Large Firms, High Concentration, High Wages*

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Abstract

How do wages and labor market transitions vary with labor market concentration? Using comprehensive French employer-employee data, I show that wages increase – contrary to what has been shown in other countries – and transition rates decrease when concentration increases. These results are found in the raw data, in regressions at the labor market level, in panel data regressions and in an event study setting in which I focus on markets undergoing large increase in concentration. I then propose a simple model of search-and-matching with a discrete number of firms, optimal vacancy posting and a fixed cost of entry. My model replicates my main two empirical findings: (1) when the entry cost increases, only the most productive firms enter, the market is more concentrated, wages are higher, and transition rates are lower; (2) given a labor market, an increase in productivity at one large firm increases wages at all firms through the increase in output at that firm and in outside option at all other firms, increases transition rates towards that firm, and reduces them towards all other firms. I quantify the markdowns on wages and show they are always relatively small. I investigate the first-best solution in which a planner chooses the distribution of workers across firms to maximize output: the planner concentrates employment among most productive firms, it increases output, mean wage, and total income to workers despite increasing concentration and unemployment. I turn to second-best implementations using individual tax and subsidy rates. By fully taxing most firms - the unproductive ones -, taxing partially the least productive firms among the operating ones, and using the tax revenue collected to subsidize the most productive firms, a planner almost achieves the first-best solution. On the contrary, simple linear tax policies do no come anywhere close to the first-best solution.

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Introduction

Product markets have become increasingly dominated by large firms over the years. A very large academic literature has focused on concentration in the product market and it has even evolved into a central point of the Biden's administration, as the recent start of Google's antitrust trial attests. Concentration on labor markets, however, has received much less attention from economists. Even more surprising: policy recommendations on labor market concentration are virtually non-existent – for instance, the Department of Justice guidelines from 2010 regarding horizontal mergers does not contain any of the words ”workers”, ”wages” or ”labor”.

Many different actors have stepped up to accuse big corporations of anti-competitive behaviors on the labor market, from unions to newspapers like the Economist, and culminating into an executive order by the White House reading: ”Consolidation has increased the power of corporate employers, making it harder for workers to bargain for higher wages and better work conditions”[1]. The goal of this paper is to provide empirical evidence of the links between labor market concentration and labor market outcomes for workers, and a structural framework to rationalize them. I then use that framework to quantify these so-called anti-competitive behaviors - namely markdowns on wages -, and study the effects of policies aimed at reducing concentration, their impacts on workers, and on the economy as a whole.

This paper uses three sets of French administrative employer-employee data: a repeated cross-section of the universe of employer-employee matches, a 8% representative employer-employee panel dataset and the definition of firms' boundaries across legal units. The completeness of the data allows me to construct precise labor market concentration measures. I use them to show that concentration and wages positively comove in the data, contrary to what was found in other countries (Rinz 2022 and Azar, Marinescu, and Steinbaum 2022 in the U.S. or Berger et al. 2023 in Norway). This result is observed in the raw data, in regressions à la Berger et al. 2023 using mean wages at the labor market level and in panel data regressions. It is also robust to different labor market definitions or concentration measures. These results are also economically important

[1] *Executive Order on Promoting Competition in the American Economy*, July 9th 2021, accessed on November 1st, 2023 here.

– in my preferred specification in the panel data, going from a market in the 10% concentration centile to one in the 90% is associated with a 6.5% wage increase.

My preferred specification relies on changes in concentration over time within the same labor market. These changes tend to be small, and one could wonder what happens when concentration changes significantly. In the last empirical exercise, I focus on large markets that undergo a large change in concentration and compare them with control markets in an event-study setting. The increase in concentration is on average due to one single firm hiring massively. At the labor market level, mean wage tends to increase slightly following the large increase in concentration. At the worker level, I match workers who worked in the labor market in the year before the shock to control workers, and show that their wage increases significantly by around 8% compared to control workers (despite a large pre-trend). Spillover effects are also present: wages of workers in nearby firms or labor markets also increase. I interpret this as evidence of a large firm receiving a productivity shock, hiring more and paying its workers more. Following the increase, workers at nearby firms need to be compensated because of an increase in their outside option even when they do not move.

Besides wages, labor market transitions behave as one would expect: larger concentration is associated with a decrease in the job-to-job flows, in the flow of unemployed workers finding a job, and, maybe more surprisingly, in the flow of employed workers losing their job. Jobs are more stable in more concentrated markets, as Berger et al. 2023 show in the Norwegian data. Following the large increase in concentration, caused by one large firm hiring, workers at the hiring firm are more likely to stay, whereas workers in nearby firms are more likely to undergo a job-to-job transition – also consistent with what one would expect.

The previous empirical results are only correlations though, as one lacks a good instrument to study the effect of concentration on the labor markets. I therefore propose a model of the labor market encapsulating the main forces I want to quantify. The model is most closely related to Berger et al. 2023 in spirit. I start from a search-and-matching framework with a discrete number of firms. Workers search on- and off-the-job and Nash-bargain over wages. Firms post vacancies to maximize expected profits taking into account that posting more vacancies lead to higher contact rates. My framework features here three sources of market power, all affecting wages: search-frictions, bargaining, and competition to hire workers. Finally I endogenize firm's entry by introducing an entry cost. Firms compute how much profits they would make in equilibrium given productivity draws at all other firms, and decide to enter the market or not. By dropping the lowest productivity firms one by one, I can numerically find the stationary equilibrium in which all remaining firms enter, and the distribution of workers and of wages at those firms.

My model replicates my main two empirical findings. In the cross-section of labor markets, by increasing the entry cost, only the most productive firms enter. The market is more concentrated. Because more productive firms pay higher wages, the mean wage is higher. And as fewer total vacancies are posted and workers have fewer firms to transition to, job-to-job transition probabilities are lower. Secondly, in a given labor market, an increase in productivity at one large firm replicates the event-study setting. It increases wages at all firms through the increase in output at that firm and the increase in the outside option of workers at all other firms. It also increases transition rates towards that firm, and reduces them towards all other firms as the increasing firm posts relatively more vacancies.

I use a subset of French data to estimate the model through a simulated method of moments, and quantify markdowns. No matter the concentration level, the median markdown remains around 0.08 and 0.15 - consistent with large worker labor market power. I decompose wages into three terms: the share of the output from the match, the penalty due to poaching, and the compensation through the outside option. By far, the largest part of the wage, around 80%, comes from the output extracted by workers. This remains true as one varies the entry cost, and hence concentration. Because most of the wage comes from output sharing, having large firms hiring more, and increasing concentration by doing so, actually leads to higher wages, profits, and output.

Finally, I turn to counterfactual policies. I solve the first-best solution, in which a planner chooses the distribution of workers across firms and the vacancy posting of each firm given the equilibrium flow rates and entry decisions of firms, to maximize output, and I compare it to the decentralized equilibrium. The planner concentrates employment among more productive firms, increasing concentration. By doing so, total output increases by 5% and wages by 11%, despite increasing unemployment by 5%. Too many firms operate in the decentralized equilibrium, and more productive firms do not post enough vacancies. I study second-best implementations in which the planner chooses individual tax and subsidy rates to incentivize firms to operate or not, and how much vacancies to post, subject to a balanced budget. I show that by fully taxing most of the firms - the least productive ones -, taxing the least productive firms among the ones operating, and using the tax revenue available to subsidize the most productive firms, the planner manages to bring output very close to the first-best solution. A simpler implementation in which the planner only chooses not to tax, or to fully tax firms, works almost as well. The core mechanisms to increase output rely on deterring most of the firms from operating, while nudging the operating firms to post either less vacancies (for the least productive) or more vacancies (for the most productive).

Lastly, I investigate how close one can come to the first-best solution using only linear taxes. I first tax output and rebate it to workers. In markets with a large number of unproductive firms, this prevents them from entering. Large firms need to compete less for workers and post fewer vacancies. The unemployment rate goes up, but employment is now concentrated at more productive firms, increasing concentration, total income, and, to a small extent, total output. In markets that are already concentrated, it only pushes large firms to post fewer vacancies and decreases total output.

The other two policies look at the entry cost. I first tax firms' output to subsidize firms' entry. Not surprisingly, as I tax output from productive firms, and help small unproductive firms to enter, total output and income decrease sharply with the tax rate. On the other hand, allowing the planner to increase the entry cost can have a positive effect on total output when too many unproductive firms are present. The intuition is the same as with the first policy experiment. As small firms crowd the vacancy market and hire a share of employment, the optimal policy is to force them out, while keeping more productive firms in. Too much concentration on the other hand, leads to too high unemployment as total vacancy posting declines when fewer firms enter. A planner would therefore choose to increase entry cost only in markets that are not sufficiently concentrated. And, in labor markets in which entry cost is initially too low, increasing it brings the economy closer to the planner's outcome.

Policy implications. My paper highlights the links between productivity, concentration and wages. More productive firms tend to be larger and pay higher wages. This leads to an increase in concentration and wages at the same time. Although intuitive, this channel seems to have been well overlooked in the academic and public discussions so far. And even though monopolistic forces are present, they tend to be relatively small compared to simple output sharing when it comes to determining wages.

The policy experiments should help inform the debate surrounding concentration: deterring the entry of small firms, despite increasing unemployment, concentrates employment in more productive and high paying firms. My results are the mirror image of Boar and Midrigan 2019, studying the links between markups and optimal policies in the product market. Concentration in itself is not necessarily detrimental to workers as long as the bargaining process over wages is enforced. Instead of trying to forcefully reduce labor market concentration, one needs first to understand the fundamental reasons behind it.

Related literature

My paper is most closely related to Berger et al. 2023. They have access to the universe of employer-employee spells in Norway, while I use the French ones. They conduct market level regressions of mean wages at the labor market level on a concentration measure, which I replicate for the sake of comparison. Both our theoretical models feature a discrete number of firms, with workers searching on- and off-the-job and bargaining for wages - in the spirit of Burdett and Mortensen 1998 with a discrete job distribution. I borrowed the contact rate between firms and workers and the optimal vacancy posting decisions of firms from their paper.

Yet notable differences are worth discussing. On the empirical part, first, and foremost, I find the opposite result in the French data than they do in the Norwegian - wages increase with concentration in France when they decrease with concentration in Norway. This result does not seem to be due to the strictness of the labor market regulation. Looking at the OECD index of strictness of employment protection for individual dismissals, France had an index of 2.50, when Norway had one of 2.33. In comparison the UK and the US had ones of 1.35 and 0.09. I exclude civil servants in my analysis, which they do not seem to do. In France, civil servants represent one third of the workforce, have lower wages, and, not surprisingly, the state has a *de facto* monopoly on those occupations. Including them in my analysis would very likely change my results (maybe even overturn them). Wages in France also tend to be set at a national level by companies operating in several locations. This behavior is supported by my theory, where wages mostly come from the output share, provided firms are as productive in all their locations - and only the most productive firms can enter some more concentrated labor markets. If large firms operate in more markets (including more concentrated ones) and consistently pay high wages thanks to a large output available to share, one recovers the positive correlation I observe. Another difference is the use of business groups in my definition of a firm, thanks to a supplementary dataset. Concentration drops by approximately 20% in my measures if I use firms instead. Larger and more productive firms tend to be part of business groups, and more productive firms pay higher wages, which reinforces my results. Labor markets in France appear much more concentrated (the typical market in Norway was a HHI of 0.1, compared to 0.2 in France) – exacerbating further the links between high concentration and high wages. Second, while Berger et al. 2023 only run market level regressions, I study two more empirical settings: panel data regressions and the event-study with large HHI changes.

On the modeling part, I do not include the many bells and whistles their framework posses. I am interested in the channel linking productivity, concentration, and wages. To reconcile my empirical findings, I introduce an endogenous entry decision. Finally, I characterize the planner's solution, second-best implementations, and then introduce tax policies and study their effects on total outcome and other labor market outcomes. These counterfactual policies are absent from Berger et al. 2023.

More generally, on the empirical side my paper contributes to a small but growing literature on the links between labor market concentration and labor market outcomes. This has been done using partial online vacancy data from *Career Builder* (Azar, Marinescu, and Steinbaum 2022 and Azar et al. 2020) and administrative data (Rinz 2022, Yeh, Macaluso, and Hershbein 2022 and Autor, Patterson, and Van Reenen 2023) from the US, from France (Bassanini, Batut, and Caroli 2020 and Marinescu, Ouss, and Pape 2021), and from other European countries (Bassanini et al. 2023). Similar comments to the ones above apply regarding the discrepancy between most of the papers listed here, which find decreasing relationships between concentration and wages, and mine. Besides, many regression settings in these papers focus only on new hires, or use a very large number of fixed effects (occupation by commuting zones and worker and firm fixed effect), so that the variation they use to capture the link between concentration and wages is often hard to make sense of.

On the theoretical side, my paper contributes to a very broad literature looking at search-frictions and their monosponic effects. Most papers display a continuum of jobs/firms (Burdett and Mortensen 1998, Manning 2003, or Postel-Vinay and Robin 2002 among many, many others), although a few recent papers have been looking at the impact of the granularity of firms on workers (Jarosch, Nimczik, and Sorkin 2019 and Berger, Herkenhoff, and Mongey 2022). With a continuum of firms, an entry decision is relatively straightforward to define. It becomes more complex when only a discrete number of firms are involved. To my knowledge, my paper is the first to propose an endogenous distribution of vacancies and of firms entering a market in a general equilibrium of the labor market.

Finally, my paper relates to a large literature on the efficiency of frictional labor markets, starting with Hosios 1990 and Mortensen and Pissarides 1994. Compared to this literature, I investigate the planner's problem with a discrete number of firms and an endogenous entry decision of firms, second-best implementations using individual tax and subsidy rates, and study the efficiency of simple tax policies on output.

Outline

The rest of the paper is organized as follow: in section 1, I briefly discuss the datasets used, the data cleaning procedure, and the labor market and concentration definitions I use. Section 2 presents my three empirical exercises. Section 3 details my model of a labor market with a discrete number of firms and endogenous entry, and shows how it replicates the empirical patterns qualitatively. Section 4 then estimates the model, shows it quantitatively does a good job at replicating the empirical correlations, and studies the implications of concentration on wages and markdowns. Finally, section 5 compares the planner's problem with the decentralized economy, studies second-best implementations, and proposes three tax policies and investigates their effects on output and other labor market outcomes.

1 Data

I present here the 3 datasets I be use, followed by the data cleaning procedure. I then go over two crucial definitions: that of the labor market and of the concentration measure.

1.1 Data sources and datasets

The three French administrative datasets involved are: *Base Tous Salariés - fichier Postes* (BTS), *Panel Tous Salariés* (PTS), and *Contour des Entreprises Profilées* (CEP)[2]. All the datasets are collected by the French Statistical Institute (*INSEE*). They are considered of high quality and have been used by many papers throughout the years, from Abowd, Kramarz, and Margolis 1999 to Bilal 2023. The BTS and the panel are based on compulsory monthly declarations (*Déclarations Sociales Nominatives*) firms have to submit regarding all of their employees for social charges. The CEP is constructed by the INSEE every year based on financial links between firms and surveys.

The datasets differ in their time coverage - the *Base Tous Salariés* is available from 1993 to 2021 while the panel is only available between 2008 and 2019 as of August 2023. Before 2009, occupations were only systematically recorded for firms with 20 or more employees – mechanically increasing concentration –, and the occupation list was modified in 2008, making it harder to have consistent results. I therefore focus my empirical analyses between 2009 and 2019 included.

The BTS comprises the universe of French employer-employee spells, recorded at the job within an establishment level for each year and each employee. It also includes spells of unemployment during which workers claimed unemployment benefits. For each year t a worker gets assigned an identification number, and all her employment spells in years t and $t-1$, along with the establishment legal number, are reported separately for each job she held in that establishment. In

[2]Access to the data, on which is based this work, has been made possible within a secure environment offered by CASD – Centre d'accès sécurisé aux données (Ref. 10.34724/CASD). For each dataset, a comprehensive list of variables is available on the CASD's website. I also want to warmly thank again Sciences Po Paris and Alfred Galichon for offering me a working space to access the data - some of which cannot be accessed outside of the European Economic Area

addition, standard demographic (sex, age), geographic (place of work at the town level) and work-related observables (occupation, beginning and end of the contract, direct and indirect income, ...) are available. One drawback of the dataset - for privacy reasons, worker's identification numbers are reshuffled in each dataset, making it impossible to track workers over more than two years[3]. I use BTS in two different ways: first statically to construct accurate concentration measures in each labor market, using only year t for each BTS[4]; second, I use it to construct transitions rates between two years, keeping only workers I observe over the two years.

The panel, on the contrary, is a standard employer-employee matched dataset that allows me to follow workers across time. It covers all individuals born in October, hence just below 10% of the French population – there should also not be systematic selection bias into the panel for the same reason. The unit of observation is again a job within an establishment for a worker in a given year. In addition to the variables available in the BTS, I also have information on tenure and work experience. As I can track workers across the years, it is helpful for my event study in which I need labor market outcomes over the years preceding and following the shock.

Finally the CEP is an attempt by the INSEE to regroup different firms, as defined by their legal registration numbers, into what economists would consider a firm based on ownership and financial links. It is very common for large firms to split up their operations into smaller legal entities with different tax identification numbers - for instance NYU (EIN: 13-5562308) and NYU Stern (EIN: 13-4168015). It is likely those different legal units do not compete with each others for workers in the same way (see for instance Cestone et al. 2023 on how firms use their internal labor markets, defined as workers part of the same business group, to exploit new growth opportunities by relocating them to new commuting zones). When I define my concentration measures, I therefore merge the different legal units belonging to the same firm, as defined by the CEP, that operate in the same labor market[5]

[3]Babet, Godechot, and Palladino 2022 proposes probabilistic matching between the different years of the BTS to create a comprehensive panel.

[4]Except for the year 2016 – roughly 10% less variables are available that year. Asking the INSEE about it, it seems due to a change in the way the tax recording was made. To alleviate that issue, I use the information in year $t-1$ of the 2017 BTS, which should contain the same observation.

[5]This approach is far from perfect as the CEP is an ongoing project and in future iterations of the paper, I will request access to a dataset containing the financial links of the firms to avoid having to rely strictly on this dataset. It does not seem to affect my results much though.

1.2 Data selection

In this section, I discuss the data selection process. As I focus on how firms use labor market concentration to influence workers' wages and transition rates, I remove all workers who do not work for a private firm by filtering through the different variables related to the employer categories and civil servant status, and manually removing all occupations clearly related to the civil service[6]. Wages of civil servants are based on fixed pay grades, and usually below wages observed in the private sector. In addition the French government has a *de facto* monopoly on some occupations such as police officers and teachers. These labor markets would therefore be extremely concentrated and mechanically bias my results downwards despite not being related to firms competition for workers.

I then keep full-time, "regular" jobs (excluding interns, jobs subsidize by the state and unemployed workers) and remove workers below 20 and above 60 years old[7], and jobs that were paid less than a monthly minimum wage over the entire year. To have time consistent labor market definitions, I create the commuting zone using the INSEE 2020 definition based on each observation's town and *département* work place, and drop the few observations that could not be matched and workers working overseas or abroad. I then check that the occupation is consistent with the official classification (PCS-ESE, 2003 version) trimmed of civil servants. I inflate all wages to 2019 euros. Finally, as is common in the labor literature, I keep a single observation per worker per year - the employer that paid the most in that given year. I call it the main spell for each worker in each year.

To compute unemployment and transitions, I proceed slightly differently. As my datasets only record unemployment spells in which unemployment benefits were claimed, I instead counted as unemployment all days in which a worker did not have a full time job. I sum up all the days of unemployment between two main spells in years t and $t + 1$ and record a spell of unemployment if the worker spent 60 days or more unemployed in between the two main spells. If anything, this definition overestimates the transitions to and from unemployment for workers who are marginally

[6]The list of 4-digit occupations I keep is available upon request.

[7]I tried keeping workers above 25 years old, and results looked the same. According to the Economic, Social and Environmental Advisory Board, the mean age for a first stable job in France in 2019 was 27 years old - accessed on August 8$^{\text{th}}$, 2023 here - whereas the mean retirement age, according to the Health Ministry was slightly above 62 years old, and was consistently above 60 over the years in this study - accessed on August 8$^{\text{th}}$, 2023 here

attached to the labor market. Trying less conservative definitions does not impact my results. I then record as a stayer a worker who had the same main employer in consecutive years with no more than 60 days of unemployment between those two spells, a job-to-job transitions (J2J) as a worker who had a different main employer and no unemployment spell, a job loss (J2U) transition as a worker who is currently at her main employer and had at least 60 days of unemployment before her next main spell, and finally, a job finding from unemployment (U2J) as a worker who spent at least 60 days unemployed since her last main employer, and has now found a new main employer.

When applying this selection procedure to the BTS, I retain between 13.7 and 16.4 million observations per year. As a comparison, the French labor force comprises approximately 30 million workers over the time span I study[8] out of which around 19 millions are employed in the private sector. Many of the observations removed are workers only marginally attached to the labor force, and should not affect my results.

1.3 Labor market definition

Definition 1 (Labor market)**.**

$$\textit{Labor market} = \textit{Occupation (3-digit)} \times \textit{Commuting zone} \times \textit{Year}$$

My preferred labor market (LM) definition is based on 3-digit occupation by commuting zone. An example of 3-digit occupations is provided in table 1.[9]

To get a better sense of how self-contained my labor market definition is, figure 1 shows how the probability of staying in the same labor market evolves with labor market concentration – defined in the next subsection. Panel A depicts the unconditional probability of staying in a market between year t and year $t+1$ based on the concentration in year t, and panel B shows the condi-

[8] According to the World Bank, last accessed here on August 8th, 2023

[9] Defining a self-contained labor market that truthfully measure one's outside option is a challenge. Several methods have been proposed to improve those definitions (see for instance Schmutte 2014 and Nimczik 2020 for network based approaches relying on workers' transitions across firms), yet they typically rely on clustering algorithms and matrix inversion that take time to run. Berger et al. 2023 proposes an interesting approach based on clustering that does not rely on matrix inversion – they use a loss function based on self-flow rates and the Herfindahl-Hirschman Index (HHI) and cluster occupations through a K-means algorithm. As a robustness check, I performed the same regressions at the 2-digit occupation level and results remained unaffected.

1-digit	2-digits	3-digits	4-digits
6 - Blue collar workers	64 - Drivers	641	641a - truck drivers
			641b - bus drivers
		642	642a - taxi drivers
			642b - other car drivers
		643	643a - delivery workers
		644	644a - garbage truck drivers

Table 1: 1- to 4-digit occupations for drivers - occupation 64

tional probability given a worker went through a job-to-job transition. The median unconditional self-flow rates and conditional on a job-to-job transitions across the markets are 76% and 33% - in the ballpark of what Berger et al. 2023 finds in the raw data with no clustering. We see the conditional probability falling dramatically with concentration. In the lower centiles, the unconditional probability lays between 30 to 45%. As most of my workers are in those lower centiles, as is discussed in 2.1, low self-flow rates in concentrated markets should not impact my results much in panel data regressions. And, as results are consistent between the panel data and the market level regressions, the low self-flow rate given a job-to-job-transition should not bias my results much.

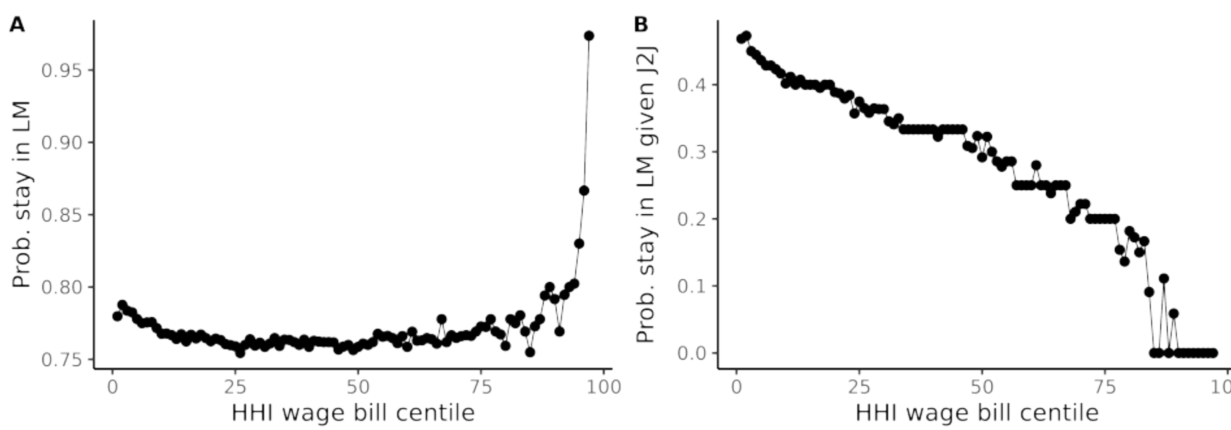

Figure 1: Probability of staying in the same LM

1.4 Concentration measures

Next, I define the concentration measures used in the rest of the paper. My preferred measure is the Herfindahl-Hirschman Index (HHI) based on the wage bill an employer pays in a given labor market, defined by:

Definition 2 (HHI wage bill)**.**

$$HHI^{wb}_{oct} = \sum_{i=1}^{N^{firms}_{oct}} \left(s^{wb}_i\right)^2 \quad with \quad s^{wb}_i = \frac{wage\ bill_i}{\sum_k wage\ bill_k}$$

For each occupation by commuting zone by year, I compute how many different firms are a worker's main employer - that gives me N^{firms}_{oct}. For each firm in that labor market, I compute the share of the wage bill (defined as the sum of all gross wages, deflated) that firm has been paying in that year - I obtain s^{wb}_i. I sum the square of those shares to obtain the HHI. As a useful benchmark, notice that if all firms pay the same wage, the HHI equals $1/N$, the inverse number of firms operating in the labor market.

The HHI is a standard concentration measure in the product market literature (see for instance Edmond, Midrigan, and Xu 2015, or more recently Burstein, Carvalho, and Grassi 2020) despite it encompasses different, and potentially opposite forces. It has also been used to study labor market concentration. Berger, Herkenhoff, and Mongey 2022 derives it from a Atkeson-Burstein-type model of the labor market. The HHI being derived from wages, one might argue that I am regressing wages on an object created through wages. Most markets contain enough workers so that a jackknife approach would not change much the results, but complicate a lot the construction of the measure for all workers in all markets when dealing with more than 10 million observations each year. I also ran most of the regressions using an HHI based on the employment share as in Berger et al. 2023, and on higher order measures of the wage bill and employment shares. Results are mostly consistent, and can be found in the appendix B.

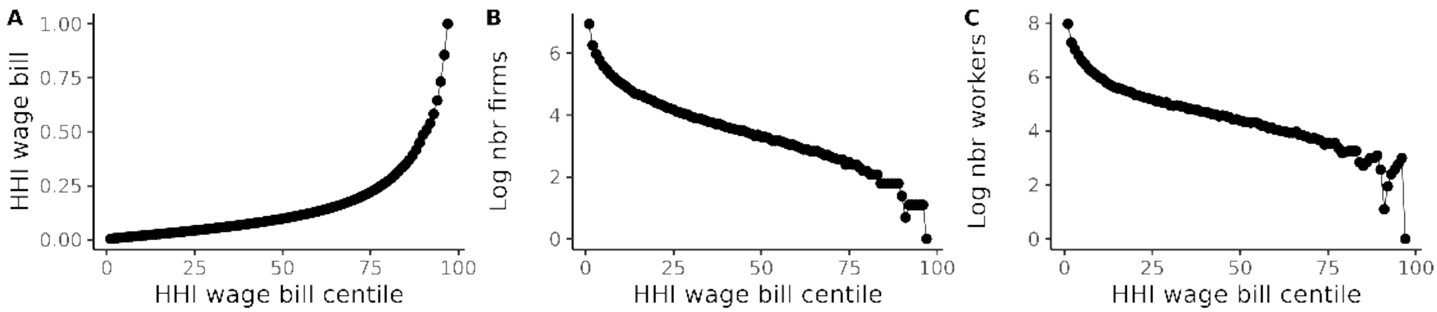

Figure 2: Cumulative distributions by HHI wage bill

2 Concentration, wages and mobility in France

I now turn to the empirical analyses of the paper. I first look at how concentration covaries with several variables in the raw data – as hinted at previously, wages and concentration are positively correlated, yet several compositional effects can bias the results. I remove them by running regressions at the market level (as in Berger et al. 2023) and at the individual level using the panel data – results remain consistent. The last empirical exercise focuses on large increases in the HHI, and, again, wages go up following the increase. Three data appendices explore how concentration varies across commuting zones and occupations (appendix A), contain additional robustness using different specifications (appendix B), and look at large HHI decreases (appendix C).

2.1 Labor market concentration

I describe first the extent of labor market concentration in France. Figure 2 plots the median level of the HHI (panel A), the median log number of firms (panel B) and of workers (panel C) by HHI centile [10]

An HHI of 0.15 is used by the American Department of Justice as a threshold for a market to be moderately concentrated. Almost two thirds of the labor markets fell under the threshold. These markets contain both much more firms and workers – a market in the 10% centile contains on average close to 150 firms and 400 workers, whereas one at the HHI = 0.15 threshold contains

[10] I have around 400k markets - 120 3-digit occupations by 300 commuting zones by 12 years. A centile encompasses around 4k markets.

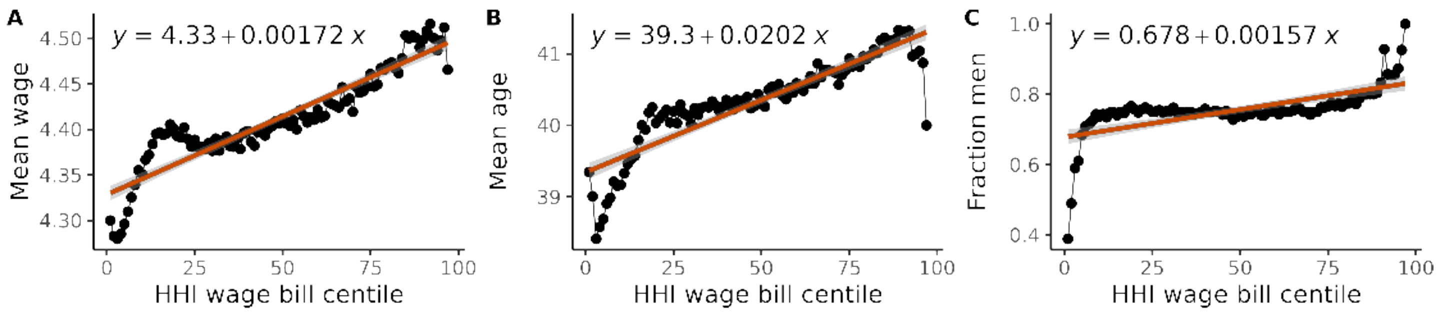

Figure 3: Median of labor market averages by HHI centile

only 20 firms and 50 workers, and one at the 90% centile fells to 4 and 13. Surprisingly, the median ratio of the number of workers per firms remain stable around 2.8 for most of the distribution. Thus most workers and firms operate in non-concentrated market - almost 91% of workers and 94% of firms fall under the 0.15 threshold when one looks at cumulative distributions.

As detailed in appendix A, most workers are living in densely populated commuting zones. Most firms tend to locate in the same commuting zones. Mechanically, these commuting zones have a lower concentration measure. It is useful to keep in mind that the distribution of workers across HHI is extremely skewed towards low concentration. Running regressions at the labor market level without reweighting (as in Berger et al. 2023) fails to recognize that the interesting welfare effects are not driven by the extremely concentrated markets. I present the raw data and the regressions at the market level first, yet I favor the panel regressions and the event study when it comes to the estimation, as I consider them more relevant for policy implications. Results are consistent across the different exercises.

2.2 Labor market outcomes and concentration in the raw data

Using the raw BTS data, I compute the average wage, the average age, the fraction of men, and the transition probabilities for each labor market. I then compute the median values of each average within a HHI centile. Results are displayed in the scatter plots in figures 3 and 4.

Panel A of figure 3 shows that, in the raw data, there is a clear upward slope between concentration and mean log wage paid in a market. This relationship is both significant and strong –

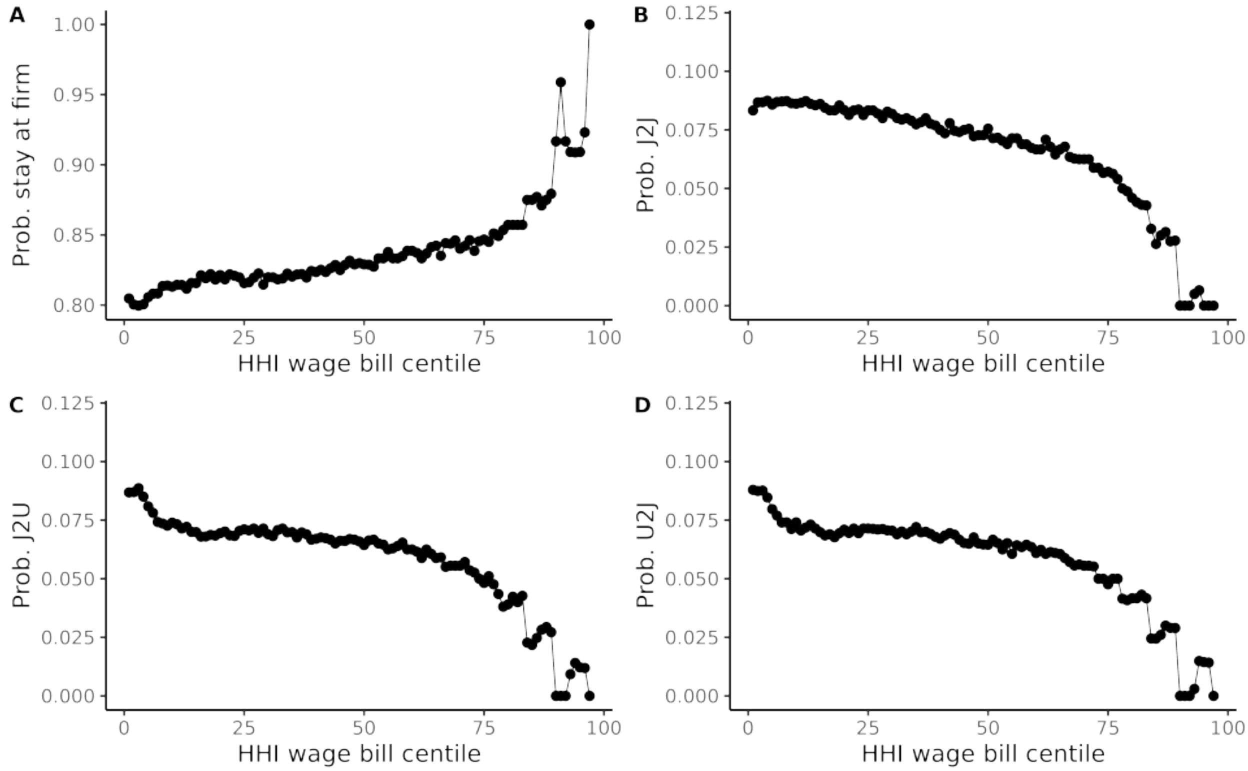

Figure 4: Median transition probabilities by HHI centile

going from the first to the last centile, real wages increase by a staggering 17%. Yet, as is evident from the other scatter plots, concentrated markets tend to differ significantly from other markets. Workers in those markets tend to be slightly older (Panel B) and the fraction of men is much higher (Panel C)[11]. With the panel data, one can also show workers in more concentrated markets have longer tenure and work experience. The different sorting patterns observed across labor market concentration could potentially explain why wages increase with concentration.

Figure 4 plots the labor market flows: the flow of workers staying at the same firm, doing a job-to-job (J2J) transition or losing a job (J2U) between t and $t+1$ based on the HHI in year t, and the flow of workers coming from unemployment between t and $t+1$ based on the HHI in

[11]The fraction of men might seem extremely high in the last panel. I excluded civil servants, that disproportionally tend to employ women; and non-concentrated markets tend to be much larger, as seen before, and to employ more women, as seen here. Combining these two effects explain the high fraction of men displayed in the scatter plot. According to the INSEE, the share of women in the whole economy was 48.4% in 2020.

year $t+1$[12]. As one could expect, a worker is less likely to undergo a J2J transition in a more concentrated market (Panel B), given that there are less firms around. Similarly, a worker is less likely to find a job from unemployment (Panel D). Yet, and maybe more surprising, a worker is also less likely to lose her job (Panel C). In a nutshell, transition rates are lower with concentration.

2.3 Removing compositional effects

I now want to control for compositional effects using standard OLS regressions at the market level and at the individual level. The first set of regressions uses the BTS and looks at how the mean wage paid in a given market varies with concentration once controlled for different sets of fixed effects. The second set is based on the panel data and allows me use additional controls at the individual level.

In both regressions, my preferred specification features an occupation by commuting zone fixed effect. I exploit the variation in concentration within a labor market across years and look at how wages vary in response. My baseline regression at the market level is:

$$\text{mean log wage}_{oct} = \nu_{oc} + \beta \text{HHI}_{oct} + \gamma X_{oct} + \epsilon_{oct}$$

where ν is a labor market fixed effect and X is an extra vector of controls containing the fraction of men, the quartiles of age composition and the ratio of the number of workers over the number of firm, to mirror the analysis in Berger et al. 2023. Results of the regressions are displayed in table 2. Standard-errors are clustered at the labor market level.

To interpret the previous results, we can see from figure 2 that a typical market in the 10% and 90% HHI centiles have HHIs close to 0 and 0.5. Thus for all the results in this section, taking half of the coefficient gives approximately the difference in wages between a market in the 10% and the 90% centiles: here, it would mean a 4.1% or 2.5% increase in the mean wage – much smaller

[12]Definitions of transitions are pretty standard: staying at the same firm means having the same main employer in years t and $t+1$ with no more than 2 months gap between the spells in year t and $t+1$; job-to-job transitions mean changing main employer with no more than 2 months gap between the spells (if the worker changes establishment or firms but stays in the same group, I do not record this as a J2J transition, although this barely affects the results); losing job or finding job means there was at least a 2 month gap period between the spell that ended in year t or started in year $t+1$ - recalls are included in those transitions.

	Mean wage	
	(i)	(ii)
HHI	0.0820***	0.0500***
	(0.0058)	(0.0060)
LM FEs	✓	✓
Add. controls		✓
Observations	407,310	407,310
R^2	0.905	0.909
Within R^2	0.006	0.045

Clustered (LM) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 2: Regression at the market level

than in the raw data, but still significant and economically large. Results using higher moments of the wage bill share, or using the employment share are available in the appendix B.1, along with results using the variation in space by controlling for an occupation by year fixed effect (but no control for the commuting zone)[13].

The previous regressions attribute the same weight to all markets. Some markets, in which only one firm employs one worker, are given as much explanatory power as the market for secretaries in Paris which is much larger. To depart from this, I could re-weight the regressions by the number of workers in each labor market. I decided instead to use the panel data. It also allows me to perform supplementary checks as more variables are available. The empirical specification becomes:

$$y_{it} = \nu_{o(i)c(i)} + \beta \text{HHI}_{o(i)c(i)t} + \gamma X_{it} + \epsilon_{it}$$

where y is the log daily wage, a dummy variable for staying at the same firm, doing a job-to-job transition (J2J) or losing one's job (J2U) next period, or a dummy variable for coming back from unemployment (U2J). I always control for a 3rd degree age polynomial, and add controls for tenure

[13] Regressions based on the employment share and using the occupation by year fixed effects are the only ones giving opposite results. Yet, as discussed in A, variation in concentration across space is hard to make sense of. Persistent differences of concentration across commuting zones are likely not the only drivers of wages.

	Daily wage (i)	Stay at firm (ii)	J2J (iii)	J2U (iv)	U2J (v)
HHI	0.1380***	0.0237***	-0.0314***	-0.0220***	-0.0223***
	(0.0120)	(0.0059)	(0.0082)	(0.0045)	(0.0045)
sex and LM FEs	✓	✓	✓	✓	✓
Add. controls					
Observations	8,749,532	7,215,124	7,215,124	7,215,124	7,215,124
R^2	0.560	0.108	0.025	0.094	0.068
Within R^2	0.127	0.054	0.011	0.042	0.029

	Daily wage (vi)	Stay at firm (vii)	J2J (viii)	J2U (ix)	U2J (x)
HHI	0.1312***	0.0194***	-0.0286***	-0.0184***	-0.0058***
	(0.0120)	(0.0060)	(0.0086)	(0.0047)	(0.0049)
sex and LM FEs	✓	✓	✓	✓	✓
Add. controls	✓	✓	✓	✓	✓
Observations	8,747,995	7,213,775	7,213,775	7,213,775	7,213,804
R^2	0.568	0.121	0.028	0.105	0.085
Within R^2	0.144	0.067	0.014	0.054	0.047

Clustered (firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 3: Panel data regressions - wage and transitions

and work experience (denoted as additional controls). In my favorite specification, I include sex and labor market fixed effects. Results can be seen in table 3, and additional specifications can be found in the B.2[14]. Standard errors are now clustered at the firm level.

Wages increase with concentration even more than at the market level – using the same computation as before, this means a 6.5% wage increase between a market in the 10% and the 90%

[14] All panel data regressions are performed using the R package fixest developed by Bergé 2018. The algorithm uses alternate projection (as in Correia 2016) to remove fixed effects – variables are demeaned group by group until the means converge. These means are the approximate fixed effects. As I deal with several million observations and a large number of fixed effects, computing and inverting the exact fixed effect matrix is impossible.

HHI centiles. This result is robust to other specifications. Transitions follow what we observed in the raw data: workers are more 1% more likely to stay at their current firm, 1.5% less likely to move to another firm, and 1% less likely to go to lose their job or find one from unemployment. The intuition here is straightforward – fewer firms operate in a concentrated market, and workers are less likely to move to another firm.

2.4 Focusing on large changes in concentration

Finally, I want to conduct focuses on large changes in concentration within a market. This is a worthwhile setting for two reasons: in terms of government interventions, large closures or, on the contrary, large openings by a firm (think of Amazon opening a warehouse for instance) tend to get a lot of attention. Understanding the potential impact on wages it may have is a relevant policy question. Second, the previous variations I was using - variation in concentration within the same market across the years - tend to be small, especially in markets with a large number of workers and firms[15]. Focusing on large variations might give us different results.

I select markets with at least 300 workers across all years, in which the HHI changed by more than 0.1 in two consecutive years. The 300 worker threshold is there to avoid small markets in which a new opening or closure mechanically affects substantially the HHI. I drop markets in which the HHI varied by 0.1 more than once. As a control market, I select markets in the same occupation, in commuting zones not surrounding the shocked markets, and for which the HHI never varied by more than 0.05. Out of my 34,000 occupation by commuting zone, I am left with 6,000 control markets spanning all occupations and commuting zones. There are 159 markets in which the HHI significantly increased once and 108 in which it decreased. Finally, to look out for potential spillover effects, I include markets geographically adjacent to shocked markets in the same occupation. More details on the composition of shocked labor market is available in appendix C.1. I discuss here the HHI increase, and leave the decrease for the appendix C.2.

Large increases in the HHI could come from mostly two sources: because of large firms grow-

[15]If one tries to estimate an AR(1) with no intercept on the HHI level in a market over the years, the autoregressive coefficient is very high. Looking at markets that always employ more than 10 workers, the median coefficient across the different markets is 0.975. Most of the variation in the HHI within a market is therefore pretty small.

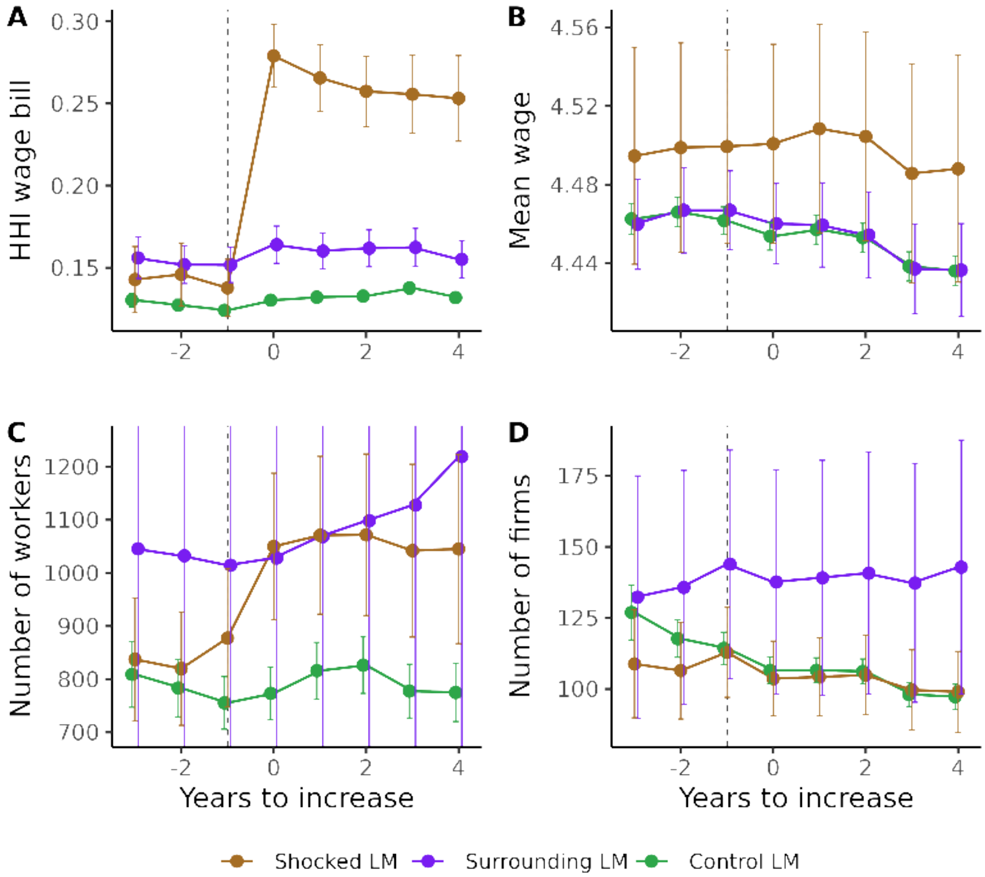

Figure 5: Large HHI increase on market level outcomes

ing (by hiring or by merging with other firms), or because of firms exiting. I argue you that the former is happening here. Figure 5 plots 4 averages: the HHI level (panel A), the mean wage (B), the number of workers (C), and the number of firms (D). The averages are taken across the markets undergoing the large HHI increase (shocked LM), the adjacent labor markets (surrounding LM) and the control labor markets (control LM). On the x-axes are the distance to the shock - with year 0 being the year at which the HHI increased, and year -1 my reference point. One can clearly see the increase in the HHI happening in the shocked markets in panel A, when the HHI in both the adjacent and the control markets remain flat. The HHI in the shocked markets, despite a small decrease in the years following the shock, remains much higher than before the shock. Although the number of firms (panel D) decreases slightly, much of the action comes from the large increase

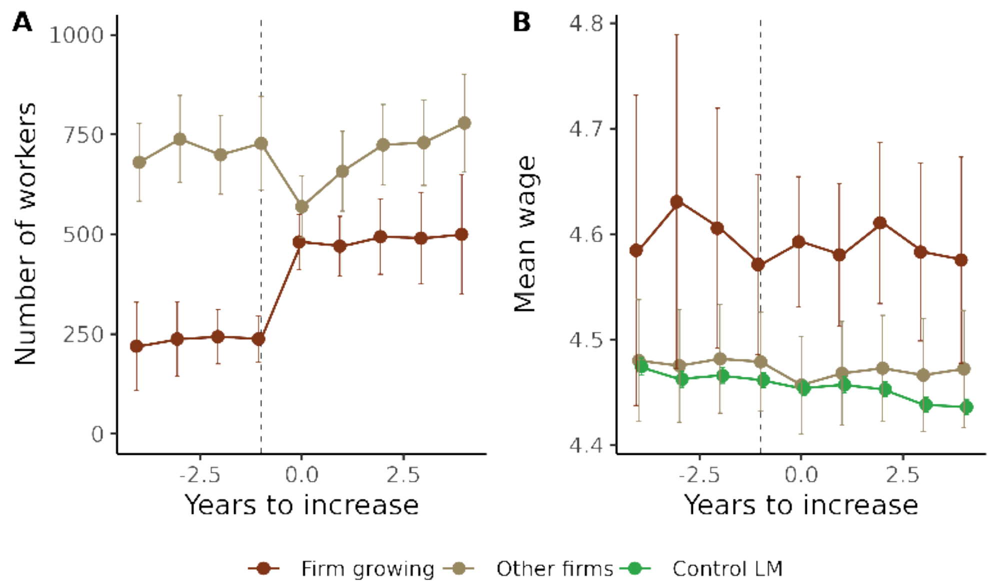

Figure 6: Growing firm versus the rest of the labor market following the HHI increase

in the number of workers - in one year, the labor market adds around 200 new workers in net. Despite the large increase in concentration, it seems like wages, if anything, went up in the shocked market compared to the control market.

The 200 new workers tend to all go to one single firm leading to the HHI increase. Indeed, I now split the shocked labor market into two: on one side, the firm that is the largest after the shock, and all the other firms. Figure 6 depicts the number of workers (panel A) in the two groups. As one can see, the firm that became the largest after the shock grew by almost 250 workers compared to the year before. Panel B plots the average wage at the dominant firm, at all the other firms in the market, and in the control markets for reference. Wages were already higher at the dominant firm before, and, if anything, increased further compared to the control markets after the shock. At the other firms in the market, wages seem to also increase. Hence, despite a very large increase in the HHI, wages increased everywhere in the years following the shock. I interpret this as evidence of an already productive firm getting an extra productivity shock, and responding to it by hiring and increasing wages. Wages of workers at other firms need to increase too to remain competitive. To test this hypothesis, I now turn to the effects at the worker level.

I select 3 different types of workers based on their firm and location in year -1: first, workers at the firm that became dominant ; second, workers in the same labor market but not at the firm that grew (nor any firms in the same business group) ; and third, workers in the adjacent labor markets but not at the firm that grew (nor any firms in the same business group again). It allows me to look at how the labor market outcomes of those different workers evolved following the increase in concentration. Compared to the above analysis, the first two types of workers are part of my shocked labor market (at the dominant firm or at all other firms respectively), whereas the third type comprises workers in the adjacent labor markets. I match them to workers in control groups based on their sex, and quintiles of the tenure at their current firm, age, work experience and firm size distributions. As I want to study how a change in workers' outside option within their labor market affected their wage and their transition probabilities, I only keep observations on workers for as long as they stayed in the labor market they were in at year -1. I am left with 574 distinct workers in firms that grew, around 6,000 at other firms in the same labor market, 47,000 in adjacent markets and 350,000 control workers that I can match.

I run event-study-type regressions on the sub-sample. I focus on the effect on the log daily wage and the probability of a worker to make a job-to-job transition next period. Accordingly, I normalize my event-study at year -1 when looking at wages, the last year before the shock, and at year -2 for the probability of doing a job-to-job transition next period. Controlling for a labor market fixed effect does not make sense anymore as I am looking at a large change within a market. Instead, following the other specification in Berger et al. 2023, I control for an occupation-by-year fixed effect. It allows me to use the variation in space of the same occupation across different commuting zones depending on if they were shocked or not. As discussed in appendix A, concentration is especially acute in some less densely populated area where wages tend to be lower. To remove that effect, I also add a commuting zone fixed effect to remove mean wages in each commuting zone. As additional controls, I add an age polynomial and a sex fixed effect. The regressions are:

$$\text{daily wage}_{i,t} = \sum_{k \neq -1} \beta_k^{\text{wage}} \cdot \mathbb{1}\{t - \tau_i = k\} + \mu_{o(i)t} + \gamma_{c(i)} + controls + \epsilon_{it}$$

$$\text{J2J trans}_{i,t} = \sum_{k \neq -2} \beta_k^{\text{J2J}} \cdot \mathbb{1}\{t - \tau_i = k\} + \mu_{o(i)t} + \gamma_{c(i)} + controls + \epsilon_{it}$$

Regressions are performed using the Sun and Abraham 2021 correction for staggered treatment, to limit contamination between treated and not-yet treated commuting zones. Even though I removed workers appearing in several of my groups, workers moving to different commuting zones or occupations could create spillover effects that contaminate my treatment groups. Sun & Abraham correction should take care of it. I ran the same regressions with standard fixed effects and results remain consistent. Standard-errors are clustered at the firm level.

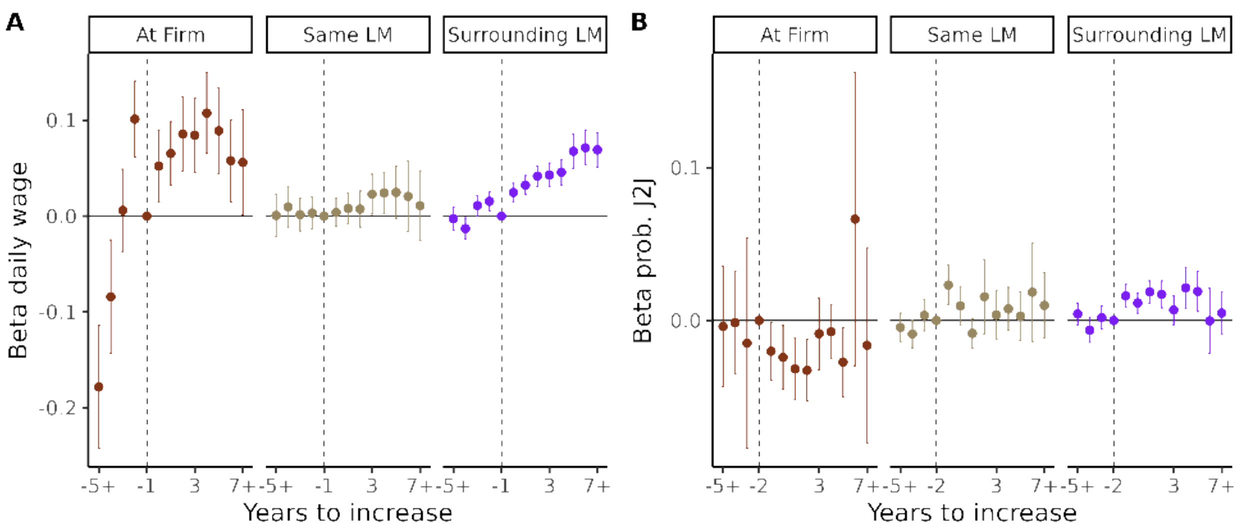

Figure 7: Large increases in concentration over workers' wages and J2J probability

Figure 7 displays an event-study plot of the coefficients both for the daily wage (panel A) and the probability of making a job-to-job transition (panel B), for the three different types of workers. Workers at dominant firms display a large pre-trend when it comes to wages. It could have been expected: it might be caused by dominant firms improving over the years before the shock and paying their workers more until they reach their optimal sizes after the large hire. Nevertheless, if anything, workers at dominant firms display a 5% to 10% wage increase in the years following the shock compared to year -1. They are also 3% less likely to do a job-to-job transition in the 4 years following the shock. Workers at firms in the same market have similar effects: their wage increases by around 2% after a few years and are 2% more likely on impact to undergo a job-to-job transition. Wages of workers at surrounding markets also display an increasing trend - their wages increasing by as much as 7% after 5 years. They are 1 to 2% more likely to perform a job-to-job transition.

This is consistent with dominant firms poaching workers within the same market as the dip in the number of workers at other firms in the same market suggested in figure 6. Wage increases at other firms are not driven either by workers joining dominant firms – results remain unchanged if I only keep workers for as long as they stay both at the same firm and in the same labor market their were in at year -1, isolating a pure outside option effect.

Results in this last section are all consistent with large firms - already more productive and therefore paying higher wages beforehand - getting positive productivity shocks. Following the shocks, wages at dominant firms increase as output to share is now larger. Wages at other firms increase too, although less, through the increase in workers' outside option. Dominant firms also post more vacancies, crowding the vacancy market and leading to more transitions towards them and less towards other firms. If anything, this is another example of a mechanism through which high concentration does not decrease wages. I now turn to a model of the labor market that can reconcile the empirical correlations presented here and quantity the effects of labor market concentration on workers.

3 Model

I now use a structural approach to move past empirical correlations and quantify the effects of firm's market power on workers. A search-and-matching framework with bargaining is a natural starting point to study how wages, labor market transitions and unemployment are affected by labor market concentration. The main departure from standard models comes from the granularity of firms as in Jarosch, Nimczik, and Sorkin 2019 or Bilal et al. 2022, and is closest to Berger et al. 2023 in spirit.

I consider a single, closed labor market with a discrete number of firms and a mass 1 of workers. Firms draw productivities and decide to enter the market. I first abstract from entry, to understand the mechanisms with a given number of firms, and come back to it at the end of this section. If firms enter, they post vacancies optimally, understanding that they can attract more workers by crowding the vacancy market - although they do not internalize they can affect the distribution of workers nor their surplus. The equilibrium can be considered as quasi-rational for this reason.

On the other side of the labor market, workers are *ex-ante* identical, are all equally productive, and search for jobs both on- and off-the-job. Search is random and wages are bargained through a simple Nash-bargaining. To make the model tractable both firms and workers are infinitely lived and risk-neutral. Time is continuous, and I consider a full information and stationary economy. Finally, firms produce using a constant return to scale with labor as the sole input.

The last set of assumptions allow me to solve the model at the match level and aggregate it only when firms consider how much vacancies to post. Without them, one needs to carry over the distribution of workers across firms in the state-space, rendering the problem untractable very quickly. Combined with optimal vacancy posting, one gets an endogenous distribution of workers across a discrete number of firms, with a consistent entry decision by firms - something very few papers can generate.

My model features three sources of frictions, that make wages depart from a competitive labor market. These forces can be mapped directly into a markdown on wages - they create firm's market power. The first friction stands from bargaining: as firms and workers bargain over wages, workers only extracts a share of the surplus that is lower than their marginal product. The second comes from standard search frictions: matching between workers and firms takes time. This is reflected in the surplus and therefore in the wage. Finally, the last friction comes from the granularity of firms. Although firms do not internalize they can affect the distribution of workers across firms nor the surpluses, the number of firms and their vacancy posting decisions affect meeting rates and hence wages. Thanks to bargaining, workers need to be compensated for the outside option they are giving up when they accept an offer. The more firms and the better those firms, the larger is the outside option of workers, and hence the larger the compensation. This last term directly captures the ”competition for workers” firms face when hiring.

3.1 Contact rates between firms and workers

The granularity of firms forces me to carefully model the contact rates between workers and firms. I draw on Berger et al. 2023 here. I denote by λ^j (resp. λ_0^j) the probability that a worker employed at firm i (resp. unemployed) is offered a job by firm j (before the bargaining starts), v_j the mass of vacancies posted by firm j and a^j the mass of workers applying at firm j (irrespective of them receiving back an offer from firm j). As is evident below, the origin of a worker (besides being employed or unemployed) does not affect the meeting probability. λ^j is be as follow:

$$\lambda^j = \Phi \cdot \xi \cdot \frac{v_j}{v} \cdot m(v_j, a^j) \cdot \frac{1}{a^j}$$

The probability of receiving an offer can be decomposed into four terms: the probability of searching which, for an employed worker, is the product of the probability of searching for a job for any worker, Φ, times the search efficiency for an employed worker, ξ. As search is random, conditional on searching, a worker meets a vacancy from firm j depending on the ratio of vacancies posted by firm j, v_j, over the sum of all vacancies in the economy, $v = \sum_j v_j$. Given the mass of vacancies and the mass of applicants at j, the number of contacts between firm j and workers a^j is determined by the matching function $m(v_j, a^j)$. Among all the contacts between firm j and the applicants a^j, a worker applying to j is selected randomly among all the applicants, and thus has a probability $1/a^j$ of receiving an offer from j. Putting all the terms together gives us the probability for a worker at any firm to receive an offer from firm j. Similarly, the probability for an unemployed worker to receive an offer is given by:

$$\lambda_0^j = \Phi \cdot \frac{v_j}{v} \cdot m(v_j, a^j) \cdot \frac{1}{a^j}$$

The only difference comes from the search efficiency of unemployed workers normalized to 1.

I now compute the mass of applicants at each firm. It is the sum of the applicants from all firms and the applicants from unemployment, $a^j = \sum_k a_k^j + a_0^j$. The mass of applicants from a firm i is given by:

$$a_k^j = n_k \cdot \Phi \cdot \xi \cdot \frac{v_j}{v}$$

It follows the same steps as above: each worker at k meets a vacancy with probability $\Phi \cdot \xi$, and conditional on meeting a vacancy, meets a vacancy from j with probability v_j/v. Denote by n_k the mass of workers are firm k, we get the previous equation. Similarly, denote by u the mass of unemployed workers, we get: $a_0^j = u \cdot \Phi \cdot \frac{v_j}{v}$. Finally, given that there is a mass 1 of workers, $\sum_k n_k = 1 - u$, we can write a^j as:

$$a^j = \Phi \cdot (u + (1-u)\xi) \cdot \frac{v_j}{v} \tag{1}$$

and λs:

$$\lambda^j = \frac{\xi}{u + (1-u)\xi} \cdot m(v_j, a^j) \tag{2}$$

$$\lambda_0^j = \frac{1}{u + (1-u)\xi} \cdot m(v_j, a^j) \tag{3}$$

Contact rates for firm j between a vacancy at j and a worker at firm i are defined similarly. Denote them by μ_i^j. We can write μ_i^j as:

$$\mu_i^j = \frac{m(v_j, a^j)}{v_j} \cdot \frac{a_i^j}{a^j}$$

As described above, for a mass of vacancies v_j and applicants a^j, there is $m(v_j, a^j)$ contacts. The contact rate per vacancy hence is $m(v_j, a^j)/v_j$. As search is random, given that a vacancy meets an applicant, there is a probability a_i^j/a^j that the worker comes from firm i. By replacing a^j in the previous equation, we can rewrite μ as:

$$\mu_i^j = \frac{m(v_j, a^j)}{v_j} \cdot \frac{n_i \xi}{u + (1-u)\xi} \tag{4}$$

$$\mu_0^j = \frac{m(v_j, a^j)}{v_j} \cdot \frac{u}{u + (1-u)\xi} \tag{5}$$

Is is then straightforward to check that the flow balance between the number of workers from i meeting firm j is equal to the mass of vacancies from j meeting a worker from i: $n_i \lambda^j = v_j \mu_i^j$.

3.2 Bargaining, surplus and wages

Now that I defined the contact rates, I can move on to the value functions. I denote by U, V_i and J_i the value functions of an unemployed worker, of a worker at firm i, and of a match with a worker for firm i. The surplus of a match is defined as $S_i = J_i + V_i - U$.

Workers and firms bargain over wages using a simple Nash-bargaining, where the outside option of the worker is taken to be unemployment. Workers move (or stay) to the firm offering them the largest value function, and firms are not allowed to make a counter-offer. More realistic bargaining schemes, such as Cahuc, Postel-Vinay, and Robin 2006, would carry similar insights at the expense of a larger state space as discussed in appendix D.2. A similar remark applies to match-specific shocks - they would allow me to better target some data moments, but would not change the mechanisms I am after, while increasing significantly the size of the state space. I therefore chose not to include them.

When meeting firm i, the outcome of the bargaining process solves:

$$w_i = \text{argmax } J_i^{\alpha} \left(V_i - U\right)^{1-\alpha}$$

where α is the bargaining power of the firm. Taking first order conditions, we recover the usual surplus split between workers and firms depending on the bargaining power:

$$J_i = \alpha S_i \tag{6}$$

$$V_i - U = (1-\alpha) S_i \tag{7}$$

Workers manage to extract a share $1-\alpha$ of the surplus. This is key to the wage determination later, and to wage markdowns firms can exert.

We can now write down the value functions as:

$$\begin{aligned}
\rho U &= b + \sum_{j=1}^{N} \lambda_0^j \left(V_j - U\right) \mathbb{1}_{\{V_j > U\}} \\
\rho V_i &= w_i + \sum_{j=1}^{N} \lambda^j \left(V_j - V_i\right) \mathbb{1}_{\{V_j > V_i\}} + \delta \left(U - V_i\right) \\
\rho J_i &= z_i - w_i + \sum_{j=1}^{N} \lambda^j \left(0 - J_i\right) \mathbb{1}_{\{V_j > V_i\}} + \delta \left(0 - J_i\right)
\end{aligned}$$

where ρ is the discount rate, b the unemployment benefits, w_i the wage at firm i (identical for all workers, as workers are identical and the bargaining is made with respect to unemployment), z_i the productivity of firm i, N the number of firms operating and δ the exogenous job destruction. Upon meeting a firm, a worker moves to that firm if the value function it would get there is higher than the current value function. If so, the flow value increase is simply the difference between the previous and the new value function. If the match is destroyed, or the worker is poached, the firm gets nothing back.

From the value functions, I can derive the value of the surplus by summing all three value functions, using the definition of the surplus and the result of the bargaining process. I get that the surplus follows:

$$\rho S_i = z_i - b - \delta S_i + \sum_{j=1}^{N} \lambda^j \left((1-\alpha) S_j - S_i\right) \mathbb{1}_{\{S_j > S_i\}} - (1-\alpha) \sum_{j=1}^{N} \lambda_0^j S_j \mathbb{1}_{\{S_j > 0\}} \tag{8}$$

Finally, I can derive the only equilibrium wage at firm i that is consistent with the value functions and the bargaining process. Both derivations are provided in appendix D.1. w_i solves:

$$w_i = (1-\alpha) \cdot z_i + \alpha b - \alpha(1-\alpha) \sum_{j=1}^{N} \lambda^j S_j \mathbb{1}_{\{S_j > S_i\}} + \alpha(1-\alpha) \sum_{j=1}^{N} \lambda_0^j S_j \mathbb{1}_{\{S_j > 0\}} \tag{9}$$

The wage at firm i is made of three terms: the share of the output a worker extracts, $(1-\alpha) \cdot z_i$, a penalty stemming from the risk a worker gets poached, $-\alpha(1-\alpha) \sum_{j=1}^{N} \lambda^j S_j \mathbb{1}_{\{S_j > S_i\}}$, and the compensation a worker gets from giving up on unemployment, both through unemployment benefits and through the offers an unemployed worker can get. The second term might be the least intuitive one. As workers search on-the-job and have a chance of getting poached, the surplus increases by a fraction of the surpluses at other firms (provided these surplus are higher than at the current firm). Firms understands workers might obtain a share of future surpluses thanks to their on-the-job search. It translates to a wage penalty in the bargaining process.

3.3 Optimal vacancy posting

To close this part of the model, I finally need to specify how firms post vacancies. Firms maximize expected profits from new matches minus vacancy costs, $c(v)$. Each vacancy has a probability μ_k^i to meet a worker at firm k (μ_0^i to meet an unemployed worker). The worker is hired if the surplus at firm i is higher than their current surplus. Firms then extract a share αS_i of the surplus of each new match. Hence, the optimal vacancy posting of firm i solves equation 10:

$$\text{argmax}_{v_i \geq 0} - c(v_i) + v_i \left(\mu_0^i(v_i) \mathbb{1}_{\{S_i > 0\}} + \sum_k \mu_k^i(v_i) \mathbb{1}_{\{S_i > S_k\}} \right) \alpha S_i \tag{10}$$

Replacing the μs and a^i, we get:

$$\text{argmax}_{v_i \geq 0} - c(v_i) + \frac{u \mathbb{1}_{\{S_i > 0\}} + \xi \sum_k n_k \mathbb{1}_{\{S_i > S_k\}}}{u + (1-u)\xi} m \left(v_i, \Phi(u + (1-u)\xi) \frac{v_i}{v_i + v_{-i}} \right) \alpha S_i$$

with v_{-i} the vacancies at all firms but firm i - taken as given. Firm i does not internalize that by posting vacancies, it can affect the distribution of workers in the economy (u and n_k), nor the surplus S_i. The equilibrium is therefore quasi-rational from the firm's perspective.

Assume the following functional forms for c and m: $c(v) = \frac{1}{1+\gamma}v^{1+\gamma}$, $m(v,a) = v^{1-\theta}a^{\theta}$. They allow me to make some progress towards determining the optimal vacancy posting. Taking the first order condition and rearranging, I can show v_i solves:

$$v_i^{\gamma}(v_i + v_{-i})^{\theta} = \kappa_i \left(1 - \theta \frac{v_i}{v_i + v_{-i}}\right) \tag{11}$$

where $\kappa_i = \alpha S_i \Phi^{\theta} \frac{u\mathbb{1}_{\{S_i>0\}} + \xi \sum_k n_k \mathbb{1}_{\{S_i>S_k\}}}{(u+(1-u)\xi)^{1-\theta}}$. It is straightforward to show that given κ_i and v_{-i}, there is a unique solution to the optimal vacancy posting for firm i. Hence, finding the equilibrium vector of vacancies amounts to a fixed point iteration. It amounts to solving a Nash equilibrium for each firm given the best responses of all other firms. Besides, if $S_i > 0$, $v_i > 0$, and all firms with a positive surplus, no matter how small, operate in this labor market - as long as there are no entry cost.

3.4 Markdowns

The model has direct links to the monopolistic competition in product market literature. Instead of markups on prices, one can look at markdowns on wages. Markdowns are defined as the difference between the wage a worker receives and the marginal product of labor, which is simply z_i here. Call η_i the markdown at firm i, η_i is such that:

$$w_i = (1 - \eta_i) \cdot z_i$$

As $\lambda^j = \xi \cdot \lambda_0^j$ and using the definition of λ_0^j, one can show the markdown is equal to:

$$\eta_i = \alpha \left(1 - \frac{b + (1-\alpha) \cdot \frac{1}{u+(1-u)\xi} \sum_j m(v_j, a^j) S_j \left(\mathbb{1}_{\{S_j>0\}} - \xi \mathbb{1}_{\{S_j>S_i\}}\right)}{z_i}\right) \tag{12}$$

Notice first that, when workers have all the bargaining power (ie $\alpha = 0$), the firm cannot impose any markdowns on workers. Hence bargaining power is a necessary (and sufficient) condition for a firm to exert a markdown on wages. Further more, the larger the bargaining power, the larger the markdown.

I now want to look at the impact of search frictions and labor market concentration. To gain some intuition of the mechanisms, assume here that all firms are equally productive - there is therefore no poaching. The surplus becomes $S_i = \frac{z-b}{\rho+\delta+(1-\alpha)N\lambda_0}$. The probability of meeting a firm from unemployment is $\lambda_0 = \frac{m(v_i,a^i)}{u+(1-u)\xi}$ and the applicants to any firm $a^i = \Phi(u+(1-u)\xi)\frac{1}{N}$. The markdown now is:

$$\eta = \alpha\left(1-\frac{b}{z}\right)\left(1-\frac{(1-\alpha)N\lambda_0}{\rho+\delta+(1-\alpha)N\lambda_0}\right) \tag{13}$$

Going back to the vacancy problem, I can now go a step further into computing v^i:

$$v_i = \left(\frac{\alpha\Phi^\theta u}{(u+(1-u)\xi)^{1-\theta}}\frac{z-b}{\rho+\delta+(1-\alpha)N\lambda_0}\frac{1}{N^\theta}\left(1-\frac{\theta}{N}\right)\right)^{\frac{1}{\gamma+\theta}} \tag{14}$$

Finally the unemployment rate solves:

$$\frac{u}{1-u} = \frac{\delta}{N\lambda_0} \tag{15}$$

I fix the parameters to the ones estimated in section 4 to look at the impact of the number of firms on the markdown, wages, the number of vacancies and the unemployment rate and the markdown. I solve the system of equations above and display the results in figure 8. As one could expect, the larger the number of firms, the lower the markdown (panel F) and the higher wages (panel B) as having more firms in the labor market increases worker's outside option. With equally productive firms, markdown falls by 66% when the number of firms increases from 1 to 250. Firms find it less profitable to post vacancies and the mass of vacancies per firm declines significantly. Indeed, with more firms operating, firms are less likely to meet a worker they could hire. This is reinforced here as firms all have the same productivity and poaching is not possible - leading to a 0 probability of undergoing a job-to-job transition (panel C). Nevertheless, the total number of vacancies across all firms increase, and therefore the unemployment rate decreases (panel D).

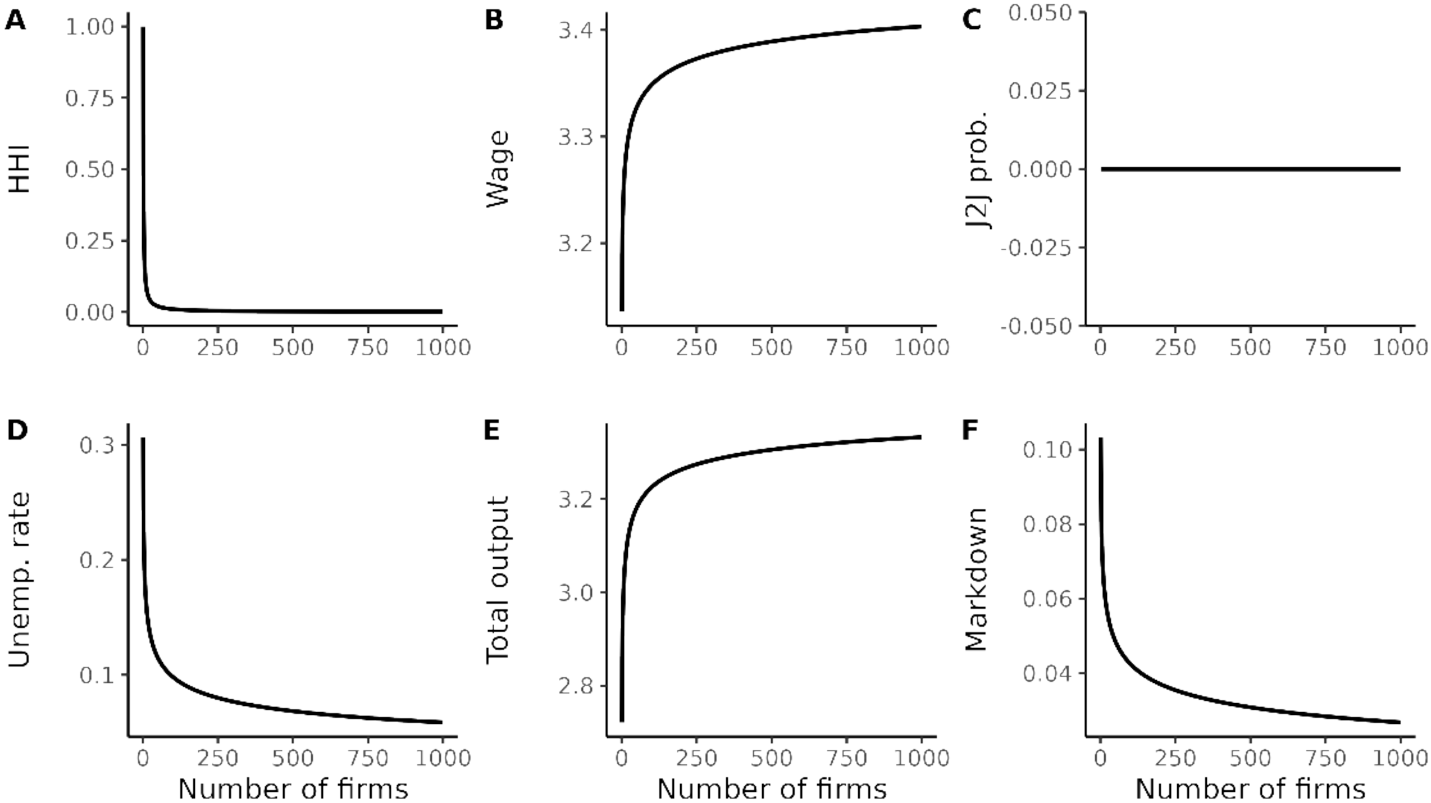

Figure 8: Mechanism of the model

Finally, total output in the labor market, net of hiring costs, increases substantially (panel E) as more workers are now employed. In this specific situation, if a planner is interested in maximizing output it should increase the number of firms as much as possible. We will see later that this result only partially holds once we allow for productivity to vary.

Concentration being equal here to $1/N$, it is clear it decreases with the number of firms (panel A). Thus, this part of the model generates a negative relationship between concentration and wages: keeping everything else equal, varying the number of equally productive firms decreases concentration and increase wages. This mechanism is at the heart of Berger et al. 2023's analysis.[16] In the next subsection I introduce an endogenous firm's entry decision. By selecting which firms enter a labor market, I recover the empirical correlations between concentration and wages.

[16]Job-to-job probability is also null - although by introducing productivity dispersion, and increasing the number of firms, the model generates an increasing job-to-job probability. This is consistent with the negative correlation between HHI and J2J probability observed in the data.

3.5 Firm's entry decision

To endogeneize firms' entry in a labor market, I introduce an entry cost. This entry cost is crucial in replicating the positive correlation between concentration and mean wages. Indeed, increasing the entry allows only the most productive firms to enter the market and increases concentration. The effect on the mean wage is less clear-cut: mean productivity in a market goes up, but the outside option of the worker might go down[17]. When estimating the model, it turns out most of a worker's wage comes from the share of output she receives. Increasing the concentration of more productive firms also increases mean wages.

When deciding whether to enter or not, firms compare life-time profits with the entry cost. As the economy is stationary, the flow of workers leaving firm i equals the flow of workers coming to firm i. A firm's per period profits is then: $\pi_i = (z_i - w_i) \cdot n_i - c(v_i)$ – it is simply the difference between output and wage bill minus hiring costs. The Bellman equation for profits reads:

$$\Pi_i = \frac{\pi_i}{\rho} = \frac{(z_i - w_i) \cdot n_i - c(v_i)}{\rho} \tag{16}$$

And a firm enters if $\Pi_i > c_f$, where c_f is the entry cost. The equilibrium with entry cost is defined as follow:

Definition 3 (Equilibrium)**.** *An equilibrium with N firms is a collection of vectors: productivity draws $\{z_i\}$, surpluses $\{S_i\}$, vacancy posting $\{v_i\}$, contact rates $\{\lambda^i\}$ and $\{\lambda_0^i\}$, distribution of workers across firms $\{n_i\}$, and wages $\{w_i\}$ such that:*

1. *Surplus for a match at firm i solves equation 8, given the transition rates and the productivity draws;*
2. *Vacancy posting is the unique solution to the Nash equilibrium defined by 11, given the surplus and the distribution of workers across firms;*
3. *Transition rates for workers satisfy 2 and 3, given the vacancy posting;*

[17] Because transition rates are also affected, it is not clear in which direction the outside option goes *ex-ante* - a worker might be more likely to meet a better firm as fewer firms crowd in the vacancy market. At the same time, fewer vacancies are likely to be posted, and overall transitions rate might decrease, decreasing the outside option too.

4. *The distribution of workers is the unique stationary distribution of the transition matrix given the transition rates and the poaching rules;*

5. *Wages satisfy equation 9 given the productivity draws, the transition rates and the surpluses.;*

6. *All firms that enter the market have a Bellman equation for profits, solving equation 16, such that* $\Pi_i > c_f$.

The equilibrium is not unique. As firms' equilibrium profits depend on the composition of firms entering, the selection process plays a role. When simulating the model, the order of selection only matters for firms at the fringe, and does not change the results much.[18]

How does the entry cost affect on labor market outcomes? I fix the parameters to their estimated value (described in the next section), and simulate labor markets with different entry costs. More details on the algorithm is provided in appendix D.3. Figure 9 shows the averages of some labor market outcomes across the different simulations.

As one can see, the entry cost is enough to replicate the main correlations observed in the raw data: increasing entry costs increases both concentration (panel A) and mean wage in the labor market (panel B); it also decreases job-to-job flows (panel C). Mean markdowns increase, as fewer firms compete for workers, yet always remain relatively small (panel F). When fewer firms enter the market, each tend to post more vacancies, but the total mass of vacancies still decreases, and unemployment rate increases (panel D). As only the most productive firms enter the market, average productivity of operating firms increase along with the share of employed workers at those firms. As a result, total output increases with the entry cost at first (panel E). Yet, when entry cost increases further, the share of output spent on the entry cost, combined with a higher unemployment rate, lead to a decline in output. As we will see later, a social planner willing to maximize can leverage this tension between removing unproductive firms while keeping many productive ones to increase average productivity, yet maintaining unemployment relatively low.

[18]If, instead of having to pay an entry costs, firms had to pay a per-period production costs, and had the capacity to borrow up to some limit - more productive firms should be able to enter, make negative profits for some period of time, borrow and wait for less productive firms to exit the market as they would reach their borrowing limit faster.

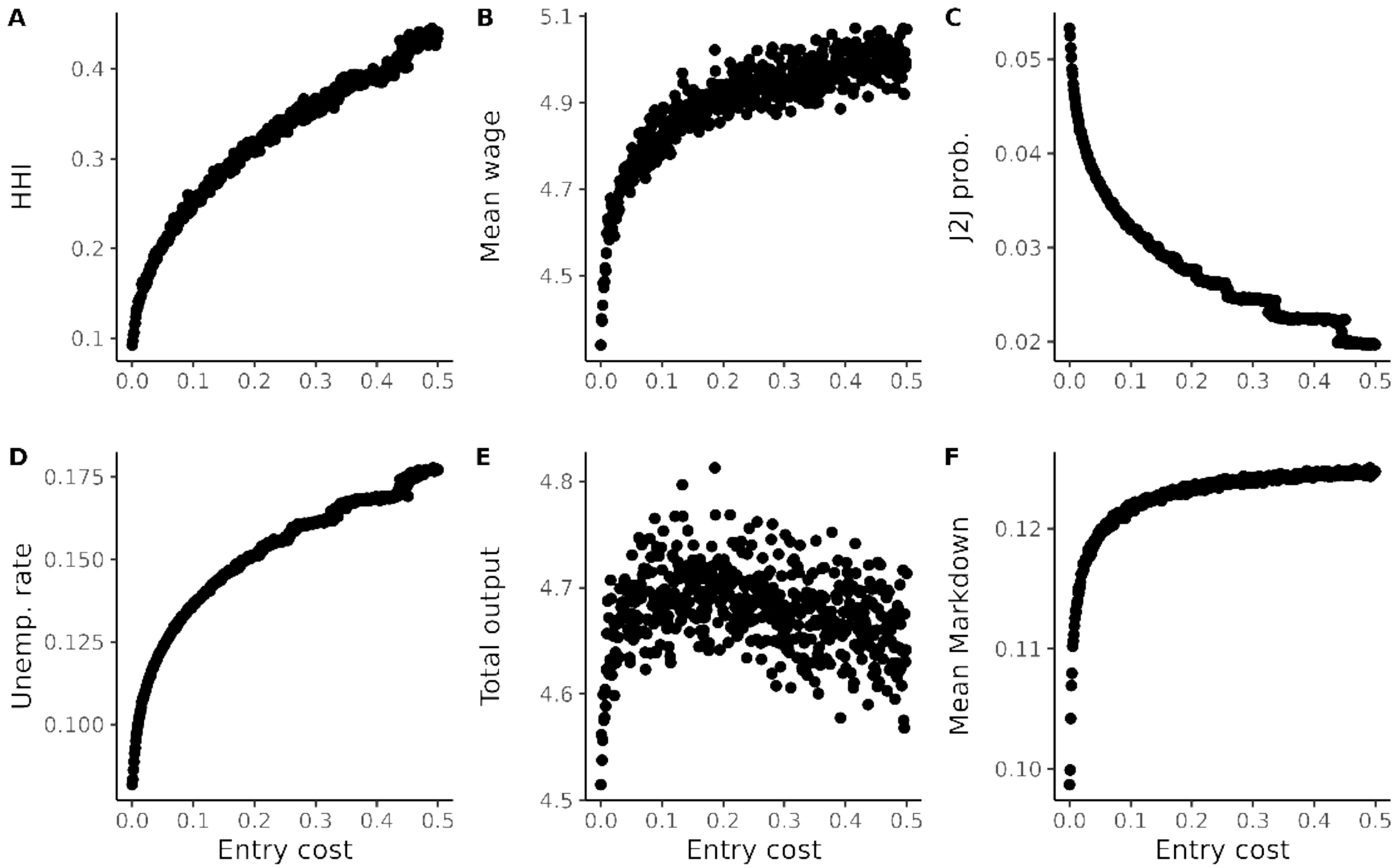

Figure 9: Entry cost on labor market outcomes

3.6 Changes in the market structure and wages

In this last theoretical section, I want to explore the effects of a change in the market structure on wages and transitions. I look at two changes: an increase in productivity at an incumbent firm, to replicate the event-study setting in my empirical part, and the entry of a new firm. For simplicity, I abstract from the entry cost - assuming all firms currently in the market were productive enough to pay the entry cost. I also assume that all firms remain in the market following the changes[19]

[19] In the event-study setting, we actually observe a small decrease in the number of firms a year after the shock. Given the model at hand, it is not hard to see how a productivity increase at one firm or the entrance of a new, productive enough firm, can drive other firms out of business. The surplus of the match at those small firms decrease because worker's outside option is larger and the firm that marginally entered might not not be able to do so anymore. My current model is static, but changing the *ex-ante* entry cost to a continuous operating cost would be isomorphic and would be enough to explain the decrease in the number of firms.

and that the relative ranking between firm's productivity is not changed to keep poaching decisions identical[20].

A change in productivity by a large firm is able to replicate the patterns I observe in the event-study. For simplicity again, let me look at an increase at the most productive firm to avoid any change in the ranking. I sort firms by productivity, and focus on a small increase from z_N to $z_N + \mathrm{d}z_N$. Taking first order perturbations, and assuming $\forall i \ \frac{v_i}{\sum v_i} << 1$[21], transition rates, worker's distribution, unemployment rate, vacancies, surpluses and wages deviations are:

$$\begin{cases} \frac{\mathrm{d}\lambda_0^i}{\lambda_0^i} = -\frac{(1-\xi)(1-\theta)}{u+(1-u)\xi}\mathrm{d}u + \frac{\mathrm{d}v_i}{v_i} - \theta\frac{\mathrm{d}v}{v} \\ \frac{\mathrm{d}n_i}{n_i} = \frac{\lambda_0^i \mathrm{d}u + (u+\xi\sum_j n_j \mathbb{1}_{\{S_i>S_j\}})\mathrm{d}\lambda_0^i + \xi\lambda_0^i \sum_j \mathbb{1}_{\{S_i>S_j\}}\mathrm{d}n_j}{\lambda_0^i(u+\xi\sum_j n_j \mathbb{1}_{\{S_i>S_j\}})} - \frac{\xi\sum_j \mathbb{1}_{\{S_j>S_i\}}\mathrm{d}\lambda_0^j}{\delta+\xi\sum_j \lambda_0^j \mathbb{1}_{\{S_j>S_i\}}} \\ \frac{\mathrm{d}u}{u} = -\frac{\sum_j \mathrm{d}\lambda_0^j}{\delta+\sum_j \lambda_0^j} \\ \gamma\frac{\mathrm{d}v_i}{v_i} = -\theta\frac{\mathrm{d}v}{v} - \frac{(1-\xi)(1-\theta)}{u+(1-u)\xi}\mathrm{d}u + \frac{\mathrm{d}S_i}{S_i} + \frac{\mathrm{d}u + \xi\sum_j \mathrm{d}n_j \mathbb{1}_{\{S_i>S_j\}}}{u+\xi\sum_j n_j \mathbb{1}_{\{S_i>S_j\}}} \end{cases}$$

The surplus and the wage would be:

$$\begin{cases} (\rho+\delta)\mathrm{d}S_i = \mathrm{d}z_i - (1-\alpha)\sum_j \left(\lambda_0^j \mathrm{d}S_j + S_j \mathrm{d}\lambda_0^j\right)\left(1-\xi\mathbb{1}_{\{S_j>S_i\}}\right) - \sum_j \left(\lambda_0^j \mathrm{d}S_i + S_i \mathrm{d}\lambda_0^j\right)\mathbb{1}_{\{S_j>S_i\}} \\ \mathrm{d}w_i = (1-\alpha)\mathrm{d}z_i + \alpha(1-\alpha)\sum_j \left(\lambda_0^j \mathrm{d}S_j + S_j \mathrm{d}\lambda_0^j\right)\left(1-\xi 1_{\{S_j>S_i\}}\right) \end{cases}$$

We now need to take a stand on what is small relative to what. Let's assume $\forall i \neq N, \mathrm{d}z_i = 0$. The change in S_N is mostly due to the change in its productivity, while the change at other firm works through the change in the outside option induced by $\mathrm{d}S_N$. Assuming changes in probabilities are small compared to the change in surplus we have:

$$\begin{cases} \mathrm{d}S_N = \frac{1}{\rho+\delta+(1-\alpha)(1-\xi)\lambda_0^N}\mathrm{d}z_N \\ \mathrm{d}S_i = -\frac{(1-\alpha)(1-\xi)\lambda_0^N}{\rho+\delta+\lambda_0^N}\frac{1}{\rho+\delta+(1-\alpha)(1-\xi)\lambda_0^N}\mathrm{d}z_N \end{cases}$$

[20]As long as other firm's productivity does not change, it is straightforward to show that the relative ranking also does not change between them.

[21]The assumption is only required for the vacancy posting and simplifies slightly the expression. One could easily relax it

The surplus at firm N increases while the surplus at all other firms decreases (potentially driving firms out of business). Wages are such that:

$$\begin{cases} \mathrm{d}w_N = \left((1-\alpha) + \frac{\alpha(1-\alpha)(1-\xi)\lambda_0^N}{\rho+\delta+(1-\alpha)(1-\xi)\lambda_0^N}\right)\mathrm{d}z_N \\ \mathrm{d}w_i = \frac{\alpha(1-\alpha)(1-\xi)\lambda_0^N}{\rho+\delta+(1-\alpha)(1-\xi)\lambda_0^N}\mathrm{d}z_N \end{cases}$$

Wages increase at firm N, and, to some extend, at other firms too as workers need to be compensated more. Finally, assuming the distribution of workers does not vary much, vacancies posted by firm N increase because of the increase in productivity. If one further assumes the change in total vacancies is mostly driven by firm N, ie $\mathrm{d}v_N = \mathrm{d}v$, then vacancies at all other firms decrease slightly:

$$\begin{cases} \left(\frac{\gamma}{v_N} + \frac{\theta}{v}\right)\mathrm{d}v_N = \frac{\mathrm{d}S_N}{S_N} \\ \gamma\frac{\mathrm{d}v_i}{v_i} = -\theta\frac{\mathrm{d}v_N}{v} + \frac{\mathrm{d}S_i}{S_i} \end{cases}$$

As vacancies decrease everywhere but at N, transition rates also follow: firm N now attracts more workers both from unemployment and from other firms, consistent with the event-study results we saw earlier. Although I take another approach to estimation, the event-study could also be a good experiment to measure some parameters – for instance the difference in wage increases between firm N and the other firms would give us α.

I now briefly turn to the entry of a new firm. Previous conclusions are going to be unchanged as most of the action comes from an increase in the outside option thanks to the new entrant. Assuming the other's firm productivity remains unchanged, and that the change in contact rates are small, we get that surpluses and wages at all other firms are:

$$\begin{cases} \mathrm{d}S_i = -\frac{(1-\alpha)\left(1-\xi\mathbb{1}_{\{S_{N+1}>S_i\}}\right)\lambda_0^{N+1}}{\rho+\delta+\lambda_0^{N+1}\mathbb{1}_{\{S_{N+1}>S_i\}}}S_{N+1} \\ \mathrm{d}w_i = \alpha(1-\alpha)\lambda_0^{N+1}S_{N+1}\left(1-\xi 1_{\{S_{N+1}>S_i\}}\right) \end{cases}$$

Workers need to be compensated for an increase in their outside option, and surplus at all firms decrease. Because of the surplus decreases, firms post less vacancies, and flows toward all firms decrease. The intuition we built when we study markdowns with equal productivities caries through with different productivities. This mechanism is again the one in Berger et al. 2023 - more firms decrease concentration and increase wages. The better the new entrant, the larger the effect is on the labor market equilibrium.

4 Estimation

I now solve and estimate the model through a standard method of simulated moments. As I have a discrete number of firms with random productivity draws, I need to simulate many different labor markets. Solving each labor market does not require more than a couple of minutes, hence estimation remains somehow possible if one parallelizes the different markets.

I speed up computation of each market by relying on matrix inversion to find the equilibrium surplus and distribution of workers (as in Achdou et al. 2022), and on fixed point iterations for the vacancy posting decisions. Each labor market typically takes a couple of seconds to solve given a distribution of productivities. I then need to iterate over the entry decisions, and solve again the labor market, until all firms remaining enter the market. A sketch of the algorithm is included in appendix D.3. Moments for the estimation are readily available through the equilibrium objects or closed form equations derived above – I avoid having to simulate workers to compute wages, as one typically needs to do when implementing more complex bargaining processes, saving me precious time.

As all labor markets are independent, I draw on NYU's computing capabilities to estimate the model. Using batch commands, I spread the different labor markets for a given set of parameters across nodes of the HPC, dividing by a large factor the time required. I start with an initial set of parameters, simulate 120 different labor markets, solve them independently on different nodes, compute the average moments across the simulations and update the parameters until I minimize my distance function.

Name	Parameter	Value	Target/Source
Bargaining power of firms	α	0.28	Shimer 2005
Discount rate	ρ	0.05	5% annual interest year
Matching function	θ	0.5	Bilal et al. 2022

Table 4: Fixed parameters

4.1 Estimation results

I fix three parameters: the discount rate at a 5% annual interest rate and the matching function efficiency to 0.5 as can be found in Bilal et al. 2022, as summarized in table 4. I also fix the bargaining power of firms from the literature following Shimer 2005.

I estimate the other parameters using the French administrative data. I take my event study set up as a reference point – I see it as an interesting middle ground between non-concentrated markets in which all firms are relatively small, and very concentrated markets. I collect the data moments by averaging across the 159 labor markets undergoing a large increase in the HHI, the year prior to the shock. The list of parameters, estimated values, targets (with their sources), and the moments are displayed in 5.

Name	Parameter	Value	Target	Data	Model	Source
Unemployment benefits	b	1.07	Ratio minimum income to mean wage	0.238	0.209	French government and BTS
Prob. receiving job offer	Φ	0.033	Unemployment rate	9.2%	9.46%	INSEE
Search intensity for emp. workers	ξ	0.342	J2J prob.	7.12%	4.76%	PTS
Prob. losing job	δ	0.059	J2U prob.	5.07%	4.39%	
Prod. dist. of firms (generalized beta dist.)	Location	2.93	25% firm size dist.	0.0017	0.0016	BTS
	Scale	16.48	Mean wage	4.50	4.50	
	Alpha	1.20	50% firm size dist.	0.0035	0.0029	
	Beta	33.46	99% firm size dist.	0.2048	0.2135	
Cost of vacancies	γ	1.17	75% firm size dist.	0.0103	0.0075	BTS
Entry cost	c_f	0.0057	Avg. nbr. firms before shock	113	82	BTS

Table 5: Estimated parameters

Most of the parameters are coming from the BTS. In addition, I have to rely on two external sources – as discussed before, my data do not allow me to characterize properly unemployment nor unemployment benefits. As a proxy for unemployment benefits, I use the minimum guaranteed revenue in France in 2019 and compare it to the mean wage I observe. Although probably an underestimation of the actual unemployment benefits workers collect, my model has nothing to say about replacement rates nor unemployment duration. As such, the minimum guaranteed revenue represents a lower bound to what workers would actually receive. If anything, it worsens worker's bargaining power in my model and tend to overestimate the importance of competition between firms[22] I cannot either measure unemployment rate in the data at a level granular enough in comparison to my labor market definition[23]. I take the mean national unemployment rate across the years of my panel data.

I can recover the other moments from the universe of data and the panel data, in addition to their empirical variance that I use as (a diagonal) weighting matrix in my SMM (for the two moments coming from external sources, I simply use the square of the data moment). As my model relies on a productivity distribution, which in turn shapes the distribution of workers and the size of the outside option, I have to pin it down carefully. Productivity translates into firm's size, therefore using different percentiles of the distribution of workers' share seems a natural choice. After trying several distributions, the one producing the best results was a generalized beta distribution. Because production is linear, profits are (almost) linear too. The only two frictions or convexities are coming from labor market frictions and the convex cost of vacancies. When using a distribution with tails, and unless introducing implausibly high vacancy costs, one firm always ended up much larger than what I observe in the data. The location and the scale of the distribution help me pin down the range of productivities firms draw from, and the α and β parameters shape the mass. I normalized the distribution so that the simulated mean wage corresponds to the mean log wage in

[22] In appendix D.2, I discuss how increasing the outside option reduces the further the competition between firms. The opposite would be true if one decreases a worker's bargaining position.

[23] I could use the absence of spells and the transitions to and from unemployment in my data. This procedure would underestimate the true unemployment rate, as it would only capture unemployment from workers eventually finding a job. As a refinement, one could use an additional dataset - *Enquête Emploi* - to get a measure of unemployment at the 2-digit occupation by year level, or, from the INSEE's website, at the commuting zone by year level. The mechanisms in my model would remain unchanged.

Moment	Data	Model
HHI_{wb}	0.138	0.125
HHI_{emp}	0.128	0.100
Mean firm size	0.0155	0.0123
Variance firm size	0.0015	0.0011
Skewness firm size	5.79	5.51
Kurtosis firm size	50.43	37.03

Table 6: Non targeted moments

the data - although this has no incidence, and normalizing it to 1 would have produced consistent results.

Following the algorithm explained above, it is straightforward to see why the entry cost would give me the number of firms operating in the market. Yet, the number of firms is not well estimated. As discussed further in the next section, allowing for more small firms to enter crowds the vacancy market, and prevents large firms from being as large as they should be according to the data.

The labor market flows have direct counterparts in the data. The unemployment rate and the flow to unemployment are estimated pretty well, yet the job-to-job flows are around half of what they should be. When measuring them in the data, I include all job-to-job transitions, whereas my model can only account for transitions up the wage ladder (as one can only be poached by a firm having a higher surplus - which happens only with more productive firms paying a higher wage). If I were to only look at transitions associated with a wage increase in the data, I would get a value closer to that of my model. [24]

Table 6 displays the non-targeted moments. My model is able to reproduce decently well the level of concentration using the two HHI indexes (based on the share of employment, HHI_{emp}, or on the share of the wage bill, HHI_{wb}), and the moments of the distribution of the share of workers. This is not surprising as I targeted the centiles of the worker's distribution and the mean wage. Lastly, my model does a decent job at replicating the empirical correlation between mean real

[24] Alternatively, I could introduce match-specific productivity shocks in my model. This would allow to create transitions back and forth between two firms, instead of up the firm's productivity ladder only. It would increase the size of my matrices though, and, with it, the computation time required for the estimation and the simulation. As it is not a crucial part of the mechanism I want to study, I decided to abstract from it at the cost of a worse estimation.

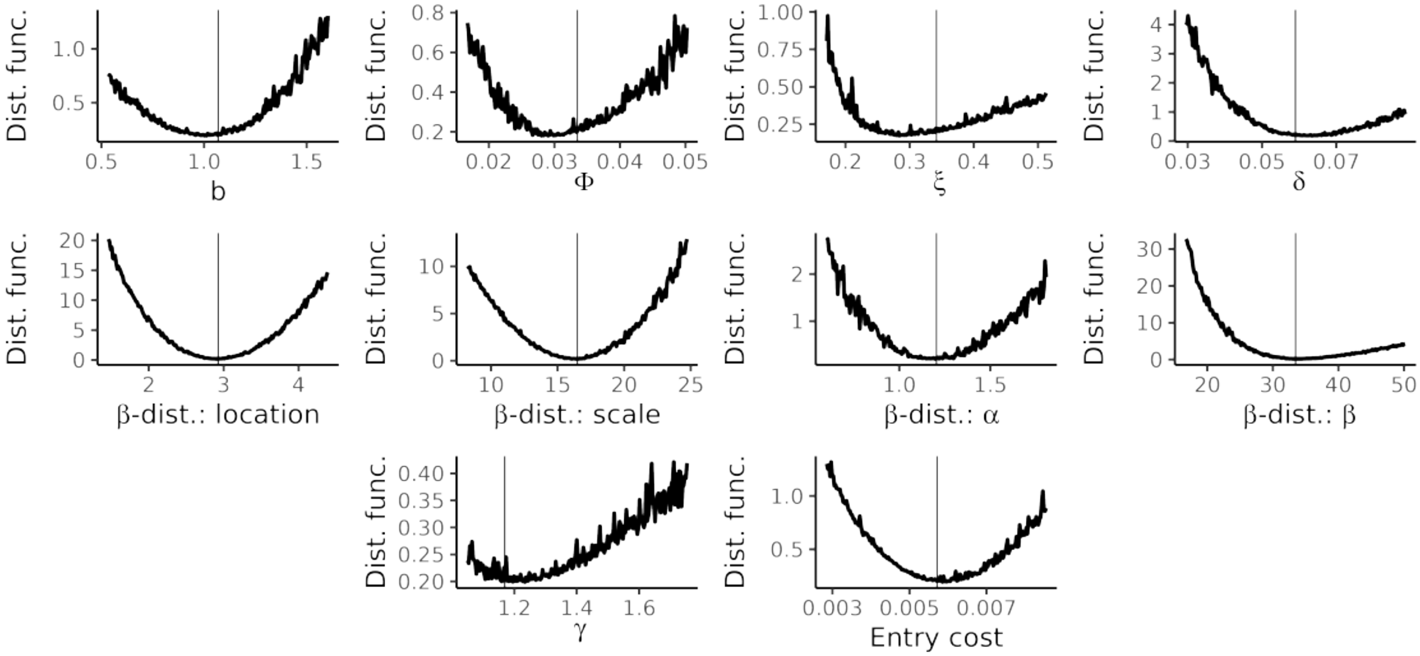

Figure 10: Sensitivity of the estimation

wage and HHI, as discussed in the next section[25], suggesting the choice of the firm's bargaining power α, although from the literature, might be close to the value I would have estimated.

Before turning to simulations from the model, I want to test how sensitive my estimation is to changes in the estimated parameters. I vary the value of each parameter around its optimal point, keeping all other parameters fixed. For each of them, I plot the distance function from my SMM procedure. The vertical bar stands at the estimated value. As one can see in 10, parameters seem to be well estimated for most of them. As soon as one departs from the estimated value, the distance function starts to increase, sometimes quite significantly.

I also tested how each parameter influences its targeted moment to check how sound the intuition underlying the estimation is. I plot the contribution to the SMM distance function of each targeted moment, when varying the parameter around its estimated value. The vertical black bar stands again at the estimated parameter. As displayed in 11 one can see that most parameters seem

[25]Results are presented separately as the estimation was done on a particular cross-section of the markets, whereas the regression is done while varying the entry cost to replicate the empirical cross-sectional results between mean wage and concentration.

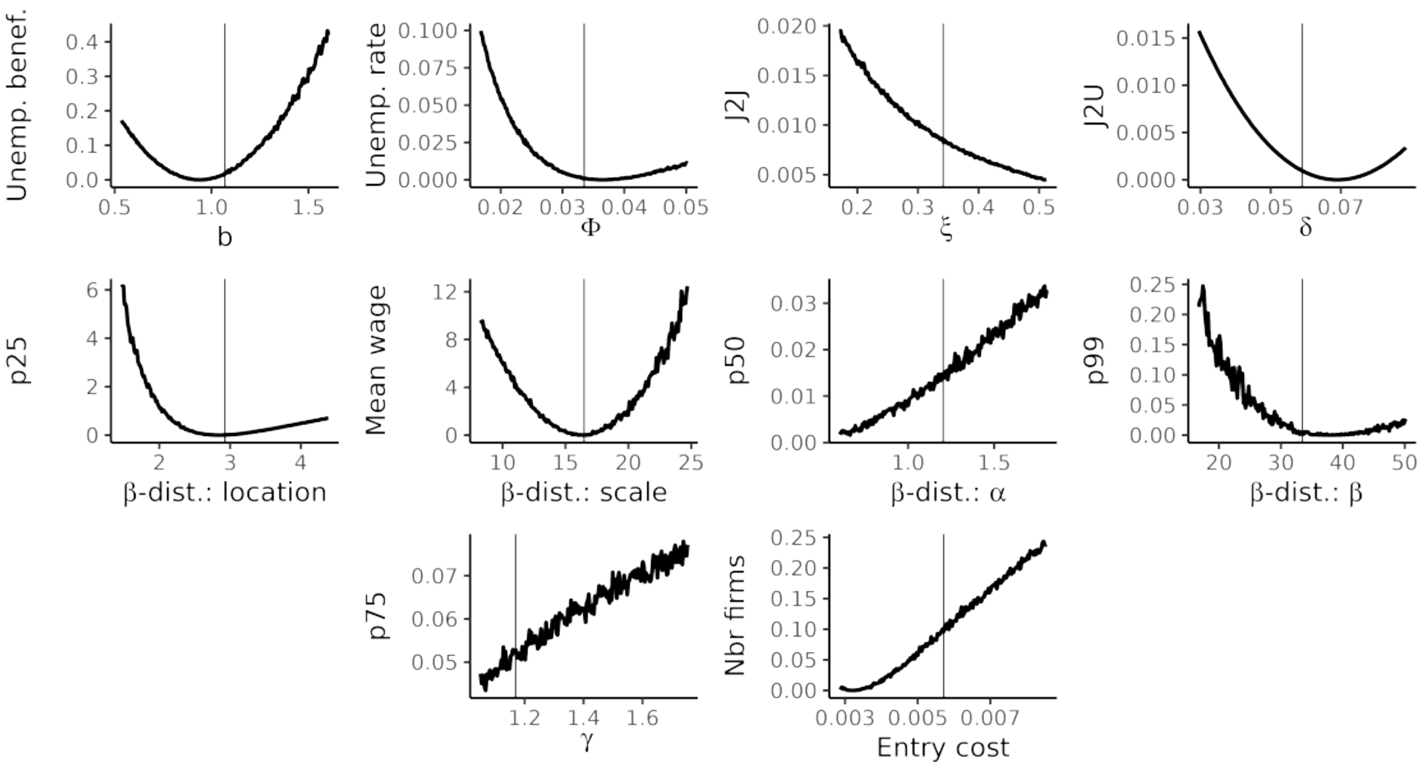

Figure 11: Sensitivity of selected moments

to influence quite significantly their own target (the entry cost does influence the number of firms significantly - yet the estimated value is far enough from its target, that the minimum is not centered at all close to the estimated value). Two parameters related to the firm's size (the α-term of the β-distribution, and the cost of vacancies γ) seem to be non-informative about their targeted parameters. It is a sign that I am likely overfitting the firm's size distribution with a generalized β-distribution.

4.2 Simulations and wage decomposition

I first run a similar regression to the ones at the market level to see how mean wage and HHI comove in the model. I vary the entry cost to change concentration levels, simulate 120 labor markets for each entry cost and recover the mean wage in the market and the HHI. I then regress

	Data - mean real wage	Baseline $\alpha = 0.28$	$\alpha = 0.50$	$\alpha = 0.75$
Coeff. reg. mean wage on HHI	2.77	2.41	4.28	8.25

Table 7: Comparing mean wage on HHI regressions in the data and in the model

the mean wage on the HHI, and compare it to the same regression in the data.[26] Results are displayed in table 7. I then reestimate my model for two different values of α, 0.50 and 0.75, simulate labor markets, as described above, and run the same regressions.

Although the slope was not targeted in the estimation, and the firm's bargaining power α was set from Shimer 2005, my model does a good job capturing the empirical comovement between mean wages and concentration. When increasing the bargaining power of firms, mean wage increases much faster with concentration than observed in the data. Were I to estimate α targeting that moment, the value I would obtain would likely be around 0.30.

Why is the slope steeper when increasing the bargaining power? Figure 12 displays the median values of the HHI and of the mean wage across the different simulations for each entry cost. When increasing the bargaining power, the wage equation 9 shows we are decreasing the relative weight of output sharing compared to the outside option - common to all workers. It compresses the wage distribution towards the outside option. As productive firms account for a larger share of the outside option, the more concentrated the market, the higher the outside option, and therefore the steeper the increase. Notice also that, with higher bargaining power, my model fails to deliver higher concentration levels, consistent with the ones observed in the data (see the scatter plot 2).

I now want to turn to wage decomposition and markdowns. Wages paid to workers have three components: a share from the output $(1-\alpha) \cdot z$, a compensation coming from the outside option workers give up on when accepting the offer $\alpha b + \alpha(1-\alpha) \sum_{j=1}^{N} \lambda_0^j S_j \mathbb{1}_{\{S_j > 0\}}$ and a penalty term firms impose on workers who have the chance of being poached $\alpha(1-\alpha) \sum_{j=1}^{N} \lambda^j S_j \mathbb{1}_{\{S_j > S_i\}}$. I want to quantify how these different terms play out depending on the level of concentration and on the worker's position in the firm's distribution of productivities. I simulate 120 labor markets for 3 different values of the entry cost. For each simulation, I isolate the firm in the 0%, 10%,

[26]The estimation is done on real wages as I chose to set the ratio of b to the mean wage in real terms.

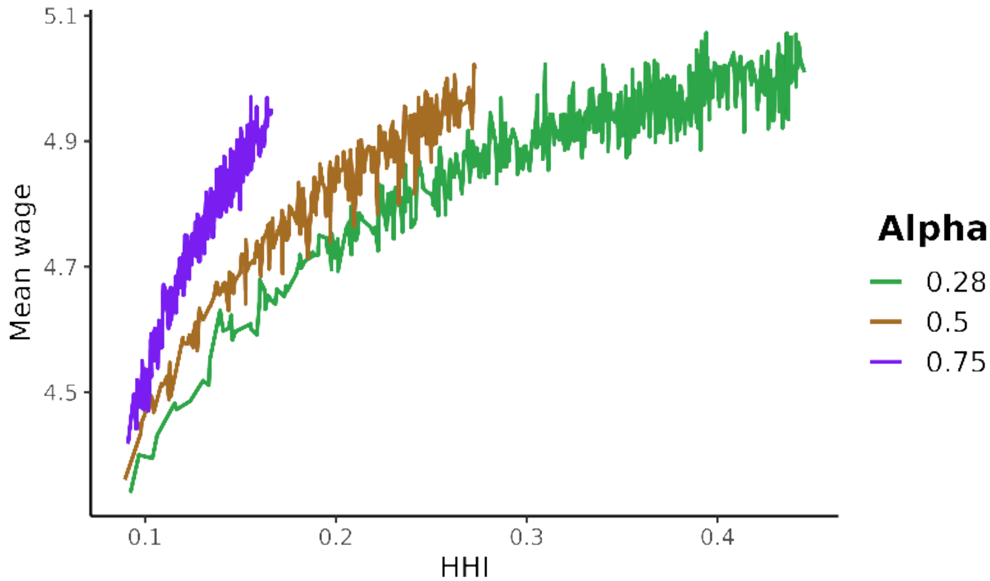

Figure 12: Mean wage and concentration in labor markets for different bargaining powers

25%, 50%, 75%, 90% and 100% percentile of the productivity distribution, and look at the total wage paid at that firm, the share of it coming from each of the three terms, the markdown applied on wages and the percentage of workers employed by that firm. Results are displayed in table 21. I check the robustness of my results to two different values of θ and one value of α in appendix E. I fix altenatively $\theta = 0.40$, $\theta = 0.60$, and $\alpha = 0.50$ (while keeping the other parameter to its baseline value) reestimate the model for the three different values, and perform the same wage decomposition. Results are virtually unchanged.

Despite the share of the wage coming from the outside option and the poaching penalty vary substantially across the firm's distribution, their sum remains pretty much constant - so that the share of wages coming from output is always around 78 to 83%, no matter the composition of firms in the labor market nor which firm the worker is at. And although markdowns tend to increase with concentration across markets and firm's productivity within markets, they remain within pretty narrow boundaries: between 0.078 to 0.135. This is due to the Nash-bargaining process over wages and the bargaining power of workers, and remains true with more complex bargaining power - for instance with Cahuc, Postel-Vinay, and Robin 2006[27]. Consistent with one's intuition, my model

[27] In fact, as the outside option of workers would be larger in their case, workers would extract a larger share of the

Fixed cost	0						
Percentile productivity	0%	10%	25%	50%	75%	90%	100%
Firm's productivity	3.15	3.21	3.31	3.53	3.87	4.30	5.87
Total wage	2.90	2.95	3.02	3.18	3.46	3.80	5.12
From output (%)	78.1	78.4	78.9	79.8	80.8	81.6	82.7
From penalty (%)	-8.9	-8.8	-8.5	-7.8	-6.7	-5.0	0
From outside option (%)	30.8	30.3	29.6	28.0	25.8	23.5	17.5
Markdown	0.078	0.082	0.088	0.098	0.109	0.117	0.129
Share workers (%)	0.02	0.02	0.03	0.06	0.18	0.62	18.83
HHI				0.092			

Fixed cost	0.01						
Percentile productivity	0%	10%	25%	50%	75%	90%	100%
Firm's productivity	3.87	3.93	4.01	4.21	4.51	4.92	5.79
Total wage	3.45	3.50	3.57	3.73	3.99	4.33	5.11
From output (%)	80.6	80.7	80.9	81.2	81.5	81.7	82.2
From penalty (%)	-7.8	-7.6	-7.2	-6.4	-4.9	-3.3	0
From outside option (%)	27.1	26.8	26.3	25.1	23.4	21.6	18.2
Markdown	0.107	0.108	0.109	0.113	0.117	0.119	0.124
Share workers (%)	0.16	0.18	0.24	0.41	1.02	3.02	24.15
HHI				0.135			

Fixed cost	0.5						
Percentile productivity	0%	10%	25%	50%	75%	90%	100%
Firm's productivity	5.16	5.19	5.25	5.38	5.62	5.76	5.85
Total wage	4.47	4.51	4.56	4.70	4.94	5.09	5.20
From output (%)	81.0	81.4	81.9	82.4	82.9	83.1	83.2
From penalty (%)	-5.3	-4.9	-4.4	-3.3	-1.9	-0.8	0
From outside option (%)	22.0	21.7	21.5	20.8	20.0	19.4	18.9
Markdown	0.112	0.115	0.12	0.126	0.131	0.134	0.135
Share workers (%)	6.19	7.13	8.69	13.57	25.4	39.48	48.81
HHI				0.439			

Table 8: Wage decomposition and markdowns by firm's productivity

delivers that dominant firms in a market charge higher markdowns, and typical markdowns are higher in more concentrated markets – yet they always remain small.

output, and markdowns would be even smaller, as discussed in appendix D.2.

5 Counterfactuals

We saw in previous sections that the entry cost and the total amount of vacancies posted can have large impact on total output. The entry cost, by removing small and unproductive firms that crowd the vacancy market, can help more productive firms to hire a larger fraction of workers and increase total output (as in seen in figure 9). Yet, increasing the number of firms increases the total amount of vacancies posted, and reduces unemployment (as in figure 8). By reducing unemployment, production also increases. There is therefore an inherent tension in the number and the composition of firms in a market, that a social planner can use to increase output.

In this section, I solve the first-best solution in which the planner controls the distribution of workers across firms and the vacancy posting of firms to maximize output, and compare it to the decentralized outcome. I then explore second-best implementations, in which a planner chooses tax and subsidy rates at the firm level subject to an overall balanced budget. By heavily taxing some firms, the planner manages to deter unproductive firms from entering. By taxing some firms relatively less, the planner incentivizes firms to reduce their vacancy posting and collects revenues it can use to subsidize the most productive firms and nudge them to increase their mass of vacancies. All in all, these second-best implementations come very close to the first best solution.

I finally investigate how far a planner can go with simple linear taxes: I tax output and rebate the gains to all worker ; use the tax to subsidize firm's entry ; or further tax entry. Appendix F details that exercises, which is briefly summarized at the end of this section.

5.1 Planner's problem - a first best solution

A social planner maximizes output. The inherent tension here is to remove small, unproductive firms that crowd the vacancy market. In addition, the planner would want to correct inefficiencies due to firm's vacancy posting, subject to equilibrium transition rates. Faced with a draw of N productivities, the planner chooses the distribution of workers across firms $\{n_i\}$ and unemployment u, the mass of vacancies each firm posts $\{v_i\}$, and the contact rates $\{\lambda_0^i\}$ such that, for all firms entering:

$$
\max_{u,\{n_i\},\{v_i\},\{\lambda_0^i\}} \sum_i n_i \cdot z_i + u \cdot b - \sum_i c(v_i) - c_f \cdot N^{\text{firms entering}}
$$

$$
\text{s.t.} \quad \begin{cases} n_i(z_i - w_i) - c(v_i) > \rho c_f \\ \lambda_0^i = \frac{1}{u+(1-u)\xi} v_i \left(\Phi(u + (1-u)\xi)\right)^\theta v^{-\theta} \\ u \sum_j \lambda_0^j \mathbb{1}_{\{S_j > 0\}} = (1-u)\delta \\ n_i \left(\delta + \xi \sum_j \lambda_0^j \mathbb{1}_{\{S_j > S_i\}}\right) = \lambda_0^i \left(u \mathbb{1}_{\{S_i > 0\}} + \xi \sum_j n_j \mathbb{1}_{\{S_i > S_j\}}\right) \\ \sum_i v_i = v, u + \sum_i n_i = 1 \\ S_i, w_i \text{ follow surplus and wage eq. 8 and 9} \end{cases} \tag{17}
$$

The first condition imposes that all firms entering make positive profits once the entry cost has been paid. The second condition comes from the definition of the contact rates. The third and fourth are the equilibrium flows of workers across the different firms and unemployment. In addition, the mass of vacancies and the mass of workers need to hold, and the wages and surpluses at each firm must be consistent with the equations derived in previous sections.

The optimization problem does not have a closed form solution, but can be solved numerically. I simulate 600 different labor markets based on the parameters estimated previously. I draw 300 different productivities and solve the decentralized economy and the planner's problem. Mean outcomes across the different simulations are reported in table 9. Consistent with what was discussed earlier, total output increases when employment is concentrated among the most productive firms. The first best outcome is therefore achieved by reducing drastically the number of firms operating - from 82 to 10. Much fewer vacancies are posted in the planner's solution, but the most productive firms post a much larger mass (as a share of total vacancies, but also in absolute terms compared to the decentralized economy). As a result, concentration measures increase more than threefold. Despite the large decrease in the mass of vacancies, the unemployment rate increases only by 5%.

As employment is concentrated among productive firms, total output increases by 5%, despite the increase in unemployment. And despite mean markdowns across firms increase, mean wages and total income to workers (defined as the sum of the wage bill and the unemployment benefits)

	Nbr of firms	HHI_{wb}	Unemp. rate	Total mass of vacancies	% vacancies posted by most productive firm
Decentralized	82	0.12	9.5%	3.85	7.3%
Planner	10	0.43	14.8%	1.59	34.2%
	Total output	**Mean Markdown**	**Mean wage**	**Wage ineq.**	**Total income to workers**
Decentralized	4.60	0.13	4.39	1.43	4.07
Planner	4.83	0.15	4.88	0.63	4.31

Table 9: Decentralized labor markets and planner's solution

increase by a staggering 11% and 5.9%. Wage inequality (defined here as the difference between the wages paid at the 90% and 10% percentiles of the wage distribution) are divided by more than 2. Increasing employment among productive firms, despite increasing concentration and unemployment, increases output, and wages, and reduces wage inequality.

It is not desirable to have only the most productive firm operating because of decreasing returns to scale. The vacancy cost function being convex, it would be too costly for a single firm to hire. Although not a planner's objective, this allows for a certain level of competition between firms, and increases wages.

5.2 Individual tax and subsidy rates - a second-best approach

I now investigate how a planner can influence firms' vacancy posting decisions through individual tax and subsidy rates, and how close it comes to the first-best solution. The planner chooses τ_i, the tax/subsidy rates for each firm. As it reduces or increases profits of firms, it influences both their entry and vacancy posting decisions. For each match, only a fraction $1 - \tau_i$ is left after tax (with the convention that $\tau_i > 0$ means firm i is taxed, and $\tau_i < 0$ means firm i is subsidized). The new surplus follows equation 18:

$$\rho S_i = (1-\tau_i)\cdot z_i - b - \delta S_i + \sum_{j=1}^{N} \lambda^j \left((1-\alpha)S_j - S_i\right) \mathbb{1}_{\{S_j > S_i\}} - (1-\alpha)\sum_{j=1}^{N} \lambda_0^j S_j \mathbb{1}_{\{S_j>0\}} \tag{18}$$

The planner's problem is then to choose $\{\tau_i\}$ in order to maximize total output with a balanced budget. As a fraction $\tau_i z_i$ is collected from each match at firm i, a planner collects/distributes $\tau_i z_i n_i$ from/to firm i. A balance budget then implies that $\sum_i \tau_i z_i n_i \geq 0$. The full second-best problem is summarized in 19:

$$\begin{aligned} &\max_{\{\tau_i\}} \sum_i n_i \cdot z_i + u \cdot b - \sum_i c(v_i) - c_f \cdot N^{\text{firms entering}} \\ &\text{s.t.} \begin{cases} \sum_i \tau_i z_i n_i \geq 0 \\ S_i \text{ follows 18} \\ \text{other eq. objects consistent with decentralized solution} \end{cases} \end{aligned} \tag{19}$$

The solution to the second-best implementation is displayed in table 10. In addition to a fully flexible system of taxes and subsidies, I compute the second-best solution in which a planner can only impose a 0% or a 100% tax on firms. This implementation corresponds to the planner choosing which firms operate, and letting them operate in a decentralized labor market with fewer firms. In that case the planner's budget is always balanced.

Both second-best implementations come close to the first-best solution. A planner restricts drastically the number of operating firms by fully taxing them. It increases concentration, and, despite increasing unemployment, output and mean wages increase substantially, bringing them within one and two percents of the planner's solution.

The typical implementation of the full system of taxes and subsidies is described in table 11. As we saw in the first-best solution, the decentralized equilibrium displays two sources of inefficiency: the entry of too many unproductive firms, and a distorted vacancy posting. Even when

	Nbr of firms	HHI_{wb}	Unemp. rate	Total output	Mean wage
Decentralized	82	0.12	9.5%	4.60	4.39
Second best with 0-1 tax	8	0.34	15.6%	4.80	4.82
Second best with taxes/subsidies	11	0.41	15.6%	4.81	4.81
Planner	10	0.43	14.8%	4.83	4.88

Table 10: Decentralized labor markets, first-best, and second-best solutions

Total tax revenue	Nbr firms subsidized	Avg subsidy	Nbr firms taxed	Avg tax
0.008	1.8	5.6%	9.6	17.4%

Table 11: Implementing the second-best solution with individual tax and subsidy rates

restricting the set of operating firms, the least productive firms operating post too much vacancies, while the most productive do not post enough. By taxing the least productive firms and using the collected taxes to subsidize the most productive ones, the planner can offset part of this distortion. Among the 11 firms operating in the second-best implementation with the full system of taxes and subsidies, a planner would tax between 9 and 10 firms at an average tax rate of 17% - the least productive firms among those 10 being taxed more than the most productive. The planner would use the tax revenue to subsidize the one or two most productive firms, using virtually all the available revenue.

5.3 How much can linear taxes achieve?

The second-best implementations described above can be complicated to implement in a reality. Instead, I investigate how close one could come to the efficient solution using simple linear taxes: I tax output and rebate the gains to all worker ; use the tax to subsidize firm's entry ; or further tax entry. Appendix F details the effects on the labor markets, which I briefly summarize here. When entry costs are not high enough, taxing output or artificially increasing the entry cost, deters the least productive firms from entering the market. Yet, increasing the entry cost forces firms to waste more money on entry, while taxing output distorts the vacancy posting of the most productive firms relatively more, and does not concentrate employment enough. In both cases, marginal gains can be made, but they both fall very short to bringing the labor market close to the efficient equilibrium by increasing output by less than 1%. Subsidizing entry by taxing firms, for obvious reasons, is never efficient. It distorts the vacancy posting in the wrong direction, and helps more unproductive firms to enter the labor market. Linear taxes can not do much in increasing total output.

6 Conclusion

This paper looks at the links between labor market concentration and labor market outcomes. Contrary to what has been found in the literature, I find that wages positively and strongly comove with concentration – wages increase by 6.5% between the 10% and the 90% centile of labor market concentration. In addition, and less surprisingly, workers are undergoing fewer transitions in concentrated labor markets. These results are present in the raw data, in market-level regressions and panel data regressions, and are robust to different concentration measures and market definitions.

To rationalize these empirical correlations, I construct a search-and-matching model with a discrete number of firms, optimal vacancy posting and endogenous entry. My model allows me to quantify markdowns and decompose wages into output sharing and two non-competitive forces (one working in favor and one against workers). Markdowns exist, but tend to always be pretty small (0.10 to 0.15) whereas the largest share of a worker's wage comes from output sharing (around 80%). I use this model to compare the planner's solution with the decentralized equilibrium. A planner would like to concentrate employment among more productive firms, and manages to increase output by 5% and wages by 11%, despite increasing unemployment. I investigate second-best implementations using individual tax and subsidy rates. By fully taxing most firms - the unproductive ones -, taxing partially the least productive firms among the operating ones, and using the tax revenue collected to subsidize the most productive firms, a planner almost achieves the first-best solution. On the contrary, simple linear tax policies do no come anywhere close to the firs-best solution.

My model has clear implications for profits and productivity. With firms' accounting data such as the *FARE/FICUS* French dataset, one can look at how they vary with labor market concentration. Backing up my model's predictions with empirical results on output per worker would be further evidence of the mechanism at play here.

That higher productivity can drive up wages and concentration at the same time, is a simple yet overlooked mechanism in the current literature. Yet this mechanism can have profound implications regarding how public policies should address concerns on labor market concentration. Understanding the reasons causing high concentration in a given labor market, rather than high concentration in itself, should therefore be a first order priority. I hope this paper will be a step in that direction.

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A Concentration by commuting zones and occupations

A.1 Concentration across commuting zones

Figure 13 plots the median HHI by commuting zones (left panel) and the population density with the 10 biggest cities (right panel). There is almost a one to one mapping between concentration and population density. This comes pretty mechanically from the fact that the HHI measures the share of the wage bill. If few firms operate with fewer workers, the share each firm employs is higher, and the HHI increases too.

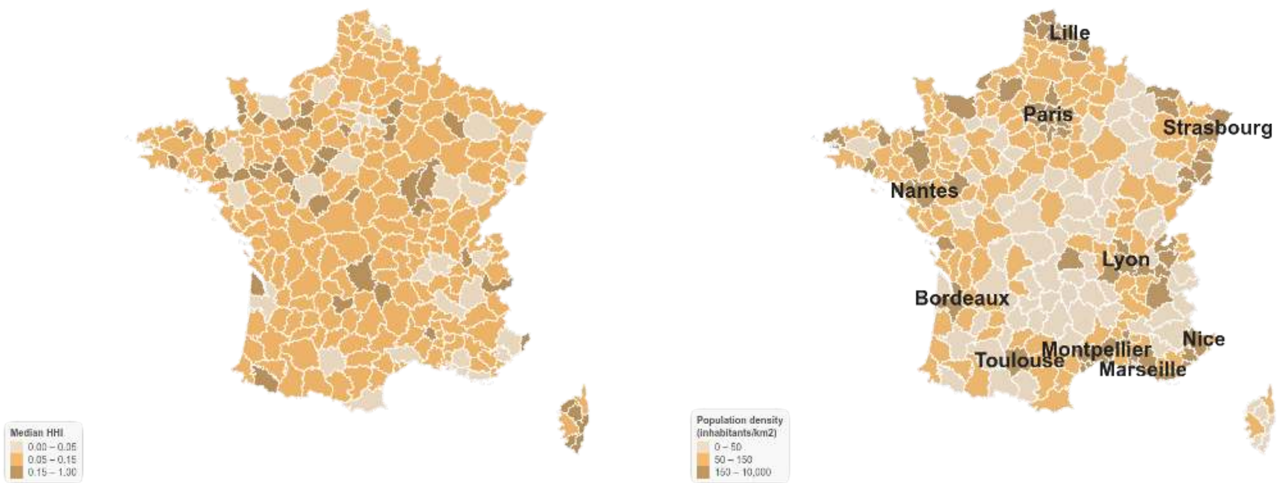

Figure 13: Median HHI by commuting zones and population density

An interesting side-note – big cities tend to be not concentrated. We have seen in the main analysis that more concentrated markets tend to pay higher wages (even in the raw data). It would seem to suggest that low density commuting zones would then pay a higher wage. This is actually not true, when one looks at the median household income by commuting zones: Paris, its suburb and other big cities have, by far, larger median income. This false intuition comes from misleading average effects. Looking at the sorting of occupations across commuting zones and its interaction with wages paid can explain why we observe these effects.

A.2 Concentration across occupations

Figure 14 displays the median HHI for each 3-digit occupation code. The different colors stand the different 1-digit occupations. Although some types of occupations, like manual workers, tend to have a few more concentrated 3-digit occupations, the overall picture is much more nuanced than for commuting zones: each 1-digit occupation seem to have both non-concentrated and concentrated occupations.

B Additional specifications in regressions

B.1 Market level regressions

	HHI_{wb} (i)	$Skew_{wb}$ (ii)	$Kurt_{wb}$ (iii)	HHI_{emp} (iv)	$Skew_{emp}$ (v)	$Kurt_{emp}$ (vi)
Coeff. mean wage	0.0820***	0.0638***	0.0554***	0.0436***	0.0345***	0.0316***
	(0.0058)	(0.0052)	(0.0049)	(0.0058)	(0.0051)	(0.0048)
Occ.×CZ	✓	✓	✓	✓	✓	✓
Observations	407,310	407,310	407,310	407,310	407,310	407,310
R^2	0.90478	0.90466	0.90458	0.90439	0.90436	0.90435
Within R^2	0.00565	0.00356	0.01087	0.00160	0.00128	0.00117

	HHI_{wb} (vii)	$Skew_{wb}$ (viii)	$Kurt_{wb}$ (ix)	HHI_{emp} (x)	$Skew_{emp}$ (xi)	$Kurt_{emp}$ (xii)
Coeff. mean wage	0.0390***	0.0398***	0.0342***	-0.0100**	-0.0020	-0.0020
	(0.0049)	(0.0049)	(0.0050)	(0.0050)	(0.0050)	(0.0050)
Occ.×year	✓	✓	✓	✓	✓	✓
Observations	407,310	407,310	407,310	407,310	407,310	407,310
R^2	0.85651	0.85654	0.85644	0.85620	0.85618	0.85618
Within R^2	0.00227	0.00249	0.00183	0.00014	6.2×10^{-6}	5.78×10^{-6}

Clustered (LM) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 12: Market level regressions - Mean wage on concentration measures

	HHI_{wb} (i)	$Skew_{wb}$ (ii)	$Kurt_{wb}$ (iii)	HHI_{emp} (iv)	$Skew_{emp}$ (v)	$Kurt_{emp}$ (vi)
Coeff. mean wage	0.0500***	0.0298***	0.0196***	0.0066	-0.0048	-0.0087*
	(0.0060)	(0.0053)	(0.0050)	(0.0065)	(0.0056)	(0.0054)
Occ.×CZ	✓	✓	✓	✓	✓	✓
Add. controls	✓	✓	✓	✓	✓	✓
Observations	407,310	407,310	407,310	407,310	407,310	407,310
R^2	0.90853	0.90844	0.90841	0.90837	0.90837	0.90838
Within R^2	0.04484	0.04390	0.04349	0.04317	0.04316	0.04321

	HHI_{wb} (vii)	$Skew_{wb}$ (viii)	$Kurt_{wb}$ (ix)	HHI_{emp} (x)	$Skew_{emp}$ (xi)	$Kurt_{emp}$ (xii)
Coeff. mean wage	0.0084	0.0106**	0.0042	-0.0530***	-0.0441***	-0.0435***
	(0.0052)	(0.0053)	(0.0053)	(0.0054)	(0.0055)	(0.0050)
Occ.×year	✓	✓	✓	✓	✓	✓
Add. controls	✓	✓	✓	✓	✓	✓
Observations	407,310	407,310	407,310	407,310	407,310	407,310
R^2	0.86416	0.86417	0.86415	0.86459	0.86446	0.86445
Within R^2	0.05550	0.05555	0.05544	0.05844	0.05754	0.05747

Clustered (LM) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 13: Market level regressions - Mean wage on concentration measures with additional controls

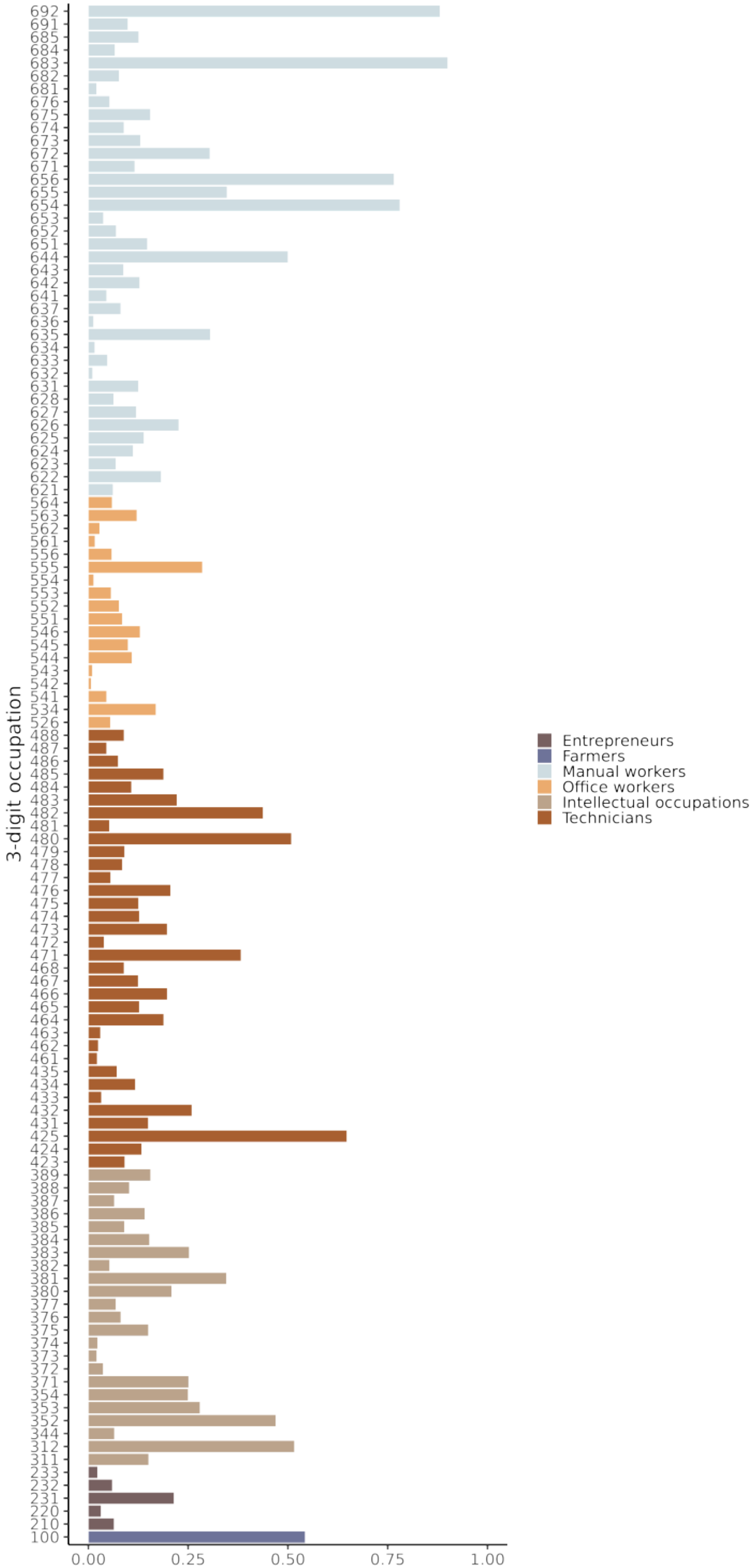

Figure 14: Median HHI by 3-digit occupation

B.2 Panel data regressions

	HHI_{wb} (i)	$Skew_{wb}$ (ii)	$Kurt_{wb}$ (iii)	HHI_{emp} (iv)	$Skew_{emp}$ (v)	$Kurt_{emp}$ (vi)
Coeff. mean wage	0.1380***	0.1402***	0.1368***	0.0189*	0.0195*	0.0165
	(0.0120)	(0.0130)	(0.0143)	(0.0106)	(0.0101)	(0.0104)
Occ.×CZ	✓	✓	✓	✓	✓	✓
Sex	✓	✓	✓	✓	✓	✓
Observations	8,749,532	8,749,532	8,749,532	8,749,532	8,749,532	8,749,532
R^2	0.55963	0.55962	0.55960	0.55957	0.55957	0.55957
Within R^2	0.12728	0.12725	0.12723	0.12716	0.12716	0.12716

	HHI_{wb} (vii)	$Skew_{wb}$ (viii)	$Kurt_{wb}$ (ix)	HHI_{emp} (x)	$Skew_{emp}$ (xi)	$Kurt_{emp}$ (xii)
Coeff. mean wage	0.0259***	0.0256**	0.0232*	0.0087	0.0086	0.0065
	(0.0065)	(0.0100)	(0.0131)	(0.0072)	(0.0111)	(0.0144)
Worker FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Observations	8,749,532	8,749,532	8,749,532	8,749,532	8,749,532	8,749,532
R^2	0.89964	0.89964	0.89964	0.89964	0.89964	0.89964
Within R^2	0.03802	0.03800	0.03798	0.03797	0.03797	0.03797

Clustered (firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 14: Panel data regressions - Daily wage on concentration measures

	HHI_{wb} (i)	$Skew_{wb}$ (ii)	$Kurt_{wb}$ (iii)	HHI_{emp} (iv)	$Skew_{emp}$ (v)	$Kurt_{emp}$ (vi)
Coeff. mean wage	0.1312***	0.1329***	0.1307***	0.0203*	0.0194*	0.0167*
	(0.0120)	(0.0127)	(0.0137)	(0.0113)	(0.0100)	(0.0097)
Occ.×CZ	✓	✓	✓	✓	✓	✓
Sex	✓	✓	✓	✓	✓	✓
Add. controls	✓	✓	✓	✓	✓	✓
Observations	8,747,995	8,747,995	8,747,995	8,747,995	8,747,995	8,747,995
R^2	0.56830	0.56829	0.56828	0.56825	0.56825	0.56825
Within R^2	0.14441	0.14438	0.14436	0.14430	0.14430	0.14430

	HHI_{wb} (vii)	$Skew_{wb}$ (viii)	$Kurt_{wb}$ (ix)	HHI_{emp} (x)	$Skew_{emp}$ (xi)	$Kurt_{emp}$ (xii)
Coeff. mean wage	0.0266***	0.0264***	0.0242*	0.0096	0.0096	0.0076
	(0.0066)	(0.0100)	(0.0132)	(0.0072)	(0.0112)	(0.0145)
Worker FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Add. controls	✓	✓	✓	✓	✓	✓
Observations	8,747,995	8,747,995	8,747,995	8,747,995	8,747,995	8,747,995
R^2	0.89970	0.89969	0.89969	0.89969	0.89969	0.89969
Within R^2	0.03842	0.03840	0.03838	0.03837	0.03837	0.03837

Clustered (firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 15: Panel data regressions - Daily wage on concentration measures with additional controls

	HHI_{wb} (i)	$Skew_{wb}$ (ii)	$Kurt_{wb}$ (iii)	HHI_{emp} (iv)	$Skew_{emp}$ (v)	$Kurt_{emp}$ (vi)
Coeff. J2J	-0.0314***	-0.0315***	-0.0305***	-0.0203**	-0.0249***	-0.0260***
	(0.0082)	(0.0090)	(0.0098)	(0.0086)	(0.0093)	(0.0101)
Occ.×CZ	✓	✓	✓	✓	✓	✓
Sex	✓	✓	✓	✓	✓	✓
Observations	7,215,124	7,215,124	7,215,124	7,215,124	7,215,124	7,215,124
R^2	0.02523	0.02523	0.02522	0.02522	0.02522	0.02522
Within R^2	0.01087	0.01086	0.01086	0.01086	0.01086	0.01086

	HHI_{wb} (vii)	$Skew_{wb}$ (viii)	$Kurt_{wb}$ (ix)	HHI_{emp} (x)	$Skew_{emp}$ (xi)	$Kurt_{emp}$ (xii)
Coeff. J2J	-0.0146***	-0.0127***	-0.0107*	-0.0124***	-0.0100**	-0.0078
	(0.0035)	(0.0047)	(0.0056)	(0.0037)	(0.0050)	(0.0058)
Worker FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Observations	7,215,124	7,215,124	7,215,124	7,215,124	7,215,124	7,215,124
R^2	0.40556	0.40555	0.40555	0.40555	0.40555	0.40555
Within R^2	0.00210	0.00210	0.00210	0.00210	0.00210	0.00209

Clustered (firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 16: Panel data regressions - J2J probability on concentration measures

	HHI_{wb} (i)	$Skew_{wb}$ (ii)	$Kurt_{wb}$ (iii)	HHI_{emp} (iv)	$Skew_{emp}$ (v)	$Kurt_{emp}$ (vi)
Coeff. J2J	-0.0286***	-0.0286***	-0.0281***	-0.0196**	-0.0240**	-0.0254**
	(0.0086)	(0.0092)	(0.0100)	(0.0093)	(0.0099)	(0.0105)
Occ.×CZ	✓	✓	✓	✓	✓	✓
Sex	✓	✓	✓	✓	✓	✓
Add. controls	✓	✓	✓	✓	✓	✓
Observations	7,213,775	7,213,775	7,213,775	7,213,775	7,213,775	7,213,775
R^2	0.02844	0.02844	0.02844	0.02844	0.02844	0.02844
Within R^2	0.01412	0.01412	0.01412	0.01412	0.01412	0.01412

	HHI_{wb} (vii)	$Skew_{wb}$ (viii)	$Kurt_{wb}$ (ix)	HHI_{emp} (x)	$Skew_{emp}$ (xi)	$Kurt_{emp}$ (xii)
Coeff. J2J	-0.0129***	-0.0105**	-0.0080	-0.0105***	-0.0075	-0.0047
	(0.0036)	(0.0049)	(0.0057)	(0.0038)	(0.0051)	(0.0059)
Worker FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Add. controls	✓	✓	✓	✓	✓	✓
Observations	7,213,775	7,213,775	7,213,775	7,213,775	7,213,775	7,213,775
R^2	0.40862	0.40862	0.40862	0.40862	0.40862	0.40862
Within R^2	0.00724	0.00724	0.00724	0.00724	0.00724	0.00723

Clustered (firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 17: Panel data regressions - J2J probability on concentration measures with additional controls

C Event study appendix

C.1 Market composition

In this section I list the composition of the treated labor markets in my event study for the HHI increase. Tables look identical for HHI decreases and are therefore not displayed, for brevity.

Although changes tend to append more in certain years (2009, 2010, 2014 and 2015) and in certain occupations (especially for occupation corresponding to the 2-digit occupation 62 - qualified blue collar workers working in the industry), all 1-digit occupations, all years, and all regions are represented in my event study, both for the HHI increase and the HHI decrease. Results should therefore not be driven by some specific occupations or commuting zones undergoing structural changes. I control for a commuting zone and an occupation by year fixed effects in my event-study regressions to alleviate further concerns.

Year	Nbr of increases	Year	Nbr of increases	Year	Nbr of increases
2009	22	2013	11	2017	10
2010	13	2014	32	2018	3
2011	12	2015	19	2019	11
2012	13	2016	13	Total	159

Table 18: Years undergoing a HHI increase

Occ.	Nbr of increases	Occ.	Nbr of increases	Occ.	Nbr of increases
344	1	484	2	628	4
376	1	485	2	633	1
377	1	486	2	634	1
383	4	534	5	641	1
384	3	541	3	643	4
385	2	544	3	644	1
387	3	545	4	652	1
388	4	546	2	653	1
431	4	551	1	654	3
461	1	553	1	655	2
462	1	554	1	671	1
465	1	564	2	672	1
466	2	621	2	673	4
467	8	622	1	674	6
473	1	623	1	675	2
474	3	624	8	676	6
475	3	625	9	684	3
477	5	626	7	Total	159
479	4	627	9		

Table 19: Occupations undergoing a HHI increase

CZ	Nbr of increases	CZ	Nbr of increases	CZ	Nbr of increases
0053	1	3209	2	7517	1
0054	1	3210	2	7520	1
0061	1	3212	1	7522	2
1101	1	3213	2	7524	3
1102	1	3215	1	7610	1
1104	2	3218	1	7614	1
1105	1	3222	4	7617	1
1106	3	4403	2	7618	1
1108	2	4406	2	7620	2
1109	1	4410	4	7621	1
1111	1	4413	1	7624	2
1112	2	4416	1	7625	1
1113	1	4417	1	8401	1
1114	2	4420	2	8405	1
1115	4	4422	1	8406	1
2401	3	4424	4	8407	1
2405	1	5201	1	8408	2
2409	1	5202	2	8409	1
2410	1	5207	1	8410	1
2413	1	5208	1	8412	1
2705	2	5212	4	8413	3
2706	1	5216	2	8415	1
2707	1	5218	1	8416	1
2709	1	5221	1	8418	1
2716	1	5302	1	8428	1
2717	1	5304	1	8435	1
2718	1	5309	1	9301	3
2805	2	5310	1	9311	1
2808	2	5315	1	9312	4
2813	3	7502	1	9313	2
2815	1	7505	4	9315	2
3203	1	7506	1	9318	1
3204	3	7508	1	Total	159
3208	1	7512	4		

Table 20: Commuting zones undergoing a HHI increase

C.2 HHI decrease

This section presents the results of the event-study for markets undergoing a large HHI decrease. I mirror the analysis performed for the HHI increase discussed previously.

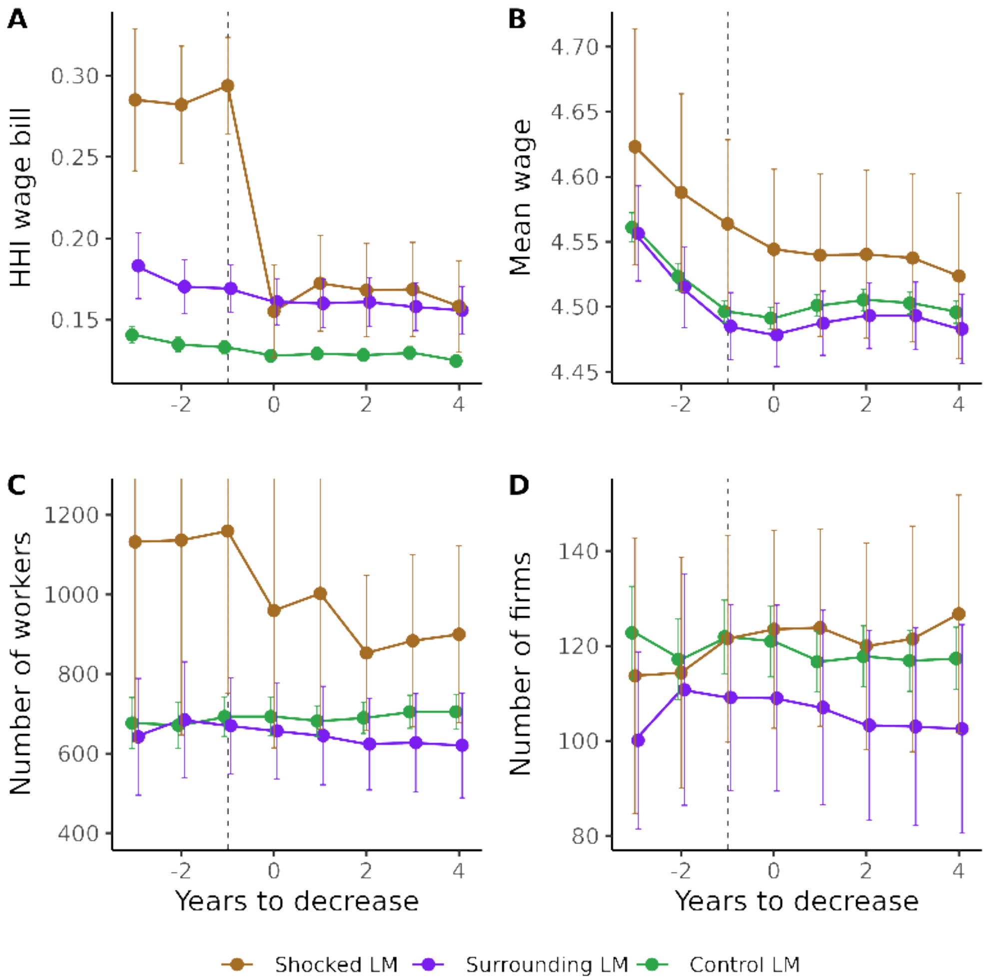

Figure 15: Large HHI decrease on market level outcomes

As one can see in figure 15, a large HHI decrease is associated with a large decrease in the number of workers and in the mean wage. Contrary to one could expect, here again we have an example of an opposite relationship to the one documented by other papers. The number of firms remain relatively stable.

Figure 16 shows the decrease is due to one single large firm firing almost half of its workforce.

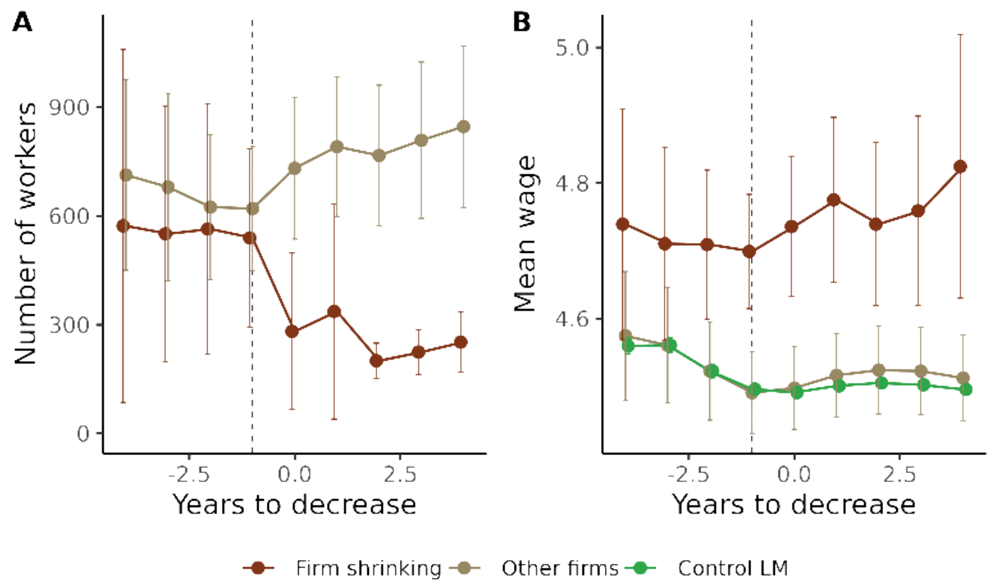

Figure 16: Shrinking firm versus the rest of the labor market following the HHI decrease

Most workers seem to be poached by other firms, as seen in the increase in the number of workers at other firms. Wages at other firms remain nearly identical to wages paid in control markets. Yet wages at the shrinking firm actually increase – a surprising result for a firm firing workers. The French labor market tends to be extremely rigid. It is both very hard to fire workers and to reduce wages, except in the first few months or years of a working contract. Penalties for firing are also proportional to the time spent at a firm. A firm having to layoff most likely chooses to keep its most experienced workers, who also turn out to be the ones earning the most. We can then see an increase in the mean wage at a shrinking firm, given the firm keeps those high-paid workers. These results do not seem to be related to concentration, and contain many confounding factors. I therefore do not think they help us in understanding the mechanisms I want to highlight.

D Model appendix - wage derivation and solution algorithm

D.1 Wage derivation

In this section I derive the surplus and wage equations from the value functions and the bargaining process. Notice first that, as $V_i - U = (1-\alpha)S_i$, we have $\mathbb{1}_{\{V_i>U\}} = \mathbb{1}_{\{S_i>0\}}$ and $\mathbb{1}_{\{V_j>V_i\}} = \mathbb{1}_{\{S_j>S_i\}}$. Hence, from the value functions we get:

$$\begin{aligned}\rho\left(J_i + V_i - U\right) = z_i - b + \delta\left(U - V_i - J_i\right)\\ + \sum_{j=1}^{N} \lambda^j \left(V_j - U - V_i - J_i + U\right)\mathbb{1}_{\{S_j>S_i\}} - \sum_{j=1}^{N} \lambda_0^j \left(V_j - U\right)\mathbb{1}_{\{S_j>0\}}\end{aligned}$$

Replacing $S_i = J_i + V_i - U$ and $V_i - U = (1-\alpha)S_i$ we have:

$$\rho S_i = z_i - b - \delta S_i + \sum_{j=1}^{N} \lambda^j \left((1-\alpha)S_j - S_i\right)\mathbb{1}_{\{S_j>S_i\}} - (1-\alpha)\sum_{j=1}^{N} \lambda_0^j S_j \mathbb{1}_{\{S_j>0\}}$$

For the wage equation, let's start from the employed worker's value function:

$$w_i = \rho V_i - \sum_{j=1}^{N} \lambda^j \left(V_j - V_i\right)\mathbb{1}_{\{V_j>V_i\}} - \delta\left(U - V_i\right)$$

Replace V_i and $V_i - U$ using the surplus to get:

$$w_i = \rho\left(1-\alpha\right)S_i + \rho U - (1-\alpha)\sum_{j=1}^{N} \lambda^j \left(S_j - S_i\right)\mathbb{1}_{\{S_j>S_i\}} + \delta\left(1-\alpha\right)S_i$$

Finally replace ρS_i and ρU to get:

$$w_i = (1-\alpha)(z_i - b) + (1-\alpha)\sum_{j=1}^{N}\lambda^j\left((1-\alpha)S_j - S_i\right)\mathbb{1}_{\{S_j>S_i\}} - (1-\alpha)^2\sum_{j=1}^{N}\lambda_0^j S_j \mathbb{1}_{\{S_j>0\}}$$
$$+ b + (1-\alpha)\sum_{j=1}^{N}\lambda_0^j S_j \mathbb{1}_{\{S_j>0\}} - (1-\alpha)\sum_{j=1}^{N}\lambda^j\left(S_j - S_i\right)\mathbb{1}_{\{S_j>S_i\}}$$

Simplify to get:

$$w_i = (1-\alpha)\cdot z_i + \alpha b - \alpha(1-\alpha)\sum_{j=1}^{N}\lambda^j S_j \mathbb{1}_{\{S_j>S_i\}} + \alpha(1-\alpha)\sum_{j=1}^{N}\lambda_0^j S_j \mathbb{1}_{\{S_j>0\}}$$

D.2 Bargaining à la CPVR

If one assumes instead a more realistic bargaining process, as the one in Cahuc, Postel-Vinay, and Robin 2006 where workers bargain with their second best offer as outside option rather than unemployment, markdowns would be even smaller. Let me present briefly what the wage equation would look like in that case.

The bargaining problem would now solve:

$$w_i = \text{argmax} J_i^{\alpha}\left(V_i - \tilde{V}\right)^{1-\alpha}$$

where $\tilde{V}$ is the second best offer a worker currently has. If the worker is unemployed, then $\tilde{V} = U$. If the worker is employed and receives another offer, the worker moves (or stay) to the firm offering her the highest value function and uses the surplus of her second best offer as a threat point, so that $\tilde{V} - U = \tilde{S}$, the surplus of the second best offer. Solving for the solution of the bargaining problem, we now have:

$$V_i - U = (1-\alpha)S_i + \alpha\left(\tilde{V} - U\right) \tag{20}$$

$$J_i = \alpha S_i - \alpha\left(\tilde{V} - U\right) \tag{21}$$

Following Lise and Postel-Vinay 2020, define σ as the share of the output a firm extracts: $\sigma = \frac{J_i}{S_i}$, then the solution to the bargaining process becomes:

$$\sigma = \alpha - \alpha\frac{\tilde{V} - U}{S_i}$$

and keeping track of σ (instead of $\tilde{V}$) is enough to know a worker's current bargaining position. By construction, we also have: $J_i(\sigma) = \sigma S_i$ and thus $V_i(\sigma) - U = (1-\sigma)S_i$. We can then write the value functions as:

$$\rho U = b + \sum_{j=1}^{N} \lambda_0^j \left(V_j(\alpha) - U\right) \mathbb{1}_{\{V_j(\alpha) > U\}}$$

$$\rho V_i(\sigma) = w_i(\sigma) + \sum_{j=1}^{N} \lambda^j \left(V_j(\sigma') - V_i(\sigma)\right) \mathbb{1}_{\{V_j(\sigma') > V_i(\sigma)\}} + \delta\left(U - V_i(\sigma)\right)$$

$$\rho J_i(\sigma) = z_i - w_i(\sigma) + \sum_{j=1}^{N} \lambda^j \left(0 - J_i(\sigma)\right) \mathbb{1}_{\{V_j(\sigma') > V_i(\sigma)\}} + \delta\left(0 - J_i(\sigma)\right)$$

where $\sigma' = \alpha - \alpha\frac{S_i}{S_j}$ as the worker extracts all the surplus from her current firm when she is poached by another firm. The surplus becomes:

$$\rho S_i = z_i - b - \delta S_i + (1-\alpha)\sum_{j=1}^{N} \lambda^j \left(S_j - S_i\right) \mathbb{1}_{\{S_j > S_i\}} - (1-\alpha)\sum_{j=1}^{N} \lambda_0^j S_j \mathbb{1}_{\{S_j > 0\}}$$

Using steps identical to (although slightly more involved than) the ones above, we can get the new wage equation:

$$w_i\left(\sigma\right) = (1-\sigma)\cdot z_i + \sigma b - \sigma \sum_{j=1}^{N} \lambda^j \left((1-\alpha)S_j + \alpha S_i\right) \mathbb{1}_{\{S_j > S_i\}} + \sigma(1-\alpha) \sum_{j=1}^{N} \lambda_0^j S_j \mathbb{1}_{\{S_j > 0\}}$$

with $\sigma \in [0;\alpha]$. Comparing this equation to the previous one, the penalty term for begin poached is now larger ($(1-\alpha)S_j + \alpha S_i$ instead of $(1-\alpha)S_j$), yet σ is always smaller than α. Given the magnitude of all the terms (as we saw in table 21), it is unlikely to decrease much the wage. As this term even vanishes at more productive firms, the markdown applied in my simple Nash-bargaining from unemployment is an upper-bound to the markdowns large firm can apply. Thus, a CPVR bargaining protocol most likely reduces markdowns and increase wages for most workers, amplifying my results.

D.3 Sketch of numerical solution

To conclude the model appendix I present a sketch of the algorithm used to solve for the equilibrium with entry cost. As one firm's surplus and vacancy posting depends on all the other firms, I need to solve for the equilibrium each time the composition of firms change. I draw 300 firm's productivity and look for an equilibrium distribution in which all firms that decide to enter make positive profits. I do this by successive iterations: I first solve the labor market assuming all firms can pay the entry cost. I then find the equilibrium profits each firm makes given the productivity of the other firms, and compare it to the entry cost to find the entry decision. As equilibrium profits depend on the productivity of all firms, I cannot simply remove firms that cannot afford paying the entry cost. Instead I need to drop firms one by one. At each iteration I remove the firm making the smallest profits if it cannot pay the entry cost, and recompute the new equilibrium. I repeat the operation until all firms decide to enter. For each entry cost, I simulate 120 different labor markets (ie different productivity draws).

1. Draw N productivities and rank firms from the lowest (1) to the highest (N);

2. Assume all firms enter and set identity of last firm to enter to 1;

3. Guess vacancy posting decisions, surpluses and distribution of workers across firms and compute the initial contact rates;

4. Given the contact rates, solve for the equilibrium surplus;

5. Given the equilibrium surplus and the distribution of workers, compute the optimal vacancy posting and update the contact rates;

6. Given the contact rates and surpluses, solve for the equilibrium distribution of workers;

7. Go back to step 4 and iterate until the distribution of workers is stationary;

8. Once the equilibrium is reached, compute the expected profits of the last firm to enter and compare them to the entry cost. If profits are above the entry cost, stop. If profits are below, drop the last firm to enter, increment the identity of the last firm to enter and go back to step 3.

E Robustness of wage decomposition to different values of θ and α

Fixed cost				0			
Percentile productivity	0%	10%	25%	50%	75%	90%	100%
Firm's productivity	3.60	3.64	3.73	3.90	4.18	4.51	5.74
Total wage	3.20	3.24	3.30	3.43	3.65	3.93	4.98
From output (%)	80.9	81	81.3	81.8	82.4	82.7	83.3
From penalty (%)	-7.4	-7.2	-7.0	-6.5	-5.6	-4.3	0
From outside option (%)	26.5	26.2	25.7	24.7	23.3	21.6	17.1
Markdown	0.110	0.112	0.115	0.120	0.126	0.130	0.135
Share workers (%)	0.00	0.00	0.00	0.10	0.20	0.60	17.80
HHI				0.083			

Fixed cost				0.01			
Percentile productivity	0%	10%	25%	50%	75%	90%	100%
Firm's productivity	4.08	4.11	4.19	4.34	4.61	4.91	5.75
Total wage	3.58	3.61	3.68	3.80	4.03	4.29	5.03
From output (%)	81.7	81.9	82.1	82.2	82.4	82.5	82.9
From penalty (%)	-6.7	-6.6	-6.3	-5.6	-4.5	-3.1	0
From outside option (%)	24.9	24.7	24.2	23.4	22.1	20.7	17.7
Markdown	0.119	0.121	0.123	0.124	0.126	0.127	0.131
Share workers (%)	0.10	0.10	0.20	0.30	0.80	2.30	21.60
HHI				0.110			

Fixed cost				0.5			
Percentile productivity	0%	10%	25%	50%	75%	90%	100%
Firm's productivity	5.14	5.16	5.22	5.33	5.46	5.62	5.74
Total wage	4.44	4.47	4.52	4.63	4.79	4.96	5.08
From output (%)	81.3	81.6	82.1	82.6	83	83.3	83.4
From penalty (%)	-4.7	-4.4	-4.0	-3.0	-1.7	-0.7	0
From outside option (%)	21.3	21.2	20.9	20.3	19.7	19.1	18.7
Markdown	0.114	0.118	0.123	0.129	0.133	0.135	0.137
Share workers (%)	5.50	6.30	7.50	11.20	18.60	32.50	42.70
HHI				0.361			

Table 21: Wage decomposition and markdowns by firm's productivity for $\theta = 0.40$

Fixed cost				0			
Percentile productivity	0%	10%	25%	50%	75%	90%	100%
Firm's productivity	2.81	2.90	3.04	3.35	3.87	4.54	6.32
Total wage	2.64	2.71	2.81	3.04	3.43	3.98	5.45
From output (%)	76.4	76.9	77.8	79.4	81	82.2	83.6
From penalty (%)	-10.6	-10.3	-9.9	-8.9	-7.2	-4.7	0
From outside option (%)	34.2	33.4	32.1	29.6	26.1	22.4	16.8
Markdown	0.057	0.064	0.075	0.093	0.111	0.124	0.139
Share workers (%)	0.00	0.10	0.10	0.30	0.70	2.40	21.50
HHI				0.133			

Fixed cost				0.01			
Percentile productivity	0%	10%	25%	50%	75%	90%	100%
Firm's productivity	3.25	3.33	3.49	3.79	4.33	4.92	6.12
Total wage	2.98	3.04	3.15	3.38	3.83	4.30	5.33
From output (%)	78.8	79.1	79.7	80.7	81.7	82.3	83.4
From penalty (%)	-9.5	-9.2	-8.7	-7.7	-5.8	-3.7	0
From outside option (%)	30.7	30.1	29.1	27	24.2	21.3	17.2
Markdown	0.086	0.090	0.097	0.107	0.118	0.125	0.137
Share workers (%)	0.20	0.30	0.30	0.60	1.60	4.60	23.80
HHI				0.152			

Fixed cost				0.5			
Percentile productivity	0%	10%	25%	50%	75%	90%	100%
Firm's productivity	5.15	5.24	5.35	5.59	5.98	6.18	6.37
Total wage	4.45	4.54	4.64	4.87	5.22	5.44	5.61
From output (%)	81.6	81.8	82.3	82.7	83.2	83.4	83.5
From penalty (%)	-6.3	-5.9	-5.3	-3.9	-2.2	-0.9	0
From outside option (%)	22.9	22.6	22.0	21.0	20.0	19.0	18.4
Markdown	0.117	0.120	0.125	0.130	0.134	0.137	0.138
Share workers (%)	5.80	6.80	8.30	12.70	24.80	38.50	47.30
HHI				0.434			

Table 22: Wage decomposition and markdowns by firm's productivity for $\theta = 0.60$

Fixed cost				0			
Percentile productivity	0%	10%	25%	50%	75%	90%	100%
Firm's productivity	3.70	3.78	3.93	4.20	4.68	5.29	7.06
Total wage	3.19	3.22	3.30	3.45	3.70	4.06	5.19
From output (%)	58.1	58.6	59.5	61.1	63.2	65.3	68
From penalty (%)	-10.2	-10.1	-9.9	-9.3	-8	-6.1	0
From outside option (%)	52.1	51.5	50.4	48.2	44.8	40.7	32.2
Markdown	0.140	0.147	0.160	0.181	0.209	0.234	0.265
Share workers (%)	0.00	0.00	0.10	0.10	0.40	1.40	18.40
HHI				0.097			

Fixed cost				0.01			
Percentile productivity	0%	10%	25%	50%	75%	90%	100%
Firm's productivity	4.05	4.13	4.25	4.52	5.01	5.52	7.12
Total wage	3.38	3.42	3.48	3.63	3.89	4.23	5.25
From output (%)	59.9	60.4	61	62.3	64.1	65.5	68
From penalty (%)	-9.8	-9.7	-9.4	-8.7	-7.3	-5.3	0
From outside option (%)	49.8	49.2	48.3	46.4	43.2	39.7	32.2
Markdown	0.165	0.172	0.181	0.197	0.220	0.236	0.265
Share workers (%)	0.10	0.10	0.20	0.30	0.80	2.20	20.10
HHI				0.107			

Fixed cost				0.5			
Percentile productivity	0%	10%	25%	50%	75%	90%	100%
Firm's productivity	5.65	5.71	5.79	5.99	6.33	6.67	6.94
Total wage	4.30	4.35	4.41	4.53	4.79	5.05	5.26
From output (%)	65.2	65.5	65.8	66.1	66.4	66.7	66.9
From penalty (%)	-7.5	-7.2	-6.6	-5.4	-3.5	-1.6	0
From outside option (%)	41.8	41.3	40.6	39.2	37.3	35.6	34.1
Markdown	0.234	0.237	0.240	0.243	0.247	0.250	0.253
Share workers (%)	3.00	3.30	4.10	6.30	11.90	21.70	33.50
HHI				0.254			

Table 23: Wage decomposition and markdowns by firm's productivity for $\alpha = 0.50$

F Counterfactuals appendix

F.1 Rebating profits to workers

I investigate simple tax policies mimicking a planner's two choices - entry and vacancy decisions. I focus on the impact on different labor market outcomes, including total output. I start by implementing a linear tax on output. As it reduces profits of firms, it influences both their entry and vacancy posting decisions. A fraction τ of the output is collected from all matches and rebated equally to all workers - both employed and unemployed. Surplus and equilibrium wages at firm i are now:

$$\begin{aligned} \rho S_i &= (1-\tau)\cdot z_i - b - \delta S_i + \sum_{j=1}^{N} \lambda^j \left((1-\alpha)S_j - S_i\right) \mathbb{1}_{\{S_j > S_i\}} - (1-\alpha)\sum_{j=1}^{N} \lambda_0^j S_j \mathbb{1}_{\{S_j>0\}} \\ w_i &= (1-\alpha)(1-\tau)\cdot z_i + \alpha b - \alpha(1-\alpha)\sum_{j=1}^{N} \lambda^j S_j \mathbb{1}_{\{S_j > S_i\}} + \alpha(1-\alpha)\sum_{j=1}^{N} \lambda_0^j S_j \mathbb{1}_{\{S_j>0\}} \end{aligned} \tag{22}$$

As only a fraction $(1-\tau)\cdot z_i$ is left available for firms to sell, it is internalized in the surplus and the bargaining process. Notice though, that as the tax is rebated to both employed and unemployed workers, the rebate does not appear in neither equations. If one had decided instead to rebate the tax to employed workers only, it would have increased the surplus of the match and decreased further the wage paid by the firm.

Surplus and wages decrease linearly with the level of the tax. Keeping everything else constant, one can see that firms with low productivity are the first to exit when τ increases. Mirroring the discussion on the entry cost, this could lead to an increase in concentration. Yet, in addition to affecting the lower tail of the productivity distribution, the tax also pushes larger firms to post relatively fewer vacancies because of the convexity of the vacancy cost.

I turn to numerical simulations. I keep the parameters from the previous estimation fixed and vary the tax from 0 to 75% of output. Above that level, almost no firms are able to operate in

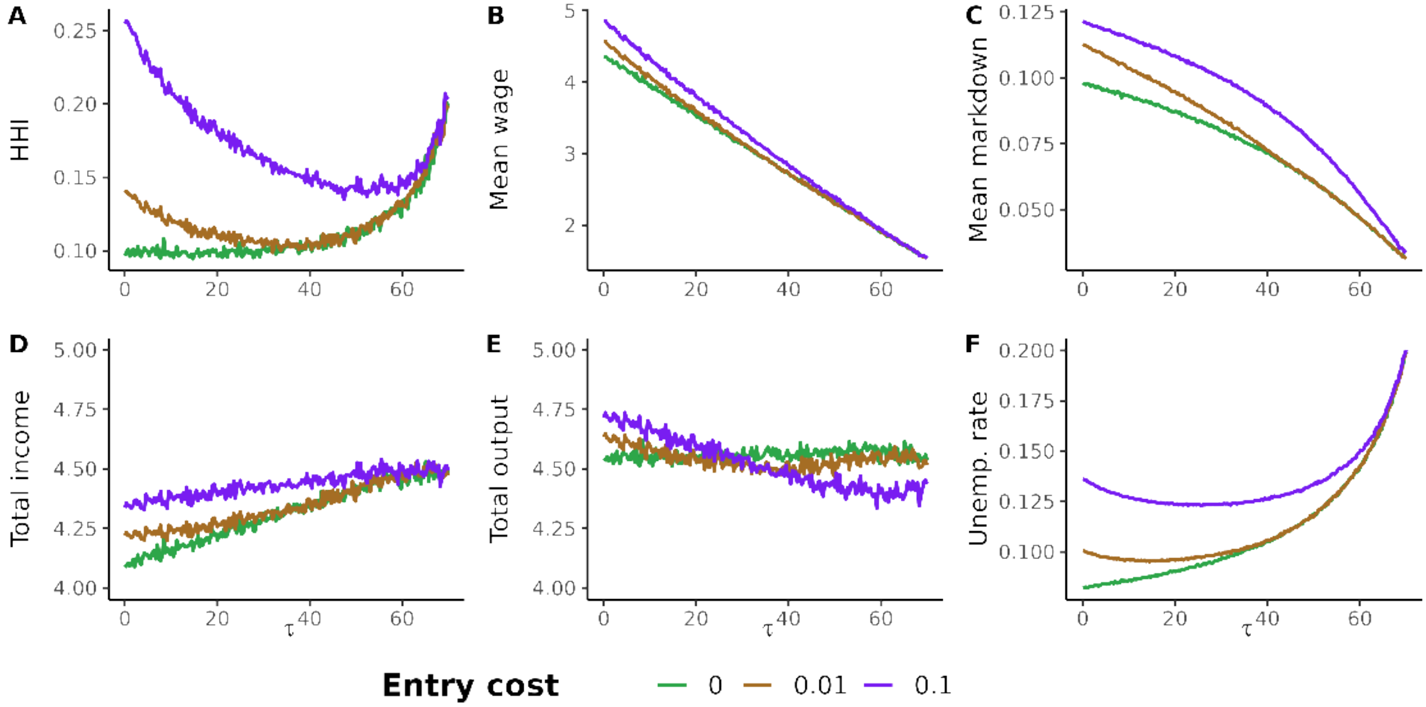

Figure 17: Taxing output and rebating it to workers

the market. For each value of τ, I simulate 120 different labor markets, mirroring what was done during the estimation. I then average the HHI, the mean wage, the mean markdown in the labor market, the unemployment rate, the total income to all workers (defined as the sum of all wages paid to workers, unemployment benefits of unemployed workers, and the total tax collected), and the total output (sum of output from firms and unemployment benefits of unemployed workers, minus entry costs and vacancy posting costs) across all simulations. Results are displayed in figure 17.

Depending on the initial composition of firms, results are very different. When no entry cost exists (green curves), concentration increases from 0.10 to 0.15 when τ increases as is depicted in panel A. Two contradictory forces compete – small firms exiting and large firms posting less vacancies, and the former dominates the latter. Instead, when high entry costs already exist (purple curves), concentration first decreases as large firms post relatively less vacancies and firms entering are productive enough to absorb an extra tax on output. When τ increases further, relatively productive firms start exiting the labor market, increasing concentration.

Consistent with the wage equation above, mean wage declines sharply -and linearly- with τ. Mean markdowns applied to wages (defined as the average across firms of$\eta_i = 1 - \frac{w_i}{(1-\tau)\cdot z_i}$) also decrease. Unemployment rate increases relatively sharply with τ as firms post less vacancies. Despite having less employed workers, and paid less overall, total income to workers increases as profits are now rebated from firms to workers. Taxing output both increases income to workers, and reduce inequalities as it shrinks the wage gap between all workers.

Coming back to the planner's objective, the effects on total output depends on the initial entry costs. When entry is not restricted, many small and unproductive firms crowd the vacancy market, preventing more productive firms from hiring a larger fraction of the workforce. Increasing τ deters those firms from entering. Despite increasing unemployment rate, a relatively larger share of the population becomes employed at more productive firms, increasing total output. In markets where unproductive firms are already not present, increasing taxes only deter large firms from posting more vacancies and hiring a larger workforce - increasing unemployment and decreasing total output. Taxing output seems to be an effective way to remove unproductive firms from the planner's perspective according to my model. It does not incentivize productive firms from posting more vacancies though, and employment is never as concentrated among productive firms as in the planner's solution.

F.2 Subsidizing or taxing entry of firms

I look at the impacts of a second set of policies - taxing output to subsidize the entry of firms or taxing entry itself. It corresponds to the planner's second tool to maximize output by deciding which firms enter. If one takes the entry cost as given (cost of building a factory for instance), a planner can still reduce it by subsidizing firm's entry (e.g. easing administrative restrictions or developing infrastructures), or, on the contrary, make it costlier to enter a market - even if that means wasting some of the output produced.

In taxing output and subsidizing entry, the surplus and wage equations remain the same as in equations 22, as output left to sell is again $(1-\tau)\cdot z_i$, but none of the worker's value functions

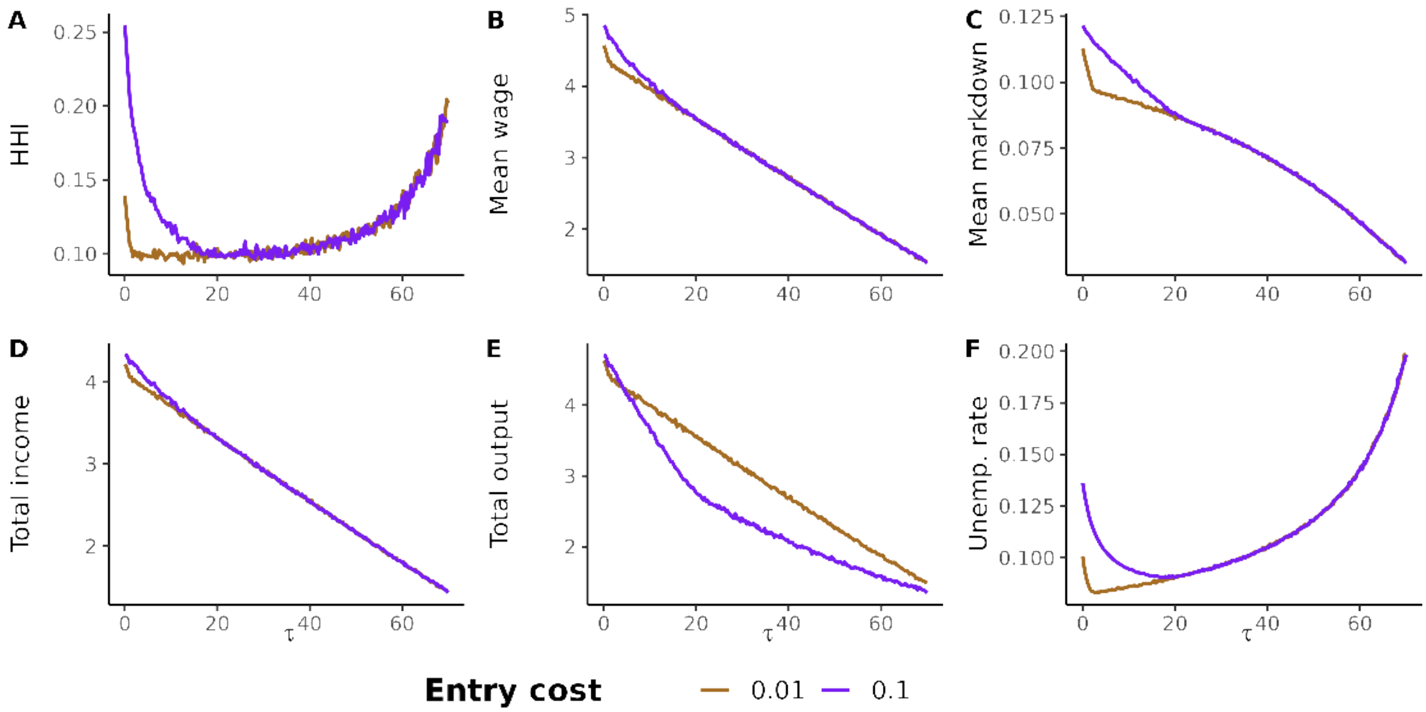

Figure 18: Subsidizing entry by taxing output at different entry costs

change compared to the equilibrium with no tax. Firm's vacancy posting decision is affected, and the more so for larger firms. Yet there is now an interesting tension happening for low productivity firms. Taxes decrease their output, making it harder for them to be productive enough to operate once they entered, but help them entering nevertheless.

I simulate the policy in the same vain as before. I need to take a stand as to how taxes are rebated to entering firms. I assume it decreases the entry cost equally for all firms that are productive enough to enter once the subsidy is factored in. I solve the equilibrium labor market as before: all firms draw a productivity, I solve for the equilibrium distribution (now with the tax), compute the equilibrium profits and compare them to the fixed cost minus the rebate (which equals the total amount collected in taxes divided by all firms). I then drop firms one by one until all firms that operate can afford paying for the discounted entry cost. Results of the simulations are displayed in figure 18.

The policy reduces concentration even more compared to the previous policy, as larger firms

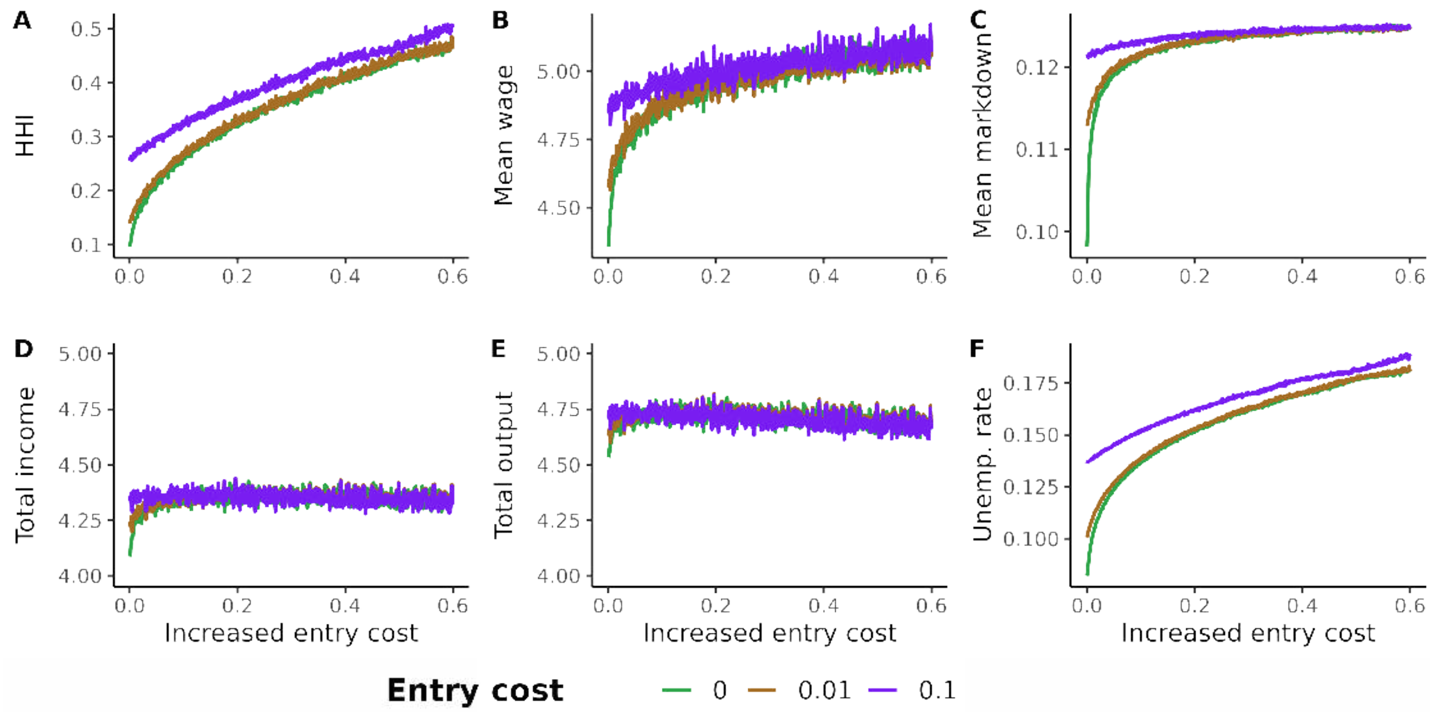

Figure 19: Taxing entry at different initial entry costs

post fewer vacancies and small firms enter the market again. Yet, as output is wasted on helping small, unproductive firms, total output, wage, and income decline sharply when unemployment increases. The planner never chooses to implement such a policy.

The last policy is more nuanced - I offer the planner the choice to increase the entry cost. It helps removing small, unproductive firms but forces firms entering to spend a larger share of their output on the entry cost. It amounts to varying the total entry cost, and results are very similar to the ones we have seen so far in this paper. Results are displayed in figure 19.

Focusing on the total output, when no entry cost exists in the fist place (green curves), the planner manages to remove small firms, allowing larger firms to control a large share of the vacancies, hiring more, and therefore producing more. The effects are small though, around 4%. Unemployment rate, concentration and markdowns increase as a result. On the contrary, when a substantial fixed cost is already preventing those small firms to enter (purple curves), increasing it further barely changes total output produced but increases markdowns, concentration and unemployment.

Depending on how hard it already is to enter a labor market, a planner might decide to abstain from intervening on the entry margin[28], or increase the entry cost to remove small firms. This policy also seems to increase total output by more than taxing production, as it does not incentivize large firms to post less vacancies, and gets closer to the first-best solution (from close to 4.53, to 4.72, but still far from the 4.83 from the planner's solution).

[28]Notice here that all the extra entry cost is wasted. If a planner had a way to recover part of that cost and rebating to workers, total output might increase as a result.