. Some theories suggest that FTCs could lower wages due to reduced bargaining power, while others argue that workers would need to be compensated for the decreased job security, resulting in compensating wage differentials. Understanding the mechanisms that determine wage formation in the presence of FTCs is crucial for understanding the full picture of their role in the labor market and the potential effects of reforms.

To inform this debate, this paper presents a simple monopsonistic model of segmented labor markets categorized by contract type, augmented by the notion of compensating wage differentials for job security. It predicts several novel facts which I then document using comprehensive administrative data from France, which sets this study apart from much of the existing literature that relies on aggregated, cross-sectional data.

By introducing a trade-off between the compensating wage differentials due to the valuation of job security and differential rent-sharing between FTCs and OECs, my model makes four predictions. The first two predictions concern the within-firm wage gap between OECs and FTCs. First, it predicts that low productivity firms pay higher wages to FTCs than OECs, while the opposite is true for high productivity firms. This stems from the fact the compensating wage differential is constant, but rent-sharing increases with productivity. Low-productivity firms would then pay low wages to both OECs and FTCs, but they have to compensate FTCs for the lower job security, leading to a firm wage premium for FTCs in low productivity firms. The second prediction is that the overall sign of the FTC-OEC wage is ambiguous. This is a direct corollary of the first prediction as it depends on the productivity distribution of firms in the economy.

The next two predictions concern differential rent-sharing. The theory predicts firms share rents less with workers on FTCs than workers on OECs. This has been discussed before in the literature, but generally in the context of bargaining. Here it comes from a

¹Interestingly, this issue has also arisen in a recent German labor court case, where it was ruled that equal tasks should be remunerated equally, regardless of the contract type (see for instance <https://www.spiegel.de/karriere/bundesarbeitsgericht-minijobber-muessen-den-gleichen-stundenlohn-bekommen-a-88f26250-208a-4413-82d4-1d07c690af41>, in German).

purely monopsonistic mechanism. Additionally, it also predicts that the degree of rent-sharing varies with the corresponding reduced-form firm labor supply elasticities.

I begin my empirical analysis by examining the aggregate wage gap in hiring wages. I focus on hiring wages to eschew the additional complexities that dynamics bring. I compute the overall gap in hiring wages between FTCs and OECs. After controlling for age, gender, occupation, industry and firm fixed effects, I find that the difference in hiring wages between FTCs and OECs is precisely estimated to be zero. This suggests that theories predicting both positive and negative wage gaps are necessary to understand the effect of FTCs on wages.² To further differentiate between these competing theories, I present several novel empirical findings.

Given that my model emphasizes the firm dimension, I then analyze the behavior of the FTC-OEC wage gap at the firm level. I show wages in OECs and FTCs vary with value added per worker with different slopes and in the way predicted by the model, generating a wage premium for FTCs in low productivity firms and wage penalty for high productivity firms. To illustrate the compensating wage differential mechanism further, I show that wages in FTCs decrease with average FTC length in firms.

I then analyze the differential rent-sharing mechanism further. Using the approach pioneered by [Card et al. \(2016\)](#) for studying the gender gap, and recently applied to the outsourcing literature by [Drenik et al. \(2022\)](#), I compare the firm wage premia for FTCs and OECs separately, which are identified from worker moves ([Abowd et al., 1999](#)). This provides a measure of the degree to which high-wage firms for FTCs are also high-wage firms for OECs.

In line with the hypothesis of reduced rent-sharing among workers on FTCs, I find that, on average, firms offering a 10% wage premium to workers on OECs only provide a 5.1% premium to workers on FTCs during the period from 2010 to 2014. This percentage is very similar to the 4.9% premium observed by [Drenik et al. \(2022\)](#) in the outsourcing context in Argentina. These findings align with the predictions of the monopsonistic model regarding differential rent-sharing.

Finally, I explore the last prediction on the variation of rent-sharing by using variation in hiring concentration by contract type in local labor markets. First, I show that FTC markets are more concentrated than OEC markets. Second, I show that for OECs the wage-value-added slope (and hence rent-sharing) decreases as OEC concentration increases as predicted by the model. Finally, I show that FTC concentration seems to affect the wage-value-added slope for FTCs very little, which suggests that concentration is a less important source of market power for FTCs than OECs.

²I exclude the possibility that this is due simply to the mandate from the law to pay FTCs and OECs equally.

This paper contributes to the literature on FTCs by providing a monopsonistic point of view which emphasizes the role of the firm and differential rent-sharing. I argue that FTCs play a crucial role when trying to understand labor market power in dual labor markets. Additionally, I emphasize the importance of compensating wage differentials and the valuation of job security when studying FTCs. Finally, I document novel empirical facts in accordance with the previous considerations. The goal is that these motivate deeper investigations, both theoretical and empirical, into the effects of FTCs on the wage structure.

The rest of the paper is structured as follows. In the following section, I give a more thorough literature review which focuses on the wage effects of FTCs. Next, I present the model, flesh out its predictions and discuss its limitations. I then present the institutional details and the data. The last three sections are empirical. I start by analyzing the average FTC-OEC wage gap. I then study firm-level heterogeneity, using both a binscatter and a firm fixed-effect approach. And finally, I explore local labor market heterogeneity, looking at the effect of concentration on rent-sharing. The final section concludes.

2 Literature review

In this section, I provide a literature review focusing on the wage effects of FTCs. This is a fairly stringent restriction, as the literature has focused surprisingly little on wage formation with FTCs. This is in stark contrast with the literature on outsourcing, where the wage effects of outsourcing are a main concern.

Theoretical literature Early on, [Bentolila et al. \(1994\)](#) suggested an “insider-outsider” view of dual labor markets, where both temporary and unemployed workers should be considered as outsiders. Part of their mechanism is the degree to which unions represent the interests of temporary workers. The prediction from this model is a wage penalty for FTCs.

The early literature also looked at the learning component of FTCs, namely that they allow firms to learn the productivity of the worker. [Blanchard and Landier \(2002\)](#) formalize the latter by embedding it into a search-and-match model. They do not tease out any conclusions on the wage. Later literature partially dismissed this, arguing that in most countries OECs have trial periods with no firing costs. This objection rings particularly true for repeated and very short FTC use.

FTCs have also been studied in an efficiency wage perspective in [Güell \(2000\)](#); [Güell and Rodríguez \(2010\)](#), where incentives in OECs are provided by higher wages, whereas the renewal rate plays that role for FTCs. This also predicts a wage penalty for FTCs.

The most explored mechanism is that firms' use of FTCs could be explained by the fact that they face temporary production opportunities. Worker-firm matches in FTCs then have a lower average surplus which implies lower wages. Additionally, because terminating temporary contracts before their date of termination is very costly, there can be situations where employers pay positive wages to unproductive temporary workers. This reduces their entry wage³. This has been modeled in [Cahuc et al. \(2016, 2020\)](#); [Daruich et al. \(2023\)](#), but the focus of all of these papers is the choice between FTC and OEC and the effect on employment and labor. Again, the prediction is a wage penalty for FTCs. [Daruich et al. \(2023\)](#) extend this model to give differential bargaining power to workers on FTCs and OECs.

On the other hand, [Rion \(2021\)](#) predicts that the wages hiring wages of OECs are lower than those of FTCs (but the continuing wages of OECs are the highest). Recently, [Créchet \(2023\)](#) has explored the role of risk-sharing between firms and workers with a trade-off between insurance and the flexibility of separation. [Franceschin \(2023\)](#) models a situation where excessive on-the-job search can be mitigated by the use of FTCs and OECs. One constant across most of these paper is that wages and in particular predictions on wages play a very minor role, and are rarely stated, making them hard to tease out.

Finally, a dimension which has not been explored in the context of FTCs and OECs is the role of job security and therefore compensating wage differentials. [Jarosch \(2023\)](#) presents a wage posting model with job security and shows that it can play an important role in understanding unemployment dynamics. [Pessoa De Araujo \(2017\)](#) looks at the role of job security in wage inequality. More generally, there has been a recent literature looking and documenting the importance of compensating wage differentials ([Sorkin, 2018](#); [Lavetti and Schmutte, 2018](#)).

Empirical literature Over the past 20 years, several papers have looked at the wage gap between FTCs and OECs using different methodologies and data (see Table 1 in [Albanese and Gallo \(2020\)](#)). All of these papers find a consistent wage penalty for FTCs, even when looking at heterogeneity along different variables (with very few exceptions). An important potential issue with all of these studies is the use of survey data, which is limited by small sample sizes, potential misreporting and also limited control variables (for instance detailed occupation information or firm identifiers).

Recently, there have been a few papers that find opposite results when using more exhaustive data. [Albanese and Gallo \(2020\)](#) found that when using administrative data,

³As far as I understand the model, the prediction concerns the full wage rather than the hourly wage, which is of less interest since it compares wages of people over different employment lengths.

restricting to hiring wages and using a stringent matching methodology based on extensive labor market history, there is a significant and big wage premium for FTCs across the entire wage distribution in Italy. Using a structural approach, [Lagrosa \(2022\)](#) also found evidence for wage premia for FTCs in Spain. On the other hand, [Daruich et al. \(2023\)](#) find that a reform that lifted constraints on the employment of FTCs allowed firms to lower labor costs by decreasing earnings of young workers. The main mechanism they put forward is a differential rent-sharing effect.

3 Theoretical discussion

In this section, I outline a simple static model to provide a framework for thinking about the empirical results. I chose this model to emphasize several dimensions that are under-theorized in the FTC literature: the role of non-atomistic firms, a segmentation between the OEC and FTC markets and the role of a job security compensating differential.

3.1 The model

In this section, I describe the model. It is a straightforward combination of [Cardoso et al. \(2018\)](#) and [Dube et al. \(2022\)](#).

Worker preferences The main novelty for the FTC literature is that I assume that workers value job security. I introduce this valuation directly into the worker utility, as in [Bonhomme and Jolivet \(2009\)](#), rather than dynamically as in [Jarosch \(2023\)](#). The main reason is that it allows me to keep the model simple and static. I therefore follow [Dube et al. \(2022\)](#) in writing the indirect utility of a worker as:

$$V(w, \delta) \equiv w + \delta \tag{1}$$

The parameter δ represents the job security valuation. To keep the model as simple as possible (and easily solvable analytically), I have taken wage and amenity to be perfect substitutes.⁴

For simplicity, I take the δ s as fixed, so that:

$$\begin{aligned} V^{\text{FTC}}(w) &\equiv V(w, 0) = w \\ V^{\text{OEC}}(w) &\equiv V(w, \delta) \end{aligned}$$

⁴This could be relaxed by introducing a CES specification, but it precludes an analytical solution.

I assume that the labor market is segmented, namely that some workers only work in OECs and some only in FTCs. I discuss this assumption in more detail below. Workers then face an idiosyncratic taste shock z_j^{FTC} or z_j^{OEC} of working at firm j . The corresponding utilities are therefore given by:

$$u_j^{\text{FTC}} = z_j^{\text{FTC}} \left(V^{\text{FTC}}(w) - V_0^{\text{FTC}} \right), \quad u_j^{\text{OEC}} = z_j^{\text{OEC}} \left(V^{\text{OEC}}(w) - V_0^{\text{OEC}} \right) \quad (2)$$

where V_0^C are the relevant outside options. I assume that the z^C are independent draws from Frechet distribution with shape parameter η^C , which implies from standard results in discrete choice theory, that the probability for a given worker of working for firm j is given by the expressions:

$$p_j^{\text{FTC}} = \frac{(w_j - V_0^{\text{FTC}})^{\eta^{\text{FTC}}}}{\sum_{i \neq j} (w_i - V_0^{\text{FTC}})^{\eta^{\text{FTC}}}} \approx \lambda^{\text{FTC}} (w_j - V_0^{\text{FTC}})^{\eta^{\text{FTC}}}$$

$$p_j^{\text{OEC}} = \frac{(w_j - V_0^{\text{OEC}})^{\eta^{\text{OEC}}}}{\sum_{i \neq j} (w_i - V_0^{\text{OEC}})^{\eta^{\text{OEC}}}} \approx \lambda^{\text{OEC}} (w + \delta - V_0^{\text{OEC}})^{\eta^{\text{OEC}}}$$

where $\lambda^C = \frac{1}{\sum_{i \neq j} (w_i - V_0^C)^{\eta^C}}$. Under the standard assumption that $J \gg 1$, which abstracts from strategic interactions (as in for instance [Cardoso et al. \(2018\)](#)), I can consider the λ^C s to be constant.

This analysis implies that firm j faces a *firm-specific* labor supply for each contract type given by:

$$L_j^{\text{FTC}}(w) = N^{\text{FTC}} \cdot p_j^{\text{FTC}} = \left(N^{\text{FTC}} \lambda^{\text{FTC}} \right) (w - V_0^{\text{FTC}})^{\eta^{\text{FTC}}},$$

$$L_j^{\text{OEC}}(w) = N^{\text{OEC}} \cdot p_j^{\text{OEC}} = \left(N^{\text{OEC}} \lambda^{\text{OEC}} \right) ((w + \delta) - V_0^{\text{OEC}})^{\eta^{\text{OEC}}}$$

where N^C are the total amount of workers in contract C .

Remark. The same result could have been derived as in [Cardoso et al. \(2018\)](#) with a indirect utility of $\log(w + \delta - V_0) + e_i$ with e_i type-II extreme.

Firm problem I take the simplest possible case for the firm side: The firm faces a fixed output price P_j^0 and has a linear production function

$$Y_j = T_j f \left(L_j^{\text{FTC}}, L_j^{\text{OEC}} \right) = T_j \left((1 - \theta) L_j^{\text{FTC}} + \theta L_j^{\text{OEC}} \right)$$

where T_j is a general TFP level of the firm and f is the production function. Additionally, this implies that workers on FTC and OEC are perfect substitutes and their relative productivity is governed by θ . I take $\theta \in [0.5, 1]$, which corresponds to the natural hypothesis that OECs are *more productive* than FTCs. This is a recurrent theme in the literature on FTCs. Finally, notice that under these assumptions, the value added by standardized unit of labor is given by $v_j \equiv \frac{P_j^0 Y_j}{f(L_j^{\text{FTC}}, L_j^{\text{OEC}})} = P_j^0 T_j$.

The firm j problem is then given by:

$$\max_{(w_j^{\text{FTC}}, w_j^{\text{OEC}})} v_j \left((1 - \theta) L_j^{\text{FTC}} + \theta L_j^{\text{OEC}} \right) - \left(L_j^{\text{FTC}} \cdot w_j^{\text{FTC}} + L_j^{\text{OEC}} \cdot w_j^{\text{OEC}} \right)$$

Finally, continuing in the spirit of making this model the simplest possible, I follow [Cardoso et al. \(2018\)](#) in taking the outside options to be given by

$$V_0^{\text{FTC}} = (1 - \theta) \cdot b, \quad V_0^{\text{OEC}} = \theta \cdot b$$

This corresponds to a situation where the outside options are given by an outside wage that could be earned in another competitive sector, with the same productivity differential indexed by θ .

3.2 Predictions

The FOC yield:

$$\begin{aligned} w_j^{\text{FTC}} &= \frac{1}{1 + \eta^{\text{FTC}}} (1 - \theta) \cdot b + \left(\frac{\eta^{\text{FTC}}}{1 + \eta^{\text{FTC}}} (1 - \theta) \right) \cdot v_j, \quad \text{for } v_j > b \\ w_j^{\text{OEC}} &= \frac{1}{1 + \eta^{\text{OEC}}} (\theta \cdot b - \delta) + \left(\frac{\eta^{\text{OEC}}}{1 + \eta^{\text{OEC}}} \theta \right) \cdot v_j \quad \text{for } v_j > b - \frac{\delta}{\theta} \end{aligned}$$

This then yields the several predictions.

Prediction 1. *Depending on the magnitude of the job security amenity δ , there can be 3 cases:*

- (i) *If δ is small, FTCs are always paid less than OECs*
- (ii) *If δ is large, OECs are always (in a reasonable range of v) paid less FTCs*
- (iii) *For intermediate values of δ , low productivity firms pay higher wages to FTCs than OECs. The opposite is true for high productivity firms. Namely, there exists $\tilde{v}$ such that:*

$$\text{If } v < (>) \tilde{v} \text{ then } w^{\text{FTC}} > (<) w^{\text{OEC}}$$

Prediction 2. *The sign of the average wage gap is therefore undetermined and can be zero.*

These first two predictions concern the within-firm wage gap between FTCs and OECs. The next two predictions are about differential rent-sharing.

Prediction 3. *There is differential rent-sharing within firm between OECs and FTCs. Namely,*

$$0 < \frac{dw^{\text{FTC}}}{dv} < \frac{dw^{\text{OEC}}}{dv} \quad \text{if} \quad \eta^{\text{OEC}} > \eta^{\text{FTC}}$$

Prediction 4. *The value-added slope contract type C increases when η^C increases. In other words:*

$$\frac{d}{d\eta^C} \left(\frac{dw^C}{dv} \right) > 0$$

The last prediction states variation in η should yield variation in differential rent-sharing as represented by the slope between wages and value-added.

3.3 Interpretation of the model

The economic mechanism behind the model can be summarized as follows. The upward sloping labor supply curves from monopsony imply positive correlation between productivity and wages. On the other hand, OECs come with a constant utility premium because of the job security. It is therefore possible that low-productivity firms that pay low wages have to pay higher wages to individuals on FTCs.

The different firm specific labor supply elasticities play a crucial role in this model. An important question is then the source of the different labor supply elasticities. As is standard in the monopsony literature, in the model presented above they come from the shape of the preference distribution of individuals, in other words from preferences over non-pecuniary job characteristics. But ultimately, the predictions rely on the reduced-forms of the labor supply curves, and it is therefore worth exploring other sources for the differential labor supply elasticities. Standard mechanisms in the literature are search frictions and mobility costs. These would seem to be lower for FTCs and would therefore suggest lower market power for FTCs. Another source which is often discussed is training cost and job-specific human capital. This has also been discussed extensively in the FTC literature. Indeed, given their short-term nature, FTCs discourage training and investments in job-specific human capital. This would lower the market power of workers on FTCs. This mechanism underlies for instance the differential rent-sharing in [Kline et al. \(2019\)](#) between new and incumbent workers.

Bargaining models can generate very similar results to monopsony models. Lower bargaining power for FTCs is sometimes discussed as a mechanism. One reason which is mentioned in [Darulich et al. \(2023\)](#) is the possibility that FTC workers are underrepresented by unions and firm-level wage agreements (this is also discussed in [Bentolila et al. \(1994\)](#)). Another possibility for lower bargaining power is due to the higher precarity of individuals on FTCs.

Another interesting mechanism is the explicit segmentation of the labor market introduced by the presence of FTCs. In general, the hypothesis that the FTC and OEC market are at least partially segmented seems reasonable. Firms generally post different vacancies for FTCs or OECs. Additionally, the pools of relevant and targeted individuals is different. There is certainly mobility between the markets, in particular from the FTC market to the OEC market, but this is still consistent with some level of segmentation. It is conceivable that this allows for stronger price discrimination for firms. It also potentially creates norms around low-wage labor market sectors.

Finally, differences in outside options between individuals on FTCs and OECs could also play an important role. For instance, it is possible that for individuals on OECs the general outside option are other firms for job-to-job transitions, whereas for FTCs the outside option is unemployment benefits. Additionally, it is also possible that the (mis)perception of outside options is different between OECs and FTCs, which could have a significant effect as was shown recently by [Jäger et al. \(2023\)](#). These could also reinforce the segmentation between the two labor markets.

3.4 Discussion of the model

In this section, I discuss the different omissions and weaknesses of the model presented above.

Dynamic considerations The model I present is a static model. It allows me to make the basic predictions of interest. On the other hand, it is clear that dynamic considerations should play an important role for FTCs. One obvious indicator for this, is that one of the main debates in the FTC literature is whether FTC are low-wage traps or stepping stones towards better jobs, which is an inherently dynamic consideration. Recently, [Jarosch \(2023\)](#) argued that job security is crucial to understand unemployment and in particular the “unemployment scar”, because it creates a job ladder with “slippery” bottom. Job security, in particular at the bottom of the wage distribution, is very related to FTCs.

Another interesting hypothesis is that the existence of FTCs creates a dual wage ladder:

while on FTCs, workers experience essentially no wage growth, and essentially only step onto the wage ladder once they are on an OEC. In other words, FTCs create a labor market segment where wage growth is absent. This expected wage progression then for instance predicts a high number of wage cuts when switching from an FTC to an OEC (as is standard in the [Postel-Vinay and Robin \(2002\)](#) literature).

Another dimension which is missed in a static model is the role of business cycles in the utilization of FTCs. FTCs are generally the first workers to leave a firm in a recession and as such they are a way for firms to ensure flexibility against shocks. This dimension has been explored in the literature, which in particular finds that firms in more volatile industries use more FTCs (see for instance [Caggese and Cuñat \(2008\)](#)).

It is clear from this discussion that an interesting avenue for future research would be to microfound the model above by for instance embedding it in search model. It would be of particular interest to endogenize δ . An interesting option could be to allow for bargaining (or posting) on wages and contract length.

Institutional context Another significant omission in the model is any institutional context. From the point of view of effect on wages, there are three institutions which seem of particular interest.

First, the existence of the prime précarité and the exemptions to it introduce interesting potential strategic considerations. The fact that certain sectors are exempt potentially introduces distortions between sectors but also has potential spillover effects across industries. The degree to which firms “incidence” away the prime précarité is also an interesting question.

Second, the minimum wage and sectoral wage minimas will affect in particular the firms ability to “incidence” away the prime précarité. For instance, for jobs at the minimum wage an FTC will necessarily be more expensive than an OEC, which suggests an additional incentive to consider for the use of OECs.

Finally, unemployment insurance will affect wage formation in a dual labor market. In particular, because unemployment insurance is an outside option which might be more salient for individuals on FTCs, than for individuals on OECs, for whom their current or equivalent jobs might be more salient. Additionally, rules such as partial unemployment insurance might increase the use of FTCs, both from a firm and a worker perspective.

4 Institutional details and data

4.1 Description of legislation

In France there are three primary types of employment contracts: open-ended contracts (OECs) or *Contrat à durée indéterminée* (CDI), fixed-term contracts (FTCs) or *Contrat à durée déterminée* (CDD), and interim (outsourcing) contracts.

The OEC is the standard contract and is the most common type of contract, accounting for around 85% of employment. These contracts have no specified end date, and employers cannot unilaterally terminate them without a valid reason. Termination of an OEC can only be justified by economic reasons, which must be substantiated and involve specific actions by the firm, or by personal reasons such as poor performance or misconduct. Consequently, firms face significant costs when terminating these contracts.

In contrast, FTCs have a predetermined end date, which is set when the contract is signed. The rules governing the termination of FTCs are as stringent as those for OECs, implying high termination costs before the designated end date. The law states that FTCs can only be used for specific purposes, such as replacing an absent employee, accommodating a temporary increase in activity, or facilitating seasonal employment. The duration of an FTC is limited by the relevant Collective Bargaining Agreement (CBA)⁵, which also specifies the number of contract renewals allowed. Generally, an FTC cannot be renewed without a valid reason, and there is a mandatory waiting period before re-employing someone on an FTC for the same position.

Furthermore, the law stipulates that wages for the same job should be identical between FTCs and OECs. If an FTC is not converted into an OEC, employers are required to pay employees an additional precarity bonus (*prime précarité*) equivalent to 10% of the total value of the contract. However, certain CBAs may lower the percentage of the *prime précarité*, and the bonus is not applicable if the employee declines the conversion to an OEC for the same job.

There is the additional case of CDD d'usage (CDD-U), which is a sectoral exemption to most of the rules mentioned above, in particular the payment of the *prime précarité*. This exemption was introduced to simplify FTC use in industries where FTCs are "standard". The sectors which are allowed to use CDD-U are fixed by a list, but the use and importance of the phenomenon is notoriously opaque and therefore hard to quantify (see for instance [Marie and Jaouen \(2015\)](#)).

⁵In general, an FTC has a maximal allowed length of 18 months, but this can vary depending on the stated reason for use of FTC, which allows in some cases for 24 months or restricts further to 9 months.

4.2 Descriptive facts

Although FTCs accounted for approximately 12% of employment (only among FTC and OEC workers ie excluding the small fraction in outsourcing and other contracts such as apprenticeships) in the period 2005 to 2014, their short-term nature results in them representing up to 90% of hires, as depicted in Figure 1. In terms of overall employment, this constitutes about five times the employment observed in the outsourcing sector, which represents around 2% of employment, highlighting the significant role of FTCs in the French labor market.

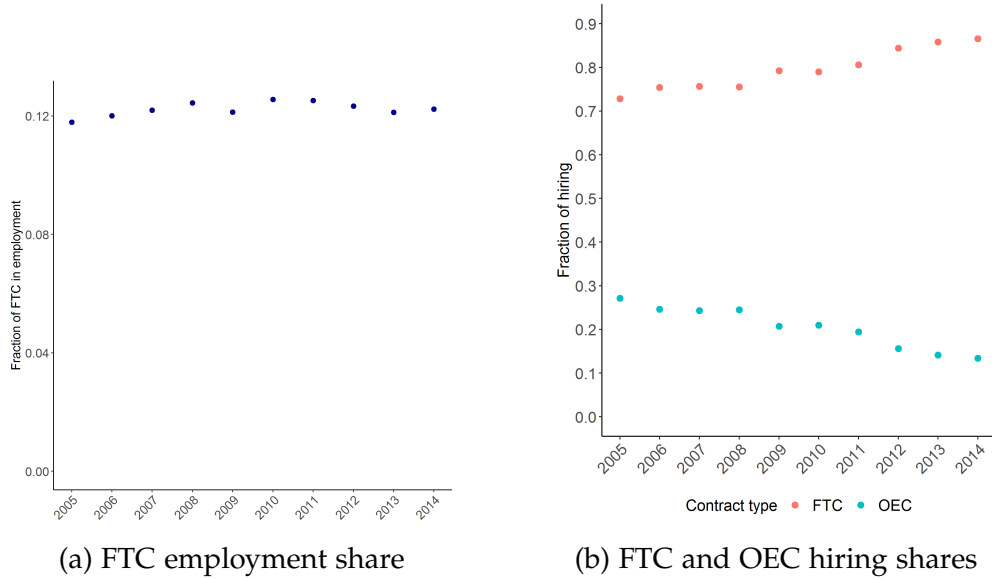


Figure 1: FTC aggregate time series

Notes: Panel 1a shows fraction of employment in FTC among FTC and OEC. It is computed from the statistically matched DADS panel described in the data section 4.3 by taking the fraction of worker in an FTC (among OECs and FTCs) at the first of each month and then averaging over the year. Panel 1b shows the fractions of FTC and OEC hiring (among OECs and FTCs) computed from the DPAE data described in the data section 4.3.

For both firms and individuals, FTCs cover diverse uses and circumstances. At the firm level, 2a shows that there is a lot of variation in the average FTC hiring rate between firms. Among all firms, 25% of firms never hire on FTCs while for bigger firms this drops to 5%. Among the latter these larger firms only around 20% of firms hire less than 25% on FTCs whereas around 40% hire at least 75% on FTCs. Figure 2b shows that average FTC length by firm is heterogeneous but more concentrated than use. Indeed, more than 50% of firms have an FTC length of less than 3 months⁶. An interesting feature of this figure are the

⁶These represent an upper bound as the graph uses contracted length rather than actual length.

kinks are the 3-month, 6-month and 12-month average lengths, suggesting a standardized use of FTC length⁷.

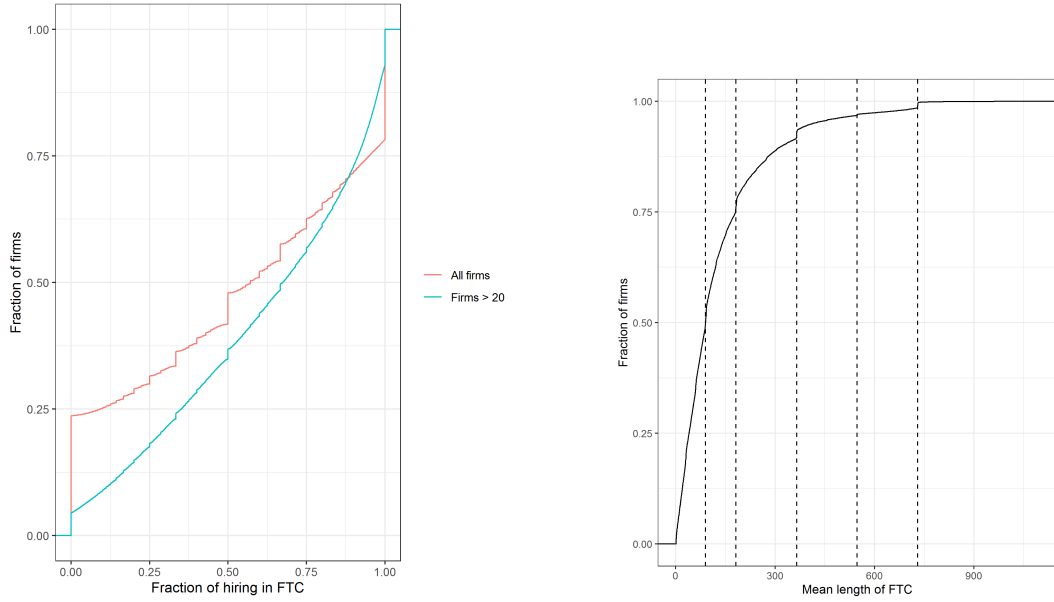
Another important dimension of FTC employment in firms is the rate of conversion into OECs which, as was argued above, is important for the case where FTCs would be used for learning about workers or to provide incentives on FTCs. Aggregate computations based on hiring data⁸ yield that over the years 2005 to 2014, only around 6% of matches (defined as a match between an individual and an establishment) which had at least one hire in FTC, also had a hire in OEC. In other words, only a small minority of FTCs are converted. At the firm level, conversion rate can be defined in two ways. In figure 2c, I show the FTC conversion rate defined as the fraction of FTCs hired in a year that will eventually (within the period) get converted into an OEC. It shows that the FTC conversion rate is concentrated at low values, but that there is again significant heterogeneity, with for instance around 25% having an FTC conversion of 20% or more. In the appendix, I show an alternative way of measuring conversion rate: the OEC conversion rate defined as the fraction of OECs hired in a year that were previously employed in an FTC at the firm. While still concentrated at the lower end, it shows a significantly wider dispersion. An important conclusion of this descriptive paragraph, which is one of the themes in this paper, is that FTC use and practices are very heterogeneous.

At the individual level, Figure 3a shows the variation of the fraction of FTC employment in 2-digit and 4-digit occupations. The occupation with the highest FTC use is Information, arts and entertainment professionals (code 35). Within the worker category (codes starting with 6) the FTC employment fraction varies from around 5% for Skilled industrial workers to around 25% for Agricultural workers. The graph illustrates the important role played by occupation in explaining FTC use and the fact that 2-digit occupation codes capture a good part but not all of that variation.

Figure 3b shows the variation of FTC employment by age. This fraction drops dramatically from nearly 70% at age 18 to around 10% at age 30. The fraction stays roughly constant until age 60 after which it increases again, which could be due to early retirements or FTCs for seniors (CDD senior). This illustrates that age plays an important role, but between 30 and 60 the FTC employment rate of 10% still represents a sizable share. While comparisons across countries are complicated because of different definitions and legislations pertaining to FTCs, it does seem to be generally true across Europe that young people are particularly employed in the FTC (see for instance Matsaganis et al. (2014)).

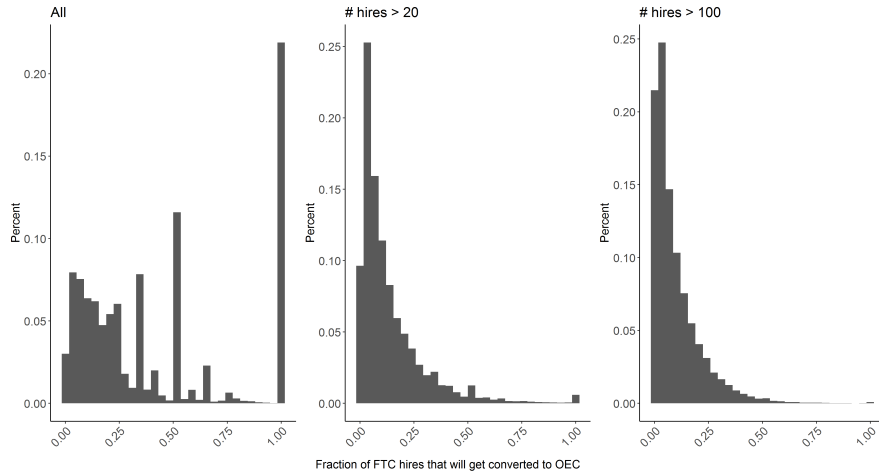
⁷In particular, it generates some question around the interpretation that firms need specific temporary contracts. An interesting potential connection is that the rounding in FTC length is an indicator of market power as Dube et al. (2018) argue about the rounding of wages.

⁸The DPAE data described in the data section below.



(a) Distribution of average FTC hiring share by firm

(b) Distribution of average FTC length in days share by firm

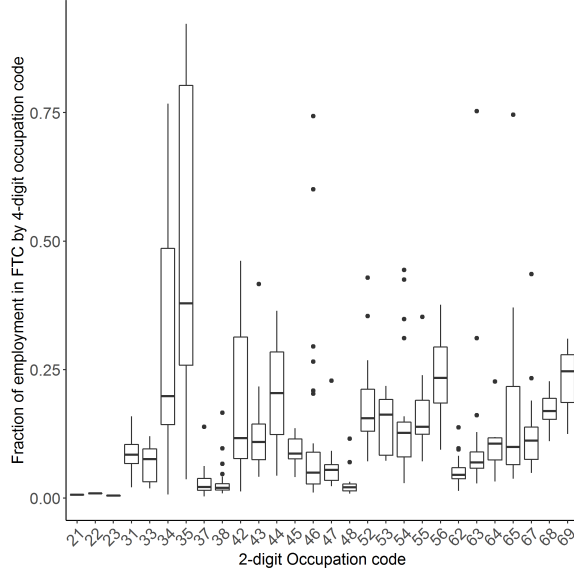


(c) Distribution of the fraction of FTCs hired in a year that will get converted into an OEC

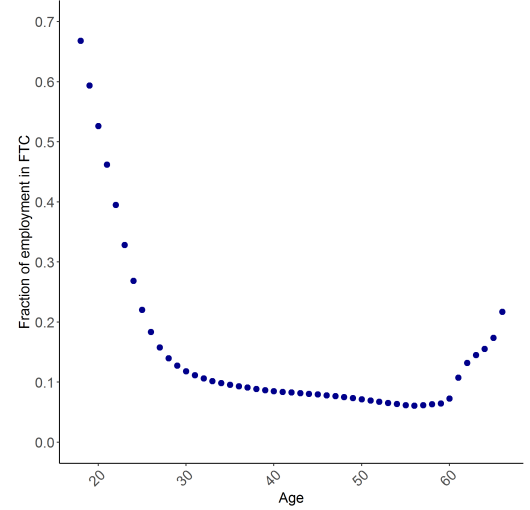
Figure 2: Distributions in different measures of FTC use at firm level.

Notes: Panel 2a shows the firm-level distribution of the average FTC hiring rate (among FTCs and OECs), averaged over the entire 2005-2014 period, for all firms (red line) and firms bigger than 20 (blue line). Panel 2b shows the firm-level distribution of average FTC length in days, averaged over the entire 2005-2014 period. The dashed lines mark 3-month, 6-month, 12-month, 18-month and 24-month contract lengths. Panel 2c shows the distribution of the FTC conversion rate defined as the fraction of FTCs hired in a year that will eventually (within the period) get converted into an OEC, among all firms, firms with more than 20 and firms with more than 100 hires. All the figures use the DPAE data described in section 4.3.

The reasons for this pattern are not immediately clear. On the one hand, it could reflect preferences of young workers for more flexible contracts. More likely, is that firms are less inclined to hire young workers on OECs and young workers have lower bargaining power. Exploring this pattern more deeply is an interesting avenue for future research.



(a) Boxplot of FTC employment fraction by 2-digit occupation code, with 4-digit code variation.



(b) Fraction of employment in FTC by age

Figure 3: Different measures of FTC use at the worker level.

Notes: Panel 3a shows a boxplot of average FTC employment by 2-digit occupation code. The variation within each 2-digit occupation code comes from the underlying 4-digit occupation codes. The occupation code description is given in table A6. The bar represents the mean, the hinges represent the 1st and 3rd quartiles. The upper whisker extends from the hinge to the largest value no further than 1.5 times the inter-quartile range from the hinge. The lower whisker extends from the hinge to the smallest value at most 1.5 times the inter-quartile of the hinge. Data beyond the end of the whiskers are called outliers. Panel 3b shows fraction of FTC employment by age.

4.3 Data

The empirical results in this paper rely on multiple administrative data sources.

Matched employer-employee data The primary data source for this study is the employer tax records, specifically the “Déclaration Annuelle de Données Sociales” (DADS). To construct a comprehensive matched employer-employee panel spanning from 2005 to 2018, I

use the statistical match approach developed by [Babet et al. \(2022\)](#). Their approach utilizes the 2-year panel form of the DADS postes files, which allow very detailed matching of individuals across year-files⁹. In the period I am studying the match quality is at 98%. One particular issue with the statistical match is that for individuals that are out of the labor market for more than a year the match breaks down as it cannot connect them anymore and they will therefore be identified as separate individuals. This should only affect a small minority of individuals. Nevertheless, I will present some robustness results using the cross-sectional DADS postes data. I discuss why my preferred approach still uses the panel version of the data just below.

This dataset then provides detailed information on each worker in the firm: total annual wages, number of hours worked, start and end date for each job, contract type, occupation, as well as individual information such as gender, age and city of residence.

I use the measure of gross wages, adjusted for inflation to 2012 euros, and create a log hourly wage variable by dividing by the number of hours. I also trim the wage measure at the 0.1% level on both sides. For most of my analysis, I focus on hiring wages. Hiring wages on OECs are defined straightforwardly as the hourly wage in the first year working for the firm.¹⁰ For FTCs the definition is slightly more complicated due to the existence of the *prime précarité*. Indeed, for any FTC spell that covers more than a single year, the wages defined as for OECs would be too low as they would not include the *prime précarité* (because it would be included only in the corresponding observation in the year the corresponding FTC spell ends in). To address this, I define hiring wages on FTCs as the wages in the first continuous spell working for the firm. This is also the reason why my preferred approach uses the panel data.

I restrict the dataset to the private sector, individuals aged between 18 and 66 and mainland France. For the main analysis, I focus on the years 2010 to 2014. I start in 2010 because before 2009, it was not mandatory to report the 4-digit occupation, which is an important control in the following regressions. Indeed, the 2-digit occupation codes separate occupations into 29 categories, which can be fairly broad.¹¹ Additionally, I limit the data to CDD and CDI, specifically excluding all individuals on interim (outsourcing) contracts.

To capture relevant work experience, I create two experience variables. The first variable, experience in firm, measures the number of years since the worker was initially hired by

⁹For more details on the procedure, see Appendix C in [Babet et al. \(2022\)](#)

¹⁰This does not mean that the wages cover a year worth of wages in the firm. Indeed, for somebody hired in December, the wage comes from that one month of employment.

¹¹The code 37 for instance covers all jobs with management responsibilities in administrative and commercial matters, which includes lawyers, accountants, PR managers, HR managers and more.

the firm. It measures the worker's tenure with the specific employer. The second variable, experience in (2-digit) occupation, measures the number of years since the worker was first hired in their current occupation. This variable helps to account for the worker's accumulated experience in their specific field of work.¹²

The classification of observations into OEC and FTC will contain some measurement error. Firstly, the contract type is self-declared in the DADS. More importantly, the DADS collapses repeat spells of an individual in the same year at the same establishment, and in particular during this collapse, if there is at least one spell in OEC, then that observation is classified as an OEC. In other words, individuals that are converted from an FTC to an OEC in the same year will be classified as only an OEC. I believe the effect of this on the results that follow should be limited because of the low rate of conversion of FTCs into OECs highlighted in the previous section.

There are two complications in the measurement of wages, which I cannot deal with directly. First, for FTCs, wages include the prime précarité. In other words, the prime précarité is not measured separately. The correct wage concept includes the prime précarité. However, as detailed above, there are selected instances when the prime précarité does not have to be paid, which could introduce omitted variable bias. The first case is when an FTC is converted to an OEC, as discussed above. Given the very low levels of conversions, this should not be too much of a problem. A more significant problem comes from the use of CDD-U (described in section 4.1) which are exempt from paying the prime précarité, but are hard to identify. I provide a robustness check for this concern in section 5.3. The second concern stems from the measurement error in hours. As was already mentioned, there is partly some measurement error in hours stemming from missing hours which are imputed by the data producer. But there is also an additional concern from the fact that the hours measure in the DADS contains paid holiday hours. The rules for FTCs and OECs are slightly different (and complicated), and leave not taken can be compensated. This could introduce distortions.

Contract declaration data My second data source is the contract declaration data, "Déclaration Préalable à l'Embauche"(DPAE), which has to be reported whenever a new contract is signed. This dataset provides a comprehensive individual-level panel that includes information about all newly signed contracts, including the starting date and type of the contract, as well as the establishment where the contract was signed. For FTCs, the DPAE also includes the specified end date of the contract. However, it does not provide any wage

¹²Both these experience measures have the defect that interruptions are not considered and experience continues accumulating. This is only a problem for the experience in occupation variable, since returns to firms are fairly rare.

information. It is unfortunately not possible to link DPAE and DADS data. In particular, comparing results between the DADS and the DPAE of similar measures shows that there are some differences between these datasets. In part this is due to the fact that for instance within a year and an establishment, multiple employment spells are merged in the DADS, but also less clear differences. For the relevant results below, I run a robustness check and show that the results are unaffected.

Until the year 2009, there is an issue in part of the data with missing end dates for FTCs as well as issues with grouping of individual identifiers. In the main analysis, I drop these observations. I conducted some robustness checks (not shown) and the differences are small.

Financial data My third data source is the near-universe of annual tax records of French firms (“Fichier Complet Unifié de Suse”, FICUS, and “Fichier Approché des Résultats d’Ésane”, FARE) that report balance sheet and income statement information. I use this dataset for firm-level measures of revenue and value-added. The main variable I use in the paper is the value added net of taxes, which I trim at the 0.1% level. The value added per worker variable is then defined by dividing value added by the effective average firm size over the year. This measure is effective because it is a legally defined notion of size which assigns certain weights to temporary workers.

5 Average FTC-OEC wage gap

As was argued above, the effect of FTCs on wages is theoretically ambiguous. Motivated by the predictions of the model, I present several empirical facts. In this section, I focus on hiring wages because as discussed above, wage dynamics significantly complicate the appropriate comparisons and harder to capture in the aggregate approach of this section. In the appendix section [A.3](#), I provide a very brief look at wage dynamics.

5.1 Methodology

To get a first aggregate characterization of the FTC-OEC wage gap, I regress log hourly wages on an indicator for being on an FTC, controlling for progressively more variables to understand what covariates play an important role. The regression reads:

$$\ln hw_{it} = \beta \cdot \text{FTC}_{it} + \tau_t + \left(X_{it} + \psi_{j(it)} \right) + \varepsilon_{it}$$

where FTC_{it} is an indicator for the employment spell being in an FTC, τ_t are year fixed-effects and $\psi_{J(it)}$ is an establishment fixed-effect where $J(it)$ represents the establishment of worker i and time t . The covariates in X play an important role in this analysis, as the goal is to obtain a wage gap for individuals that are as comparable as possible. I discuss the specific choice of covariates below. The regression above is used to generate some descriptive facts about the FTC-OEC wage gap. It should not be interpreted causally.

A first potential issue is that the parametric choice for the regression specification will only imperfectly control for the effect of the chosen observables. There is also a significant potential for omitted variable bias as our controls are unlikely to capture unobserved components of match quality or potentially relevant features of the labor market history of the worker. Finally, the decision about whether to add individual fixed-effects merits a separate discussion. On the one hand, they are a powerful tool to address time-invariant confounders, which are hard to capture using controls. But importantly, they change the identification of the wage gap as it is then identified from comparison of switches between FTCs and OECs *within* individuals. These are then affected by the dynamic considerations I have already mentioned, and therefore answer a different question than what we are interested in this section. In particular, using individual fixed effects necessarily implies that individuals are no longer compared at the same age and experience.

5.2 Results

The results from the regression are shown in Table 1.

The gap without any controls stands at -13% . Controlling for age halves that gap. This captures a general experience effect, in part consistent with the FTC use by age highlighted above. Interestingly, industry does not alter the gap significantly. The gap reduces to almost zero once occupation is controlled for. This is not surprising as FTCs are more used in lower-paid occupations. The gap is a very precisely estimated zero when restricting to comparison within firm by controlling for firm fixed-effects. In the appendix, I show that this results does not change when using less fine 2-digit occupation codes (Table A7) and looking at the earlier period between 2005 and 2009 (Table A8).

5.3 Discussion and robustness

The main conclusion from this table is that several of the different mechanisms mentioned above have to play a role since they are compensating each other on average. In particular, this confirms the possibility raised in Prediction 2. As such, this average zero actually

Table 1: FTC-OEC hiring wage gap regression over the period 2010 to 2014

	Log hourly wage						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FTC	-0.1311*** (0.0022)	-0.1215*** (0.0022)	-0.0673*** (0.0021)	-0.0701*** (0.0014)	-0.0037*** (0.0007)	0.0058*** (0.0006)	-0.0006 (0.0006)
Observations	33,277,570	33,277,570	33,277,570	33,277,570	33,277,570	33,277,570	33,277,570
R ²	0.02689	0.04358	0.12355	0.27117	0.54488	0.55270	0.67677
Within R ²	0.02682	0.02333	0.00747	0.00879	3.52×10^{-5}	8.49×10^{-5}	6.92×10^{-7}
Year fixed effects	✓	✓	✓	✓	✓	✓	✓
Sex fixed effects		✓	✓	✓	✓	✓	✓
Age fixed effects			✓	✓	✓	✓	✓
Industry fixed effects				✓	✓	✓	✓
Occupation fixed effects					✓	✓	✓
Exp. in occ. fixed effects						✓	✓
Establishment fixed effects							✓

Notes: This table reports the result from the regression of log hourly wage on an indicator for whether the observation is in an FTC, and a set of fixed-effects over the period 2010 to 2014. Log hourly wage is computed as gross wage divided by number of hours, inflation-adjusted into 2012 euros, trimmed at 0.1%, and FTC wages are aggregated over the FTC spell. Age is separated into 5 year bins. Industry is a 38 level code for industries. Occupation is the 4-digit PCS code. Experience in occupation is the number of years since the individual first practiced the 2-digit occupation of the observation. The results are clustered at the establishment level.

*p<0.1; **p<0.05; ***p<0.01.

conceals more than it reveals and a systematic heterogeneity analysis is necessary to gain more insights into the mechanisms

Expectation from the law The intent of the existing law is a priori fairly clear. It requires that two individuals with identical “qualifications” and identical job should be paid the same independently of contract type. Importantly, as was confirmed by the courts¹³, this *does not* include the prime précarité. In other words, according to the law, when comparing individuals in identical jobs and same qualifications, the individual in an FTC should have an hourly wage premium of 10%. This decreases on average once the exceptions to the prime précarité are considered such as for instance the CDD-U, where the prime précarité does not have to be paid (see Section 4.1 for more details).

Even before considering the results, it is unclear how this should play out in practice. First, the definition of identical job and qualification is somewhat vague. Second, it is unclear how well-informed workers are about their rights to the prime précarité. More importantly, the enforcement is in general up to workers as they can make their claim in front of the courts. But this is costly and complicated for workers.

¹³see for instance <https://www2.liaisons-sociales.fr/210-10-queelles-sont-les-regles-a-respecter-en-matiere-de-salaire-et-autres-avantages-financiers/> (in French, accessed in August 2023)

The aggregate zero from Table 1 can therefore have different factors influencing it. It could be consistent with the prime précarité being paid rarely, resulting in a zero gap. On the other hand, it could also be consistent with the prime précarité premium, being (illegally) “incided” away by firms, through lower wages. While these considerations certainly play a role, I argue below that the mechanisms laid out in the theory play a more important role because of the heterogeneity patterns I observe.

Panel versus cross-sectional data To alleviate concerns about the statistical match panel data (such as the quality of the match or the panel interruption due to prolonged inactivity as discussed in section 4.3), Table A9 presents the same regression as 1 using the cross-sectional DADS postes data. As discussed previously, this implies that FTC wages are not aggregated over the spell, resulting in potential under-estimation because the prime précarité is missed. To “control” for this effect, Table A10 shows the same regression using the statistical match data, but without aggregating FTC wages over the spell. The regression with all fixed-effects yields a large and significant negative gap of -1.86% , but it is identical to the estimate using the panel data in Table A10. This therefore suggests that using the cross-sectional data rather than the panel makes little difference *except* for the error related to not aggregating FTC wages, which appears significant. Indeed, the significant decrease from 0% to around -2% is consistent, at least in sign, with a significant underestimation of FTC wages when not aggregating over the spell, as was discussed in section 4.3. This shows that the use of the panel data should be preferred.

Age restrictions Figures 3b showed that age plays an important role for employment in FTCs, representing a large share of employment for individuals under 30, stabilizing thereafter and increasing again after age 60. I therefore present the result of the same regression as in Table 1, but restricting to individuals aged between 30 and 60 in Table A11. The FTC-OEC gap with all controls is very slightly positive at 0.6%, but the qualitative conclusion of a zero average wage gap is unaltered. This is not to say that understanding the exact role of age in the use of FTCs is not in part at least related to other mechanisms and worth exploring. This is left for future research.

Dealing with CDD-U As noted earlier, accounting for CDD-U is complicated because the legislation itself is extremely unclear. The criteria don’t align with industries or jobs and there is suspected wide misuse of CDD-U (see for instance Marie and Jaouen (2015)). I therefore use the very rough classification by industries developed in Marie and Jaouen

(2015)¹⁴ to separate the data into industries that are concerned by CDD-U and sectors that are not. This classification is very rough as many of the industries should only be very partially affected.

Table A12 shows that the results of the regression with all controls for these two sets of industries are essentially identical at around 0%¹⁵. If anything, the signs go in the opposite direction of what would be expected.

Effect of measurement error I discussed the measurement error due to the misclassification of FTCs as OECs within a single firm spell and argued that it should be minimal given the low numbers of within-firm conversions. The sign of the effect of this misclassification depends on the sign of the OEC-FTC wage gap, but it will tend to decrease the gap. While this pushes the aggregate wage gap towards zero, it also suggests that the heterogeneity that we document below is if anything understated.

6 Firm-level heterogeneity

Prediction 1 of the toy model above emphasized role of firms in understanding wages in the presence of FTCs and in particular the within-firm dimension of the wage gap. In this section, I therefore study the FTC-OEC gap at the firm level.

6.1 Binscatter approach

I create a firm level dataset by collapsing the data at the firm and year level. The data is then merged with the financial data from the FARE-FICUS dataset. This procedure involves selection on firms, as for example I only keep firm-year observations that hired both FTCs and OECs, but also the financial data is slightly more imperfect for smaller firms. The selection is shown in the appendix Table A13, which shows that it selects bigger firms and the average wage is slightly lower.

¹⁴They use the A38 classification into industries and consider A (agriculture, sylviculture et pêche), C (industrie manufacturière), F (construction), H (transport et entreposage), I (hébergement et restauration), J (information et communication), K (activités financières et d'assurance), M (activités spécialisées, scientifiques et techniques), N (activités de services administratifs et de soutien), P (enseignement), Q (santé et action sociale), R (arts, spectacles et activités récréatives) to be the industries that are potentially allowed the use of CDD-U

¹⁵The estimate on the full sample is slightly different than the one in Table 1 because the regression is computed on the sample used in the heterogeneity sample after merging with financial data, which results in some data loss. Importantly, the estimates are nearly identical.

Correlation with valued added per worker In figure 4, I explore Predictions 1 and 3, by looking at the correlation between wages in FTCs and OECs and value added per worker. The figure shows binscatters of average firm level log hourly wages in FTCs and OECs against log value added per worker. The first panel presents raw data. In the second, wages are residualized on year, gender, age, occupation, experience in occupation and industry. In the third panel, log value added per worker is additionally residualized on the same variables. These figures are produced using a dataset where I have trimmed the bottom 10% of the value added distribution. I discuss this choice in more detail below.

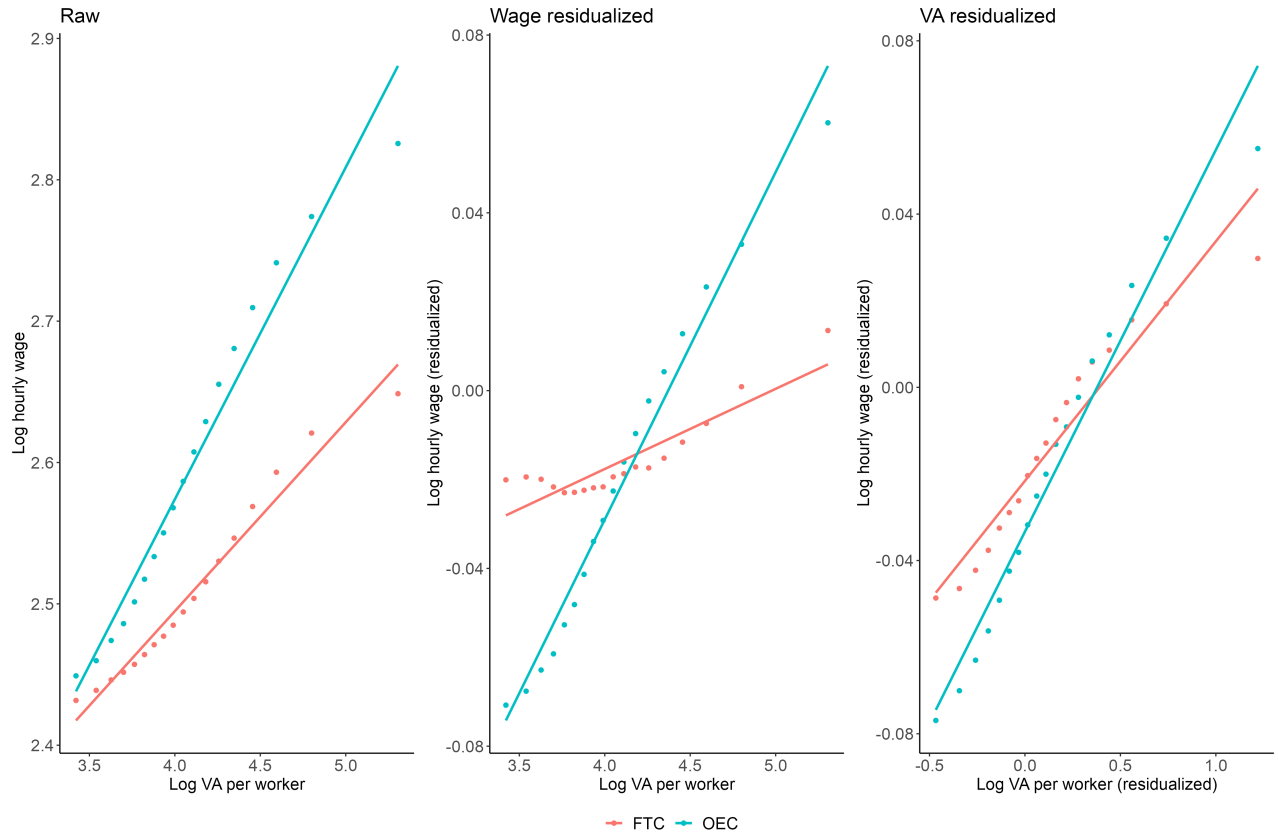


Figure 4: Average firm-level log hourly wage in FTCs and OECs as a function of value added per worker, raw, wage residualized and VA residualized.

Notes: The first panel shows the binscatter of average log hourly wage at the firm-year level against log value added per worker. In the second panel, wages are residualized with respect to year, gender, age, occupation, experience in occupation and industry. In the third panel, log value added per worker is additionally residualized with respect to the same variables. The bottom 10% in terms of value added per worker are trimmed.

All three panels exhibit a behavior strikingly in line with the predictions of the simple model above. The slope of FTC wages with valued added per worker is significantly lower

than for OEC wages, as predicted by Prediction 3. Once wages are residualized, Figure 4 shows that low valued added per worker firms pay higher wages to FTC workers whereas the opposite holds true for high valued added per worker firms. The additional residualization of value added per worker significantly increases the FTC slope, which suggests that especially for FTCs wages and value added correlated to industry and occupation.

The slopes in Figure 4 can be quantified to give a very rough estimate of firm-level labor supply elasticities. The appendix Table A14 reports an elasticity of around 8.5% for OECs and 5.4% for FTCs (when both wages and value added are residualized). Interestingly, the OEC value is on the higher end of the estimates in the literature, whereas the value for FTCs exactly onto the commonly cited value of value (see for instance Manning (2021)).

In the appendix Figure A9, I show the same figure but for individuals aged 30 and above. The conclusions are the same but the magnitudes are different. The gaps at both ends are smaller and the elasticities are 9.8% for OECs and 7.8% for FTCs¹⁶ This suggests that the labor market power of firms decreases significantly when eliminating younger workers.

In the appendix Figure A10, I show the same figure but without trimming the bottom 10% of the value added distribution. The figures show that the bottom 10% exhibit an opposite behavior to the rest. A quick analysis did not reveal any obvious covariate that predicted this behavior. A more detailed analysis of this fact would be interesting, but is left for further research.

Correlation with average FTC length Having explored the predictions of the model, I now turn to another important dimension of FTCs, their length. The model does not give predictions about FTC length, but given that one of the main mechanisms is job security, FTC length is a highly relevant dimension. Indeed, as was illustrated above, there is significant variation in average FTC length, which suggests different practices and uses. As before, Figure 5 shows average firm-level log hourly wage in FTCs and OECs as a function of average FTC length in days, both raw and residualized.

Strikingly, once residualized, wages in FTCs decrease with average FTC length, which is in line with the interpretation of compensating differentials for job security. In the last panel, for average residualized FTC length above zero, the same pattern holds. On the other hand, the slopes reverse for lower values residualized FTC length. The interpretation of this is unclear, but it may be related to the same factors that affect binscatters for low productivity firms mentioned above.

¹⁶Regression table not shown in this document.

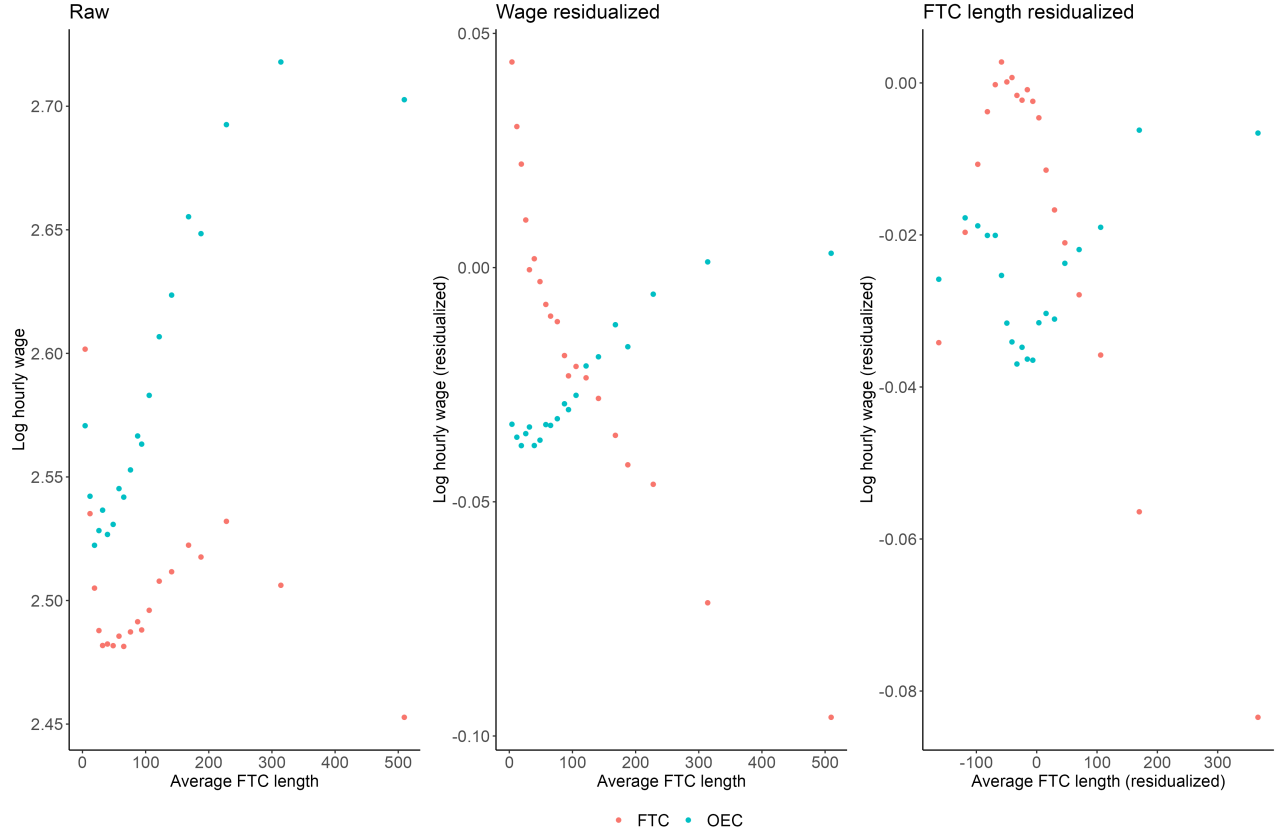


Figure 5: Average firm-level log hourly wage in FTCs and OECs as a function of average FTC length in days, raw and residualized.

Notes: The first panel shows the binscatter of average log hourly wage at the firm-year level against with average FTC length in days. In the second panel, wages are residualized with respect to year, gender, age, occupation, experience in occupation and industry. In the third panel, average FTC length is additionally residualized with respect to the same variables.

Discussion Importantly, in the appendix Figure A11, I show that the FTC-OEC wage gap is still decreasing with residualized value added per worker, within FTC length quartiles. Interestingly, the sign switch of the gap is only present for the third FTC length quartile (and maybe the second), whereas the first and fourth are respectively always positive and always negative. This is consistent with the model for different values of the job security parameter δ . For firms with very short FTCs, the wage compensation always dominates, whereas the opposite holds true for firms which offer long FTCs.

Another important dimension is industry. The appendix Figure A12 shows that the FTC-OEC gap is decreasing in every industry. There are two industries for which the sign of the gap does not switch. In financial and insurance activities, the gap is always negative,

whereas for education, human health and social activities¹⁷, the gap is always positive. This makes intuitive sense as for instance, the human health and social activities in France are known to use a lot FTCs, and in particular short-term FTCs. The proposed model therefore also seems to hold within industry. On the other hand, it is also clear that there is a lot of heterogeneity across industries, which could reflect different mechanisms. Finally, in the appendix Figure A13 I show the residualized FTC-OEC wage gap by year. The graph is very similar across years, which suggests that the results so far are robust to business cycle effects.

6.2 How are pay premia shared between OEC and FTC workers?

In this section, I present a different way of evaluating the differential rent-sharing hypothesis. I will compare and correlate firm pay premia for FTCs and OECs within firms using the AKM approach pioneered in Card et al. (2016) and used in the context of outsourcing in Drenik et al. (2022). This provides a measure of the degree to which high-wage firms for FTCs are also high-wage firms for OECs. In the main body of the paper, I will implement the approach as described in Kline et al. (2020), but in the appendix I also present the alternative approach implemented in Drenik et al. (2022). The advantages of this approach are that firm pay premia capture aspects of wage setting directly. Additionally, the methodology is better suited to account for sorting patterns of workers to firms.

Methodology As in the previous section, I restrict the analysis to hiring wage, defined as the wages in the first year working for an establishment (aggregated across the first spell for OECs). I then estimate an AKM specification *separately* for OECs and FTCs. Formally, I estimate the following specification:

$$\ln hw_{it} = \alpha_i^C + \psi_{J(it)}^C + X_{it}\beta^C + \varepsilon_{it} \quad (3)$$

where C is either FTC or OEC. I will discuss an alternative approach with a joint estimation approach below. The α_i^C are individual fixed effects, and $\psi_{J(it)}^C$ are firm-contract type specific fixed effects, where $J(it)$ denotes the firm of worker i at time t . The controls include 2-digit occupation, experience in occupation and age fixed-effects.

The identification hypothesis for this approach are the standard identification assumptions in the AKM, namely strong exogeneity of the residuals. In the context of AKM, this translates to the hypothesis of exogenous mobility of workers between firms, which rules

¹⁷I excluded public administration and defense from the data

out for instance selection of workers into firms based on the match-specific component (see for instance [Card et al. \(2016\)](#) for a more detailed discussion). It additionally imposes that there be no serial correlation and a strong hypothesis on linearity and symmetry of the effects. This is generally considered a strong assumption, but it is still standard in the literature. In my context, I need to make this assumption separately for OECs and FTCs. It is not a priori evident whether how this affects the credibility of the assumptions.

These regressions are estimated on leave-one out connected sets, which are connected sets of firms which stay connected even when dropping one worker. The restriction to a connected set is a well-known fact in the AKM literature to obtain well-defined firm fixed effects. The additional restriction of a leave-one out connected set comes from [Kline et al. \(2020\)](#) who give a methodology for correcting the variance components of the estimated fixed-effects, even in the presence of heteroskedasticity (henceforth the KSS approach, compared with the standard Plug in approach). This is necessary because variance components are biased due to limited mobility bias. The correction will be necessary for me when I compare the firm fixed effects. This restriction comes at the price of a fairly strong restriction as illustrated in Table 2. In particular, the average and variance of the wages is higher in the restricted set.

Table 2: Effect of restriction to the leave-one-out connected set

	FTC		OEC	
	Full	Leave-one-out connected set	Full	Leave-one-out connected set
Number of workers	9,732,262	2,533,388	11,130,752	2,433,793
Number of firms	858,645	336,053	1,026,383	315,309
Number of observations	17,334,367	5,885,385	15,943,203	4,598,481
Average log hourly wage	2.55	2.59	2.68	2.71
Median log hourly wage	2.46	2.48	2.56	2.58
Variance of log hourly wage	0.12	0.15	0.19	0.18

Notes: This table shows summary statistics of the data, before and after the leave-one-out connected set restriction.

Table 3 shows the results from the variance decomposition of the two separate by contract type AKM regressions. The variance is higher for OEC than for FTCs, but interestingly the firm component is significantly more important for FTCs than OECs (13% of the variance versus 7% of the variance). Conversely, person effects are more important for OECs than FTCs.

The estimation above yields a separate firm fixed effect for FTC and OEC workers. Figure 6a shows a raw binscatter of the correlation between the two sets of fixed effects. Until an OEC firm effect of -0.35 , the relation is constant. In figure 6b, I therefore restrict to firm effects above that threshold, bin the observations by OEC firm effect ventiles and then normalize the firm effects so that the lowest ventile has zero firm effects. This does not affect the slope which is the quantity of interest.

Table 3: Variance decomposition for the separate by contract AKM specifications

	Fixed-term contracts	Open-ended contracts
<i>Variance of wages</i>	0.15	0.19
<i>Variance of person effects</i>		
Plug in	0.058	0.076
Homoscedasticity only	0.032	0.057
Leave Out	0.037	0.054
<i>Variance of firm effects</i>		
Plug in	0.025	0.019
Homoscedasticity only	0.019	0.014
Leave Out	0.020	0.013
<i>Covariance of firm and person effects</i>		
Plug in	0.005	0.004
Homoscedasticity only	0.009	0.008
Leave Out	0.008	0.009

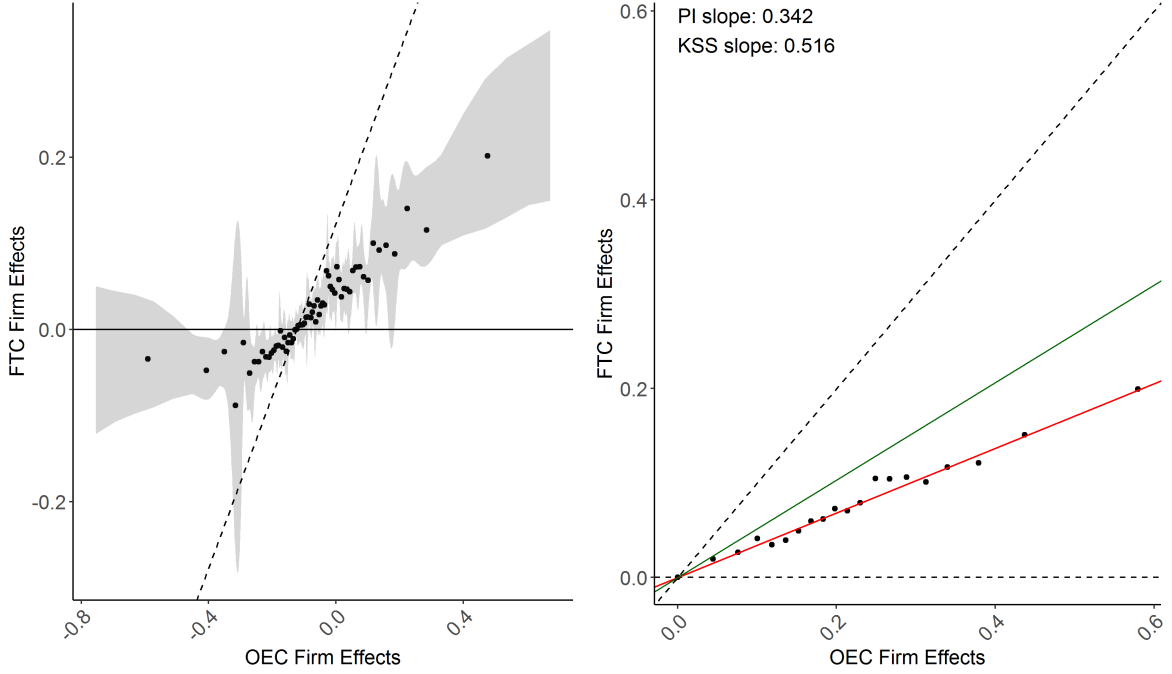
Notes: This table shows the result of the variance decomposition for wages by contract type. To illustrate the importance of the corrections, it shows the values of the variance decomposition for three different methods. Plug-in corresponds to the uncorrected approach, Homoscedasticity only is the correction by [Andrews et al. \(2012\)](#) and Leave Out is the correction advocated by [Kline et al. \(2020\)](#).

As was already noted in [Card et al. \(2016\)](#), the simple regression of FTC firm effects on OEC firm effects is biased because of the errors in the estimation of the firm effects. Here, I follow the approach in [Kline et al. \(2020\)](#) to correct for this error. It simply notices that the bias of the regression comes from the denominator of the regression coefficient which involves the variance of the OEC firm effects¹⁸, which is biased. They therefore simply multiply the estimated regression coefficient by a correction factor given by $\frac{\text{var}_{\text{Plug In}}(\psi^{\text{OEC}})}{\text{var}_{\text{Leave Out}}(\psi^{\text{OEC}})}$. This correction factor comes out to 1.5. The plug in slope is 0.34 and the KSS corrected slope is therefore 0.51. The regressions are reported in the appendix table [A15](#).

Discussion Figure [6b](#) reports that the OEC and FTC pay premia trace out a slope of 0.51. In other words, if we compare two firms, A and B, and B offers 10% pay premium for its OEC workers compared to firm A, then the corresponding pay premium for FTC workers at B compared to A is predicted to be 5.1%. Therefore, firms do seem to share some of their pay premia with FTC workers but only about half what OEC workers get.

There are two benchmarks, which are also represented in Figure [6b](#) by the dashed lines. If for instance the market for FTCs was perfectly competitive, then firms would not pay

¹⁸Indeed, the coefficient in the regression of FTC firm effects on OEC firm effects is $\frac{\text{cov}(\psi^{\text{FTC}}, \psi^{\text{OEC}})}{\text{var}(\psi^{\text{OEC}})}$



(a) Raw binscatter of OEC firm effects against FTC firm effects. (b) Restricted plot of OEC firm effects against FTC firm effects, binned by ventiles.

Figure 6: Firm-level pay premia sharing between FTC and OEC workers.

Notes: Panel 6a shows binscatter of OEC firm effects against FTC firm effects. Observations are weighted by total number of person-year observations in a firm. The firm effects are estimated separately using a standard AKM specification. The binscatter is produced following the recommendations by Cattaneo et al. (2022) and using their package for inference. The bands are 95% confidence bands. The dashed line is simply for reference of a slope of 1. In panel 6b, I restrict to firm after the kink, namely firms with OEC firm effects larger than -0.35 . I then bin the observations by OEC firm effect ventiles (weighted by total number of person-year observations) and normalize the lowest ventile to have zero firm effects. The red line represents the estimated OLS slope of the data. The green line represents the slope when correcting for measurement error induced bias by multiplying a correction factor $\frac{\text{var}_{\text{Plug In}}(\psi^{\text{OEC}})}{\text{var}_{\text{Leave Out}}(\psi^{\text{OEC}})}$.

any wage premia to FTC workers, which would yield a slope of zero. On the other hand, if there was no differential rent-sharing at all, then the firm premia would be identical yielding a slope of 1. The result reported above falls between the two.

Most closely related is Drenik et al. (2022) who compare the pay premia of temporary outsourced workers to regular workers. They find a slope of 0.49, very close to the result in this paper. On the other hand, Card et al. (2016) find a slope of 0.89 when comparing pay premia of men and women and Kline et al. (2020) find a slope of 0.98 when comparing the pay premia of younger and older workers.

Robustness As a robustness check, I also implement the alternate methodology in [Drenik et al. \(2022\)](#). They estimate a modified AKM specification, which allows for the firm fixed effect to vary by contract type. Formally, I estimate the following specification:

$$\ln hw_{it} = \alpha_i + \psi_{J(it)}^{C_{it}} + \varepsilon_{it} \quad (4)$$

where α_i are worker fixed effects, and $\psi_{J(it)}^{C_{it}}$ are firm-contract type specific fixed effects. The superscript C_{it} indicates the contract type the worker i is employed in at time t , and $J(it)$ denotes the firm of worker i at time t . For purely computational reasons, I do not include controls in this specification¹⁹.

It is intuitively appealing to estimate the regression jointly. One important difference to the methodology above is that the individual fixed effect is not differentiated by contract type anymore. This a priori a more constraining hypothesis than the previous approach (especially given the discussion in the literature about productivity differences between contracts). On the other hand, simultaneous estimation should have more power. Ultimately, I chose this method for robustness because the econometric properties of this approach are less clear. In particular, the bias-correction applied above is not readily adaptable. Instead, [Drenik et al. \(2022\)](#) apply a split-sample IV approach to correct for the measurement error bias. It consists in splitting the data in half randomly and estimating the fixed effects separately, and then instrumenting the OEC firm effects in one split by the OEC firm effects in the other split. While intuitive and often used (see for instance [Babet et al. \(2022\)](#) or [Bassier et al. \(2022\)](#)), there are no well-established econometric guarantees.

I report the result from these regression in table [A16](#), which shows an uncorrected slope of 0.36, very close to the previous estimate of 0.34. The corrected slope, corrected using the split-sample IV approach, is 0.42, somewhat lower than the result in the main section, but the result of significant differential rent-sharing stands.

7 Local labor market heterogeneity

In this section, I explore whether variation in concentration in local labor market generates variation in differential rent-sharing as is predicted by prediction [4](#). This is predicated on the idea that concentration can be used as a proxy for labor market power. This approach is now standard in the literature (see for example [Marinescu et al. \(2021\)](#), [Azar et al. \(2020\)](#)), but it has also been repeatedly emphasized that concentration is an imperfect proxy for labor market power (for instance [Bassier et al. \(2022\)](#) find small correlations between

¹⁹In robustness not reported here, I checked that the omission of controls only had a very limited effect

concentration and labor market power).

I first describe how I measure local labor market concentration, using Labor Market Herfindahl-Hirschman Index (HHI). A novelty in this paper is that I consider concentration separately for FTCs and OECs following the hypothesis that these two markets are relatively segmented. The results in this section suggest that this is a reasonable hypothesis. I then compute the slope of wage-value-added curve by FTC and OEC HHI quartile.

7.1 Measuring labor market concentration

I define the local labor market level as the interaction between a commuting zone and an occupation. I measure hiring concentration by a Labor Market Herfindahl-Hirschman Index (HHI) in hiring as a proxy for labor market power. I follow the standard definition of the HHI (see for instance [Azar et al. \(2020\)](#) or [Marinescu et al. \(2021\)](#)) with two modifications. First, I compute an aggregated HHI over the 2010 to 2014 period (rather than yearly). I do this to smooth over some of the idiosyncratic time variation. Second, since part of the argument of the model is that FTC and OEC labor markets are segmented, I also compute the HHIs separately by contract type.

I denote the set of firms hiring in occupation o in commuting zone z at time t by $\mathcal{J}_{o,z,t}$. The number of workers hired by firm j is denoted $\mathcal{N}_{j,o,z,t}$. The firm's (aggregated) labor market $s_{j,o,m}^L$ share is then given by:

$$s_{j,o,z}^L = \frac{\sum_t \mathcal{N}_{j,o,z,t}}{\sum_t \sum_{k \in \mathcal{J}_{o,z,t}} \mathcal{N}_{k,o,z,t}}$$

The labor market HHI, $\text{HHI}_{o,z}$, is then given by the sum of these shares squared over all firms in the LLM:

$$\text{HHI}_{o,z,t} = \sum_t \sum_{j \in \mathcal{J}_{o,z,t}} s_{j,o,z}^2$$

Table 4 shows summary statistics for the distribution of the HHIs by contract type. Rows 3 and 4 of the table show the same summary statistics after the merge with the firm-level data. I discuss this further below. The median HHI for FTCs is at 0.07 which is similar to what [Marinescu et al. \(2021\)](#) find (for global HHI).²⁰ Interestingly, the median HHIs for OECs is a bit lower. This holds for both median and mean, before and after merge. The fact FTC markets are more concentrated than OECs is another mild confirmation for our hypothesis that $\eta^{\text{OEC}} > \eta^{\text{FTC}}$.

The table above already shows a difference between the distributions of the HHI by

²⁰They use 4-digit occupation codes.

Table 4: Summary of the FTC and OEC labor market HHI distribution.

	Minimum	Q1	Median	Mean	Q3	Maximum
HHI FTC	0.001	0.034	0.076	0.190	0.198	1.000
HHI OEC	0.000	0.019	0.048	0.159	0.136	1.000
HHI FTC after merge	0.001	0.006	0.012	0.028	0.033	1.000
HHI OEC after merge	0.000	0.003	0.007	0.018	0.019	1.000

Notes: This table shows summary statistics for the distributions of aggregated labor market hiring HHI over the period 2010 to 2014 at local labor market level defined as commuting zone and occupation. Rows 3 and 4 show the same summary statistics after the merge with firm-level data, which is necessary for the results below.

Table 5: Cross-table of firm-occupation observation by FTC and OEC HHI quartiles.

		HHI OEC			
		Q1	Q2	Q3	Q4
HHI FTC	Q1	99,724	38,685	8,677	1,028
	Q2	40,690	60,457	36,905	9,779
	Q3	3,762	35,705	70,078	38,392
	Q4	4,643	12,261	32,431	98,588

Notes: This table shows the number of firm cross occupation observations by FTC and OEC HHI.

contract type. Additionally, the correlation between the two is 0.51 (appendix Figure A14 also shows this correlation), which while significant, still leaves a lot of room for separate variation, which is consistent at least partially with the hypothesis that the two markets are segmented. Table 5 additionally confirms this by showing the number of firm cross occupation observations across FTC and OEC quartiles: the correlation is clear, but there is also large variation when fixing one HHI. All of these observations are consistent with an at least partial segmentation of these two markets.

7.2 Results

The goal of this section is to verify prediction 4, which states that decreases in η^C should decrease the corresponding slope between average wages and value-added per worker. I therefore check whether increases in concentration, which correspond to decreases in η^C , satisfy this prediction. Because of the correlation between the FTC and OEC HHI measures I will show the variation in the slope when varying the corresponding HHI quartile and

holding the other HHI quartile constant.

To match with the local labor market definition, I collapse the data to the firm and occupation level. Namely, I compute average wages in FTCs and OECs at the firm and occupation level. As before, I residualize wages on year, gender, age, experience in occupation and industry. I then merge the HHI information. I also merge the financial data, and in particular value-added per worker information. Notice that this measure of value-added per worker is constant at the firm-level and will therefore be identical across the occupation cells within a firm. As before, I also residualize value-added per worker.

Figure 7 shows the slopes of log hourly wages (FTC wages in panel 7b and OEC wages in panel 7a) against log value-added per worker, by FTC and OEC HHI quartiles. As before, both wages and value-added are residualized.

For OECs, prediction 4 seems to be confirmed. Across all FTC quartiles, the slope decreases when the OEC quartile increases. On the other hand, for FTCs, the slopes seem to be fairly constant, if not even slightly increasing.

7.3 Discussion

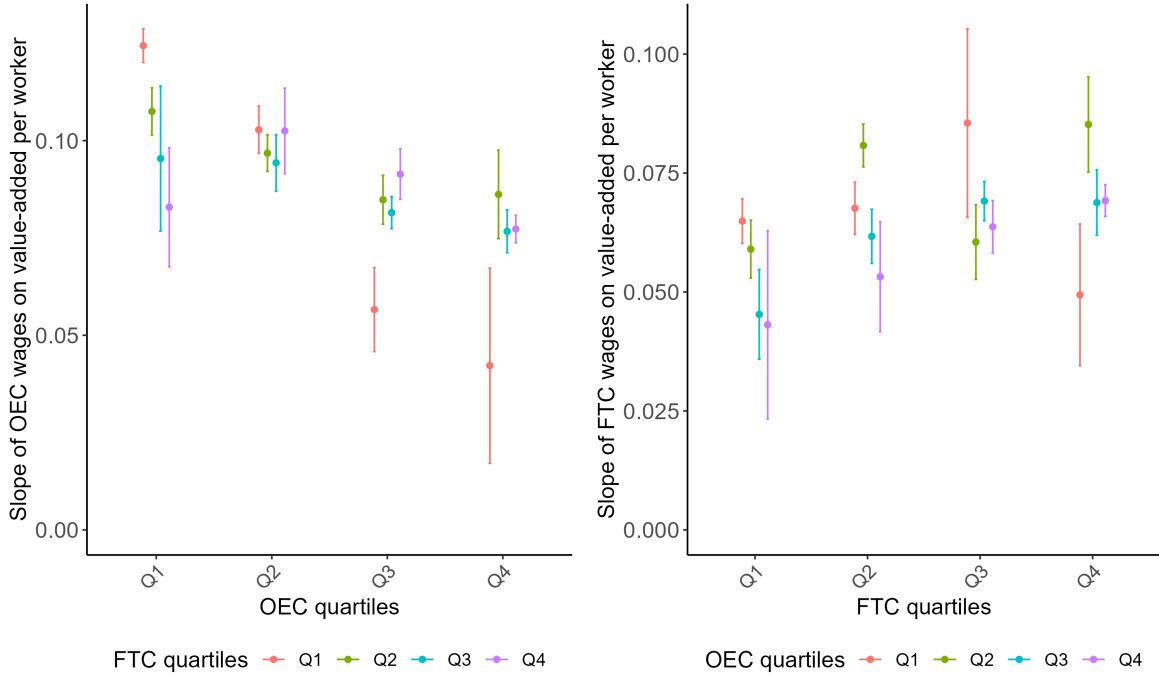
The fact that prediction 4 bears out for OECs but FTCs is an interesting observation. I give a few tentative explanations below, but further exploration is left for future research.

As was discussed above, the labor supply elasticities, and therefore ultimately the labor market power, can come from many different sources. In particular, it is possible that the dominant sources vary between the OEC and FTC markets. The results above suggest that concentration does play a significant role in labor market power for OECs, whereas it does not for FTCs. This is consistent for instance with the hypothesis that for FTCs, other sources are more important such as lower bargaining power (maybe due to less union coverage). It is also possible that variation in concentration capture different aspects of labor markets for different contract types (for instance outside options, see [Bassier et al. \(2022\)](#) for a related discussion).

8 Conclusion

In this paper, I explore the effect of fixed-term contracts on the wage structure, both theoretically and empirically. I start by providing a monopsonistic model of segmented labor markets categorized by contract type, augmented by the notion of compensating wage differentials for job security.

I start by documenting that the average wage gap is precisely estimated to be zero. This



(a) Slopes of log hourly OEC wage against log value-added per worker, both residualized, by OEC and FTC HHI quartiles. (b) Slopes of log hourly FTC wage against log value-added per worker, both residualized, by OEC and FTC HHI quartiles.

Figure 7: Slopes of log hourly wages against log value-added per worker, both residualized, by OEC and FTC HHI quartiles.

Notes: The figure on the left shows the slope coefficient from a regression of residualized value-added per worker on residualized log hourly wages of OECs, by OEC HHI quartiles on the horizontal axis and FTC HHI quartiles in colors. The residualization variables are year, gender, age, experience in occupation and industry. The regression is computed at the firm cross occupation level. Standard errors are clustered at the firm level. The right graph replaces OEC wages by FTC wages, and the variation along the horizontal axis is now FTC HHI quartiles and the colors are OEC HHI quartiles.

strongly suggests the existence of mechanisms which have opposing effects on the sign of the wage gap, such as compensating wage differentials and differential rent-sharing in my model.

I then document significant differential rent-sharing between contract types, using both a descriptive approach and an approach based on the estimation of firm wage premia. This is in line with the mechanisms advocated in the model. I additionally document that rent-sharing varies with local labor market concentration for OECs, but not for FTCs.

The results in this paper open interesting avenues for future research. From a theoretical perspective, a microfounded general equilibrium model would allow to more cleanly identify consequences for policy. Empirically, it would be important to further understand

the various rationales and mechanisms underlying the heterogeneity in the use of FTCs and how they affect wages. In particular, the role of management and firm organization is an interesting avenue.

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A Appendix

A.1 Additional figures

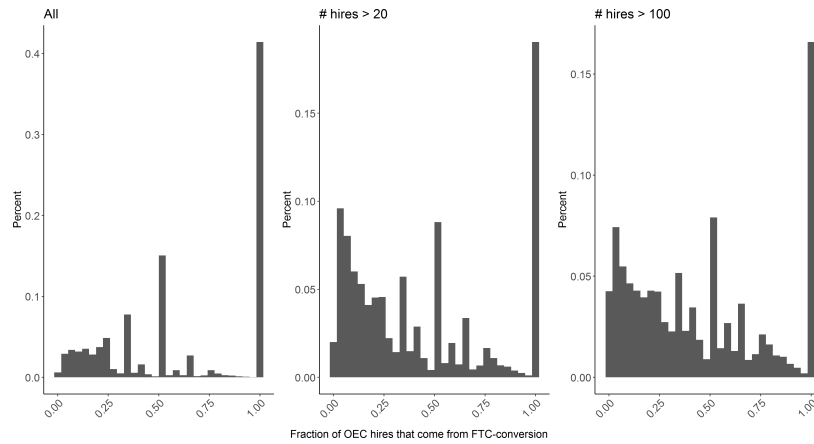


Figure A8: Distribution of the fraction of OECs hired in a year that were previously employed in an FTC at the firm

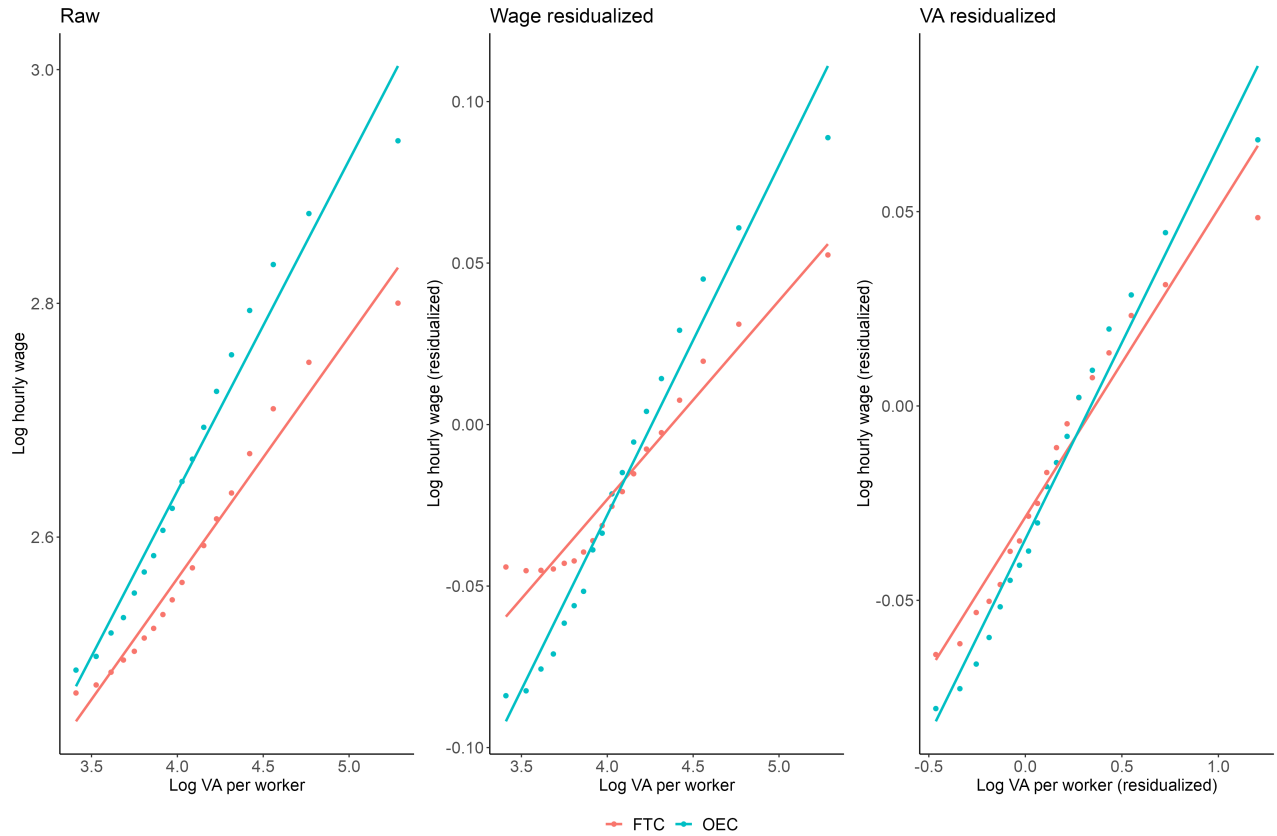


Figure A9: Average firm-level log hourly wage in FTCs and OECs as a function of value added per worker, raw, wage residualized and VA residualized and additionally restricted to workers aged over 30.

Notes: The first panel shows the binscatter of average log hourly wage at the firm-year level against with log value added per worker. In the second panel, wage are residualized with respect to year, gender, age, occupation, experience in occupation and industry. In the third panel, log value added per worker is additionally residualized with respect to the same variables. The bottom 10% in terms of value added per worker are trimmed. The sample is restricted to individuals aged over 30.

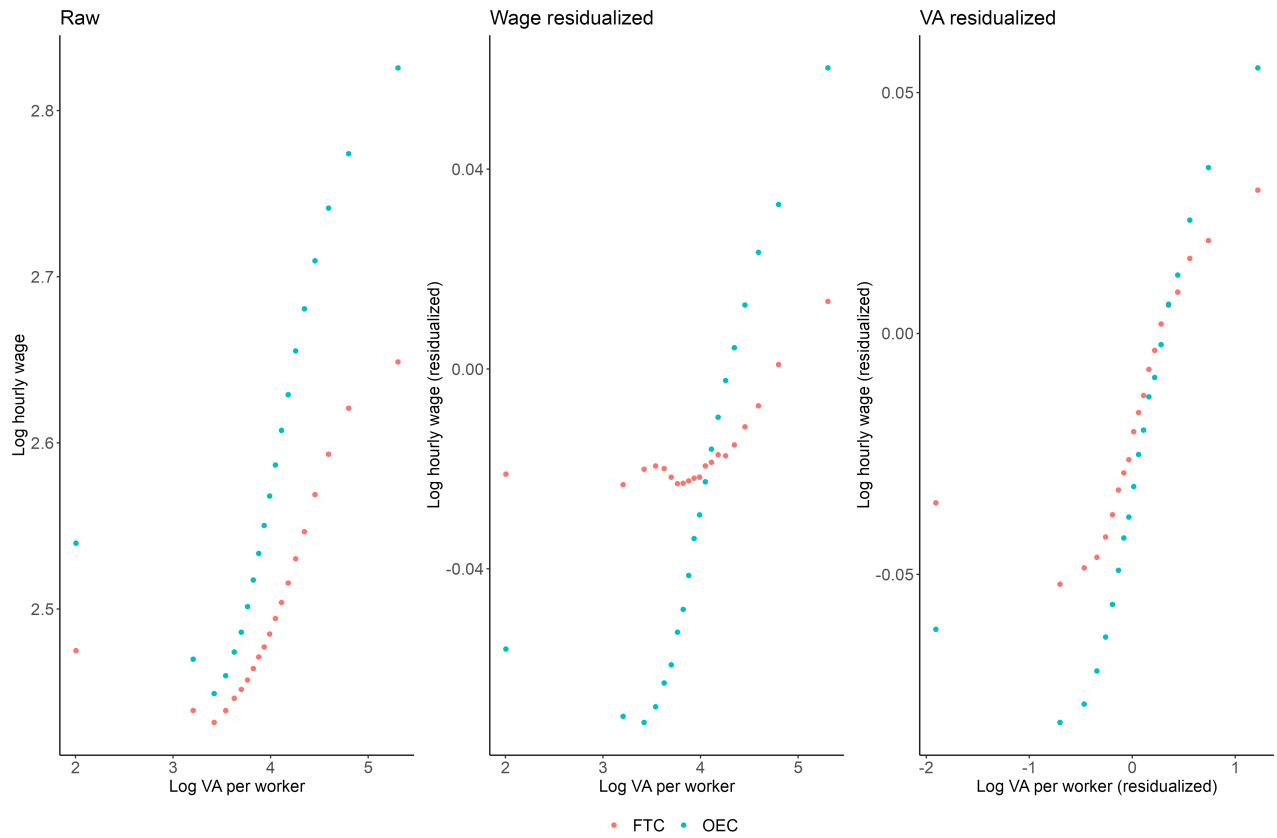


Figure A10: Average firm-level log hourly wage in FTCs and OECs as a function of value added per worker, raw, wage residualized and VA residualized. Full sample

Notes: The first panel shows the binscatter of average log hourly wage at the firm-year level against with log value added per worker. In the second panel, wage are residualized with respect to year, gender, age, occupation, experience in occupation and industry. In the third panel, log value added per worker is additionally residualized with respect to the same variables.

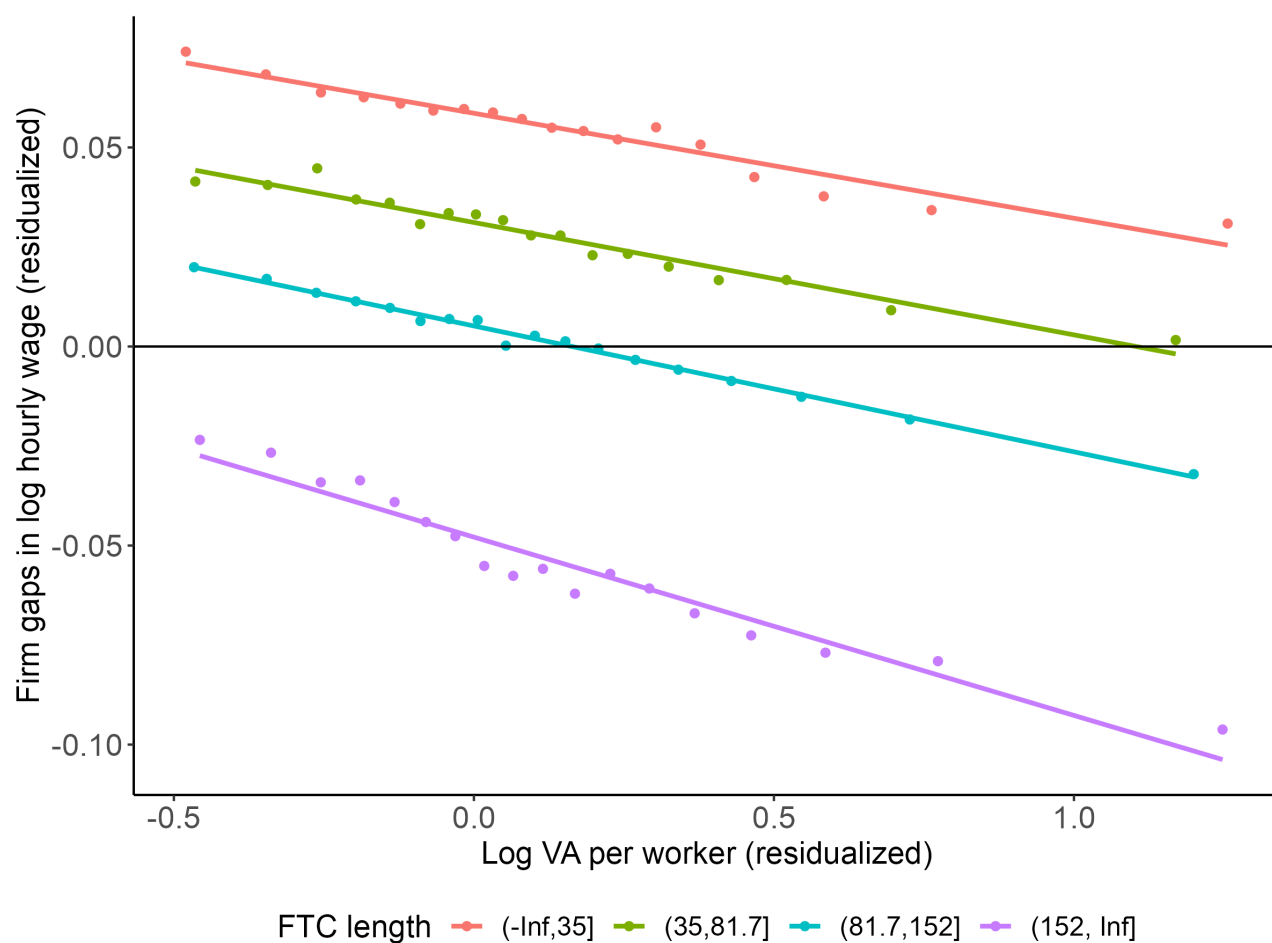


Figure A11: Average residualized firm-level log hourly wage in FTCs and OECs as a function of residualized value added per worker, by average FTC length quartiles.

Notes: The figures shows residualized average firm-level FTC-OEC wage gap as a function of residualized value added per worker, by average FTC length quartiles.

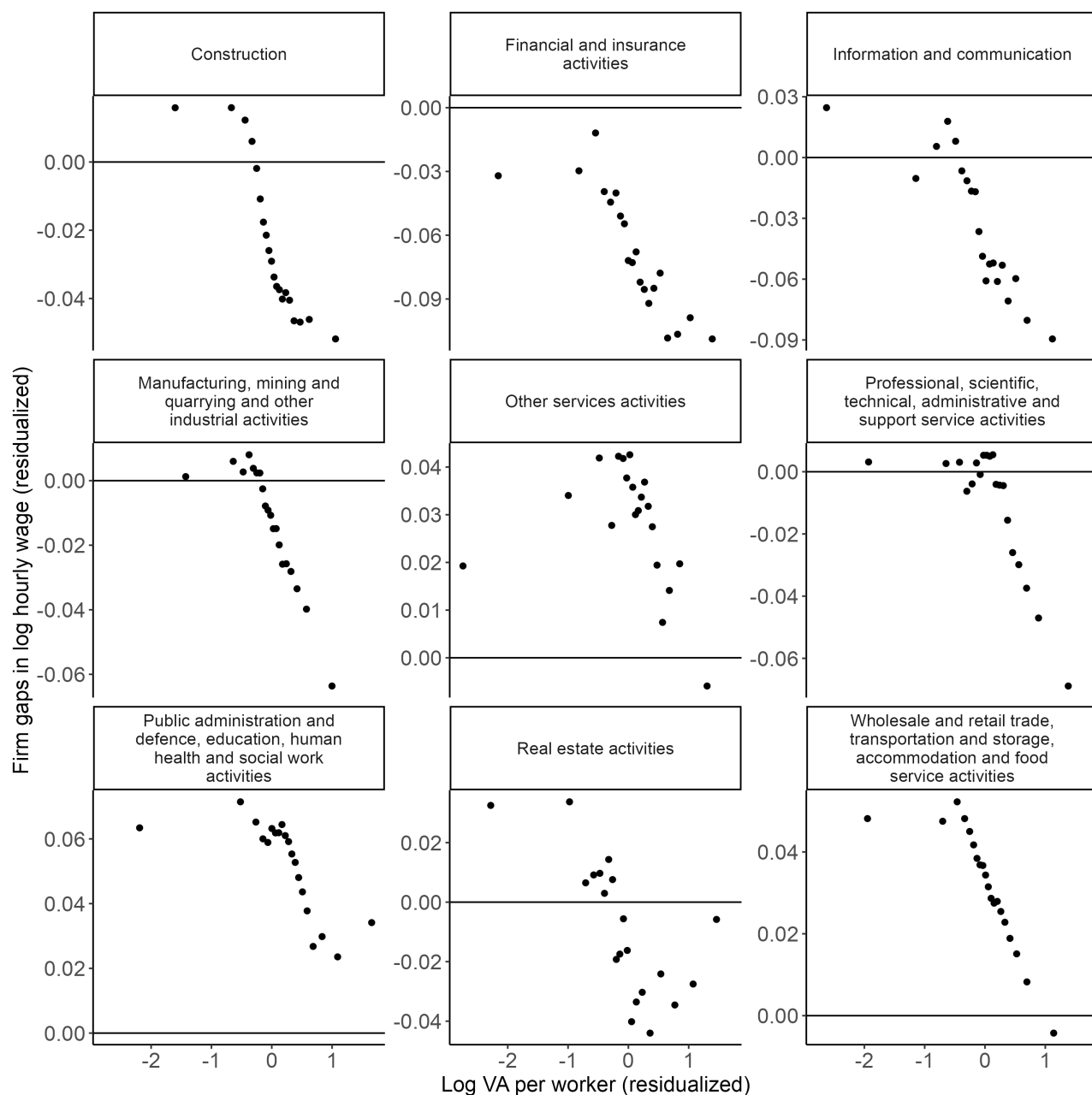


Figure A12: Residualized average firm-level FTC-OEC wage gap as a function of residualized value added per worker, by industry.

Notes: This shows residualized average firm-level FTC-OEC wage gap as a function of residualized value added per worker, by industry. Industry is defined at a broad level with 10 different industries.

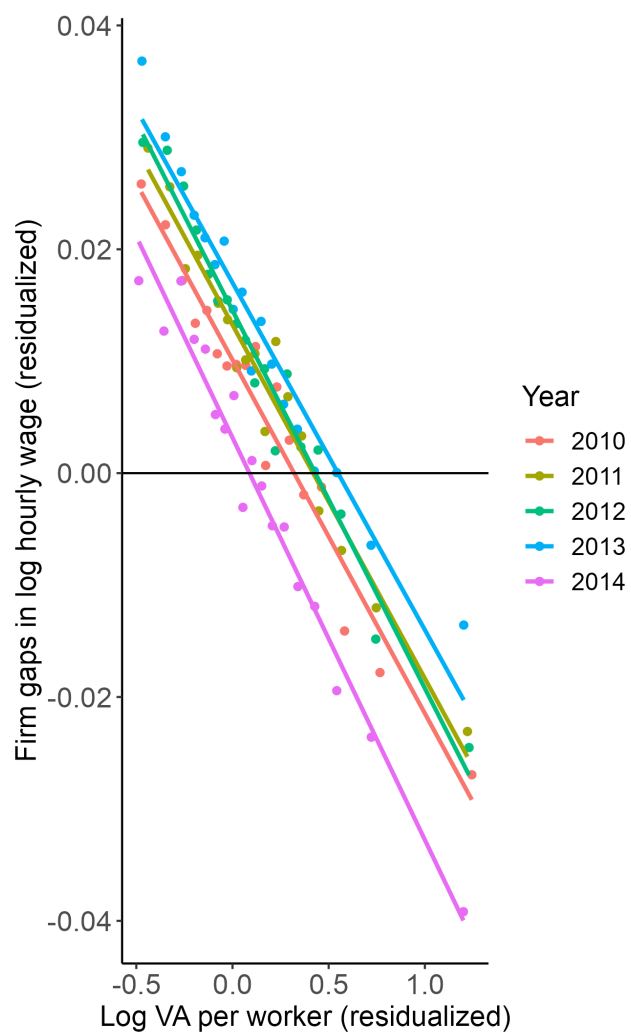


Figure A13: Residualized average firm-level FTC-OEC wage gap as a function of residualized value added per worker, by year.

Notes: This shows residualized average firm-level FTC-OEC wage gap as a function of residualized value added per worker, by year.

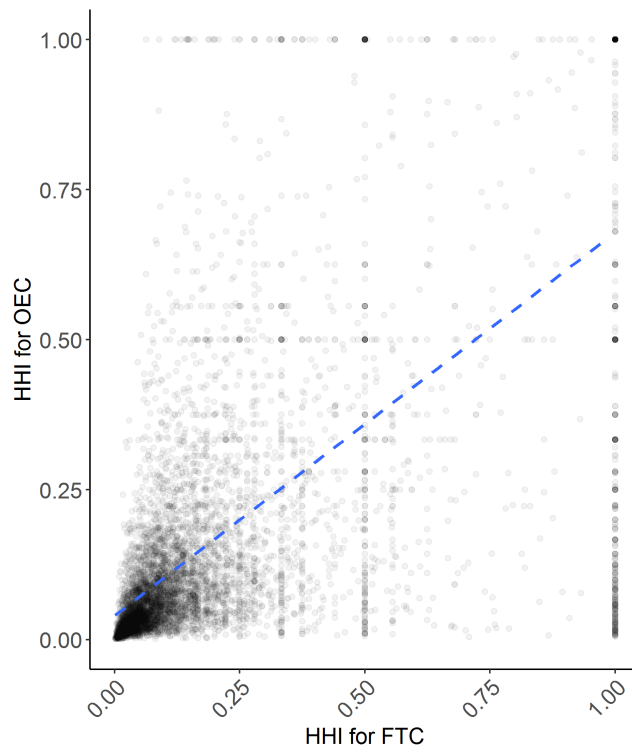


Figure A14: Plot of FTC HHIs against OEC HHIs.

Notes: This figure is a scatter plot of local labor market HHIs for FTCs and OECs. The blue line is the slope from an OLS regression.

A.2 Additional tables

	English description	French description (short)	French description (long)
10	Farmers	Agriculteurs	Exploitants de l'agriculture, sylviculture, pêche et aquaculture
21	Craftsmen	Artisans	Artisans
22	Shopkeepers and similar	Commerçants et assimilés	Commerçants et assimilés
23	Entrepreneurs with more than 10 employees	Chefs d'entreprise de plus de 10 personnes	Chefs d'entreprise de plus de 10 personnes
31	Liberal professions	Professions libérales	Professions libérales
33	Civil service executives	Cadres de la fonction publique	Cadres administratifs et techniques de la fonction publique
34	Teachers and scientists	Professeurs et professions scientifiques	Professeurs et professions scientifiques supérieures
35	Information, arts and entertainment professionals	Professions de l'information, de l'art et des spectacles	Professions de l'information, de l'art et des spectacles
37	Administrative and sales executives	Cadres administratifs et commerciaux	Cadres des services administratifs et commerciaux d'entreprise
38	Technical business executives	Cadres techniques d'entreprise	Ingénieurs et cadres techniques d'entreprise
42	Primary and vocational education professions	Professions de l'enseignement primaire et professionnel	Professions de l'enseignement primaire et professionnel, de la formation continue et du sport
43	Health and social work professionals	Intermédiaires de la santé et du travail social	Professions intermédiaires de la santé et du travail social
44	Religious	Religieux	Ministres du culte et religieux consacrés
45	Intermediate civil servants	Intermédiaires de la fonction publique	Professions intermédiaires de la fonction publique (administration, sécurité)
46	Business intermediaries	Intermédiaires des entreprises	Professions intermédiaires administratives et commerciales des entreprises
47	Technicians	Techniciens	Techniciens
48	Production supervisors	Agents de maîtrise de production	Agents de maîtrise (hors maîtrise administrative)
52	Civil servants	Employés de la fonction publique	Employés administratifs de la fonction publique, agents de service et auxiliaires de santé
53	Police, military and private security officers	Policiers, militaires et agents de sécurité privée	Policiers, militaires, pompiers, agents de sécurité privée
54	Company administrative employees	Employés administratifs d'entreprise	Employés administratifs d'entreprise
55	Commercial employees	Employés de commerce	Employés de commerce
56	Personal service workers	Personnels des services aux particuliers	Personnels des services directs aux particuliers
62	Skilled industrial workers	Ouvriers qualifiés de type industriel	Ouvriers qualifiés de type industriel
63	Skilled craft workers	Ouvriers qualifiés de type artisanal	Ouvriers qualifiés de type artisanal
64	Transport drivers	Conducteurs du transport	Conducteurs de véhicules de transport, chauffeurs-livreurs, coursiers
65	Machine and warehouse operators	Conducteurs d'engins et magasiniers	Conducteurs d'engins, caristes, magasiniers et ouvriers du transport (non routier)
67	Low-skilled industrial workers	Ouvriers peu qualifiés de type industriel	Ouvriers peu qualifiés de type industriel
68	Low-skilled craft workers	Ouvriers peu qualifiés de type artisanal	Ouvriers peu qualifiés de type artisanal
69	Agricultural workers	Ouvriers agricoles	Ouvriers agricoles, des travaux forestiers, de la pêche et de l'aquaculture

Table A6: Description of 2-digit occupation codes

Table A7: FTC-OEC hiring wage gap regression, controlling for 2-digit occupation codes rather than 4-digit.

	(1)	(2)	(3)	Log hourly wage		(6)	(7)	(8)
				(4)	(5)			
FTC	-0.1311*** (0.0022)	-0.1215*** (0.0022)	-0.0673*** (0.0021)	-0.0701*** (0.0014)	-0.0006 (0.0010)	0.0096*** (0.0009)	-0.0045*** (0.0006)	0.0265*** (0.0005)
Observations	33,277,570	33,277,570	33,277,570	33,277,570	33,277,570	33,277,570	33,277,570	33,277,570
R ²	0.02689	0.04358	0.12355	0.27117	0.50588	0.51625	0.66253	0.87947
Within R ²	0.02682	0.02333	0.00747	0.00879	9.57×10^{-7}	0.00023	4.29×10^{-5}	0.00141
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Sex fixed effects		✓	✓	✓	✓	✓	✓	✓
Age fixed effects			✓	✓	✓	✓	✓	✓
Industry fixed effects				✓	✓	✓	✓	✓
Occupation (2 digit) fixed effects					✓	✓	✓	✓
Exp. in occ. fixed effects						✓	✓	✓
Establishment fixed effects							✓	✓
Individual fixed effects								✓

Notes: This table reports the result from the regression of log hourly wage on an indicator for whether the observation is in an FTC, and a set of fixed-effects over the period 2010 to 2014. Log hourly wage is computed as gross wage divided by number of hours, inflation-adjusted into 2012 euros, trimmed at 0.1%, and FTC wages are aggregated over the FTC spell. Age is separated into 5 year bins. Industry is a 38 level code for industries. Occupation is the 2-digit PCS code. Experience in occupation is the number of years since the individual first practiced the 2-digit occupation of the observation. The results are clustered at the establishment level.

*p<0.1; **p<0.05; ***p<0.01.

Table A8: FTC-OEC hiring wage gap regression for the 2005 to 2009 period

	Log hourly wage							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FTC	-0.1410*** (0.0022)	-0.1277*** (0.0021)	-0.0615*** (0.0021)	-0.0702*** (0.0015)	-0.0007 (0.0010)	0.0043*** (0.0010)	-0.0042*** (0.0006)	0.0243*** (0.0007)
Observations	37,213,647	37,213,647	37,213,647	37,213,647	37,213,647	37,213,647	37,213,647	37,213,647
R ²	0.02703	0.04802	0.13030	0.26505	0.54538	0.55049	0.67913	0.89014
Within R ²	0.02698	0.02249	0.00540	0.00752	1.02×10^{-6}	4.44×10^{-5}	3.62×10^{-5}	0.00113
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Sex fixed effects		✓	✓	✓	✓	✓	✓	✓
Age fixed effects			✓	✓	✓	✓	✓	✓
Industry fixed effects				✓	✓	✓	✓	✓
Occupation (2 digit) fixed effects					✓	✓	✓	✓
Exp. in occ. fixed effects						✓	✓	✓
Establishment fixed effects							✓	✓
Individual fixed effects								✓

Notes: This table reports the result from the regression of log hourly wage on an indicator for whether the observation is in an FTC, and a set of fixed-effects over the period 2005 to 2010. Log hourly wage is computed as gross wage divided by number of hours, inflation-adjusted into 2012 euros, trimmed at 0.1%, and FTC wages are aggregated over the FTC spell. Age is separated into 5 year bins. Industry is a 38 level code for industries. Occupation is the 4-digit PCS code. Experience in occupation is the number of years since the individual first practiced the 2-digit occupation of the observation. The results are clustered at the establishment level.

*p<0.1; **p<0.05; ***p<0.01.

Table A9: FTC-OEC hiring wage gap regression over the period 2010 to 2014 using cross-sectional DADS postes data

	Log hourly wage					
	(1)	(2)	(3)	(4)	(5)	(6)
FTC	-0.1330*** (0.0024)	-0.1229*** (0.0024)	-0.0680*** (0.0024)	-0.0776*** (0.0015)	-0.0132*** (0.0007)	-0.0186*** (0.0006)
Observations	33,745,136	33,745,136	33,745,136	33,745,136	33,745,136	33,745,136
R ²	0.02553	0.04265	0.12141	0.26967	0.52699	0.65580
Within R ²	0.02541	0.02198	0.00702	0.00987	0.00039	0.00067
Year fixed effects	✓	✓	✓	✓	✓	✓
Sex fixed effects		✓	✓	✓	✓	✓
Age fixed effects			✓	✓	✓	✓
Industry fixed effects				✓	✓	✓
Occupation fixed effects					✓	✓
Establishment fixed effects						✓

Notes: This table reports the result from the regression of log hourly wage on an indicator for whether the observation is in an FTC, and a set of fixed-effects over the period 2010 to 2014. Log hourly wage is computed as gross wage divided by number of hours, inflation-adjusted into 2012 euros, trimmed at 0.1%. Compared to table 1 the data used is cross-sectional DADS postes data, rather than the statistical match panel data. This also means that FTC wages are *not* aggregated over the FTC spell (see discussion in section 4.3). Age is separated into 5 year bins. Industry is a 38 level code for industries. Occupation is the 4-digit PCS code. Experience in occupation is the number of years since the individual first practiced the 2-digit occupation of the observation. The results are clustered at the establishment level.

*p<0.1; **p<0.05; ***p<0.01.

Table A10: FTC-OEC hiring wage gap regression over the period 2010 to 2014 with FTC wages not aggregated over the spell.

	Log hourly wage					
	(1)	(2)	(3)	(4)	(5)	(6)
FTC	-0.1387*** (0.0022)	-0.1291*** (0.0022)	-0.0750*** (0.0021)	-0.0792*** (0.0014)	-0.0136*** (0.0007)	-0.0186*** (0.0006)
Observations	33,277,572	33,277,572	33,277,572	33,277,572	33,277,572	33,277,572
R ²	0.02987	0.04654	0.12600	0.27194	0.54437	0.67216
Within R ²	0.02978	0.02612	0.00921	0.01112	0.00047	0.00076
Year fixed effects	✓	✓	✓	✓	✓	✓
Sex fixed effects		✓	✓	✓	✓	✓
Age fixed effects			✓	✓	✓	✓
Industry fixed effects				✓	✓	✓
Occupation fixed effects					✓	✓
Establishment fixed effects						✓

Notes: This table reports the result from the regression of log hourly wage on an indicator for whether the observation is in an FTC, and a set of fixed-effects over the period 2010 to 2014. Log hourly wage is computed as gross wage divided by number of hours, inflation-adjusted into 2012 euros, trimmed at 0.1%. Compared to table 1, FTC wages are *not* aggregated over the FTC spell (see discussion in section 4.3). This is done to facilitate the comparison with table A9 which uses cross-sectional data and therefore cannot do that adjustment. Age is separated into 5 year bins. Industry is a 38 level code for industries. Occupation is the 4-digit PCS code. Experience in occupation is the number of years since the individual first practiced the 2-digit occupation of the observation. The results are clustered at the establishment level.

*p<0.1; **p<0.05; ***p<0.01.

Table A11: FTC-OEC hiring wage gap regression over the period 2010 to 2014, restricted to individuals aged 30 to 60.

	Log hourly wage						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FTC	-0.1239*** (0.0031)	-0.1138*** (0.0030)	-0.1113*** (0.0030)	-0.1079*** (0.0020)	-0.0141*** (0.0008)	-0.0027*** (0.0008)	0.0067*** (0.0006)
Observations	17,407,406	17,407,406	17,407,406	17,407,406	17,407,406	17,407,406	17,407,406
R ²	0.01889	0.04379	0.04906	0.26643	0.58327	0.58937	0.72328
Within R ²	0.01868	0.01613	0.01551	0.01598	0.00043	1.56×10^{-5}	8.41×10^{-5}
Year fixed effects	✓	✓	✓	✓	✓	✓	✓
Sex fixed effects		✓	✓	✓	✓	✓	✓
Age fixed effects			✓	✓	✓	✓	✓
Industry fixed effects				✓	✓	✓	✓
Occupation fixed effects					✓	✓	✓
Exp. in occ. fixed effects						✓	✓
Establishment fixed effects							✓

Notes: This table reports the result from the regression of log hourly wage on an indicator for whether the observation is in an FTC, and a set of fixed-effects over the period 2010 to 2014. Individuals are restricted to ages between 30 and 60 years old. Log hourly wage is computed as gross wage divided by number of hours, inflation-adjusted into 2012 euros, trimmed at 0.1%, and FTC wages are aggregated over the FTC spell. Age is separated into 5 year bins. Industry is a 38 level code for industries. Occupation is the 4-digit PCS code. Experience in occupation is the number of years since the individual first practiced the 2-digit occupation of the observation. The results are clustered at the establishment level.

*p<0.1; **p<0.05; ***p<0.01.

Table A12: FTC-OEC hiring wage gap regression over the period 2010 to 2014, by industries which can potentially use CDD-U.

CDD-U industries	Log hourly wage		
	Full sample (1)	FALSE (2)	TRUE (3)
FTC	0.0027*** (0.0007)	-0.0034*** (0.0006)	0.0053*** (0.0009)
Observations	22,241,559	5,746,543	16,495,016
R ²	0.68068	0.67568	0.67818
Within R ²	1.96×10^{-5}	4.79×10^{-5}	6.76×10^{-5}
Year fixed effects	✓	✓	✓
Sex fixed effects	✓	✓	✓
Age fixed effects	✓	✓	✓
Industry fixed effects	✓	✓	✓
Occupation fixed effects	✓	✓	✓
Exp. in occ. fixed effects	✓	✓	✓
Establishment fixed effects	✓	✓	✓

Notes: This table reports the result from the regression of log hourly wage on an indicator for whether the observation is in an FTC, and a set of fixed-effects over the period 2010 to 2014 over the full sample, and for two sets of industries depending on their right to use CDD-U. The sample is different from 1 because it is the sample that is used in the heterogeneity analysis, after matching with financial and other firm data. As can be seen from the the estimate on the full sample, the estimates are nearly identical. Log hourly wage is computed as gross wage divided by number of hours, inflation-adjusted into 2012 euros, trimmed at 0.1%, and FTC wages are aggregated over the FTC spell. Age is separated into 5 year bins. Industry is a 38 level code for industries. Occupation is the 4-digit PCS code. Experience in occupation is the number of years since the individual first practiced the 2-digit occupation of the observation. The results are clustered at the establishment level.

*p<0.1; **p<0.05; ***p<0.01.

Table A13: Firm selection when creating the firm-level dataset

Restriction	Number of observations	Number of firms	Mean firm size	Mean log hourly wage
Full data	3231096	1241254	10.32	2.57
FTC-OEC gap	1105368	535224	23.31	2.56
Financial data	937934	452965	22.61	2.56
Hiring information	895988	434706	23.16	2.55
Missing FTC length information	815437	400756	24.49	2.56
Missing VA information	784633	384635	24.64	2.55

Notes: This table shows the regression log hourly wage for FTCs and OECs on log value added per worker, restricted to the range of value added per worker above 3.5 identified manually from figure 4. Columns (1) and (2) are for raw wages, whereas (3) and (4) are residualized with respect to year, gender, age, occupation, experience in occupation and industry. Standard errors are clustered at the firm level.

*p<0.1; **p<0.05; ***p<0.01.

Table A14: Regression of log hourly wage on log value added per worker, restricted to the appropriate value added per worker range.

	Log hourly wage		Residualized Log hourly wage			
	FTC (1)	OEC (2)	FTC (3)	OEC (4)	FTC (5)	OEC (6)
Log Value Added per worker	0.1326*** (0.0009)	0.2319*** (0.0012)	0.0188*** (0.0006)	0.0774*** (0.0007)		
Residualized Log Value Added per worker					0.0545*** (0.0007)	0.0855*** (0.0007)
Observations	687,912	687,912	687,912	687,912	690,357	690,357
R ²	0.06846	0.12787	0.00230	0.03748	0.01536	0.03620
Adjusted R ²	0.06846	0.12787	0.00230	0.03748	0.01536	0.03620

Notes: This table shows the regression log hourly wage for FTCs and OECs on log value added per worker, restricted to the same range of value added per worker as in figure 4. Columns (1) and (2) are for raw wages, whereas (3) and (4) are residualized with respect to year, gender, age, occupation, experience in occupation and industry and (5) and (6) log value added per worker is residualized with respect to the same variables. Standard errors are clustered at the firm level.

*p<0.1; **p<0.05; ***p<0.01.

Table A15: Regression of FTC firm effects on OEC firm effects.

	FTC-FFE	
	(1)	(2)
(Intercept)	0.0440*** (0.0018)	0.0445*** (0.0018)
OEC-FFE	0.3082*** (0.0134)	0.3387*** (0.0155)
Observations	148,916	140,911
R ²	0.08380	0.08799
Adjusted R ²	0.08379	0.08799

Notes: This table reports the regression of FTC firm effects on OEC firm effects, weighted by total number of person-year observations by firm. The firm effects are estimated separately using a standard AKM specification. Column (1) reports the regression on the full data. Column (2) restricts to firms with an OEC firm effect greater than -0.35 . This threshold is chosen manually to correspond to the linear section in Figure 6a.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A16: Regressions of FTC firm effect on OEC firm effects, estimated jointly and restricted after the kink.

	FTC firm effect		FTC firm effect, 1st split	
	(1)	(2)	(3)	(4)
(Intercept)	0.0100*** (0.0013)	0.0117*** (0.0015)	-0.1107*** (0.0031)	-0.1019*** (0.0036)
OEC firm effect	0.3702*** (0.0124)	0.3803*** (0.0163)		
OEC firm effect, 1st split			0.3512*** (0.0150)	0.4190*** (0.0194)
Observations	184,695	63,463	63,463	63,463
R ²	0.14929	0.17817	0.14002	0.13479
Adjusted R ²	0.14929	0.17816	0.14000	0.13478

Notes: This table reports the regression of FTC firm effects on OEC firm effects, weighted by total number of person-year observations by firm. The firm effects are estimated jointly without controls. I also split the data in two randomly stratified at the individual level. Column (1) reports the regression on the full data, restricting to firms with an OEC firm effect greater than -0.35 . Column (2) estimates the same regression on the subsample of firms which get selected for the leave-out connected set on the first random subsample. Column (3) reports the regression of FTC firm effect in the first split on the OEC firm effect in the first split. Column (4) finally reports the result of the previous regression where I instrument the OEC firm effect in the first split by the OEC firm effect in the second split. This is done to correct for the measurement error bias. In both column (3) and (4), the observations have been restricted to have OEC firm effects (in the first split) larger than -0.2 , a threshold identified manually in a binscatter (not reported in the paper).

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

A.3 Wage dynamics in the presence of FTCs

A thorough discussion of wage dynamics is outside the scope of this paper. In lieu of this, I will simply provide the results of a basic event-study approach. The goal is to illustrate the potential existence of the dual wage ladder mentioned above and encourage further investigation into this topic.

Methodology Instead of restricting to hiring wages, I now use the full matched DADS panel as described in section 4.3. For workers with several jobs, I additionally restrict to the dominant job which I define as the job with the highest hourly wage.²¹ This restriction is necessary to define the transitions from FTCs to OECs but it is also restrictive as it for instance drops the wages of non-dominant wages. I then restrict to individuals that have at least one transition from an FTC to an OEC, and for the few instances with more than one such switch I restrict to the first switch.

I then run an event-study *without* a control group:

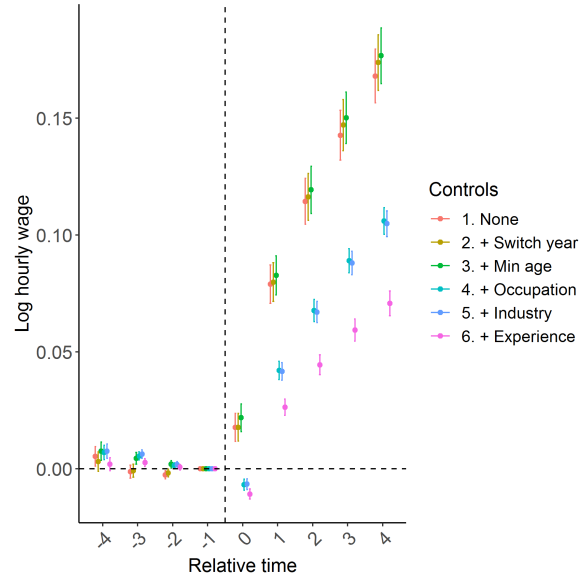
$$\ln hw_{it} = \sum_{k \neq 0} \mathbb{1}[\text{Year}_t - \text{Year_transition}_i = k] + X_{it} + \varepsilon_{it}$$

where the controls X_{it} include a year-of-switch fixed effect, minimum age over the period of the worker, occupation, industry and second order polynomial of within-firm experience.

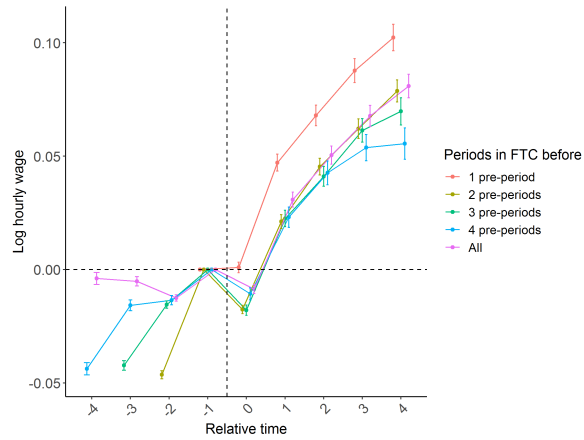
Results In figure A15a, I present the event-study around an FTC to OEC without any restrictions. The figure has two interesting features. First, it suggests little to no wage growth while on FTC and significant wage growth once on an OEC. Second, it suggests that on average workers take a wage cut when switching from an OEC to an FTC. Importantly, the wage cut only appears once occupation has been controlled for. Figure A15b changes this picture slightly. It restricts to individuals with no career gap (generally unemployment) around the transition and to individuals which have not had an OEC before the transition. These restrictions are meant to deal with possible confounders due to irregular careers and focus only on individuals that have only been on FTCs and then switch to an OEC. The

²¹For the small fraction of individuals for which this doesn't result in a single job, I further use the number of days and then number of hours.

figure additionally mitigates composition effects by disaggregating depending on the number of years in FTC before the transition. The specification used is the one which controls for year-of-switch fixed effect, minimum age over the period of the worker, occupation, industry and second order polynomial of within-firm experience. As opposed to the previous figure, individuals with different numbers of years before the transition experience wage growth on FTCs, as opposed to when they are all grouped together, which is indicative of a composition effect. It remains true that individuals on average experience a wage cut when transitioning from FTCs to OECs.



(a) Event study for individuals transitioning from FTCs to OECs



(b) Event study for individuals transitioning from FTCs to OECs, restricted to individuals without a career interruption and no instance of an OEC before the transition.

Figure A15: Event studies around FTC to OEC transition