Granular Search, Market Structure, and Wages

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Abstract

We develop a model where labor market structure affects the division of surplus between firms and workers. In a model of random search and large employers, workers might apply to another job controlled by the same employer in the future. This possibility endows firms with size-based market power. The reason is that outside options are truly outside the firm: firms do not compete with their own vacancies. Hence, a worker's outside option is worse when bargaining with a larger firm, and wages depend on market structure. We calibrate the model to Austrian data and find that such size-based market power depresses wages.

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There has been a revival of interest in understanding the effect of market power on many aggregate outcomes, including wages. Recent and standard approaches to modeling market power in the labor market have built on the monopsony tradition of Robinson (1933) (e.g., Card et al. (2018), Berger, Herkenhoff, and Mongey (2021), Lamadon, Mogstad, and Setzler (2020), MacKenzie (2018) and Haanwinckel (2020)). The core idea in these models is that there is a tight link between prices and quantities. Given a finite (residual) labor supply elasticity to the firm, firms "underhire" and "underpay" relative to the perfectly competitive benchmark. In this paper, we develop a new model of labor market power which reflects fundamentally different forces.

There are two related motivations to develop a new model. First, there is evidence from labor market settings that changes in market structure sometimes affect prices but not quantities, which is not a prediction of the standard model. For example, Prager and Schmitt (2021) study hospital mergers and find that merging employers reduce wages but not employment. Our second motivation is that in general—and as emphasized by Hemphill and Rose (2018)—changes in market structure can affect wages through changes in bargaining leverage (rather than labor supply elasticities): intuitively, given a fixed amount of surplus, if market structure gives some firms more bargaining leverage than other firms, then they will pay lower wages. Such a model naturally generates effects of market power on prices but not quantities: if bargaining is bilaterally efficient, then the terms of trade (prices) are affected, but not the allocations (quantities). While this bargaining leverage idea is natural, we do not know of a labor market model that relates the bargaining leverage of employers to market structure.

We develop a model of size-based market power by building on the structure of a canonical search and bargaining model in the Diamond-Mortensen-Pissarides tradition, but relaxing the assumption of a continuum of firms. Our model features bargaining between firms and workers, and hence allows us to study differences in bargaining positions. By relaxing the assumption of a continuum of firms, we allow for differences in firm size and market structure. The model shows how differences in size and market structure translate into variation in bargaining positions.

Our model builds from a distinctive prediction of the (random) search perspective on labor markets: once we relax the assumption of a continuum of firms, workers face a positive probability of re-encountering past employers. Naturally, workers are more likely to re-encounter larger firms (i.e., firms with a higher market share). Why does the possibility of a future re-encounter affect the bargaining position of a firm? As is standard, wages depend on a worker's outside options, which capture alternative job opportunities that a worker might find. If we add large firms to the standard set-up and leave everything else unchanged, then a large firm competes with itself since the worker's outside option includes the firm's own future vacancies.

Instead, in our model, firms are not their own competitors: in particular, outside options are truly outside the firm and their own future vacancies are not part of the worker's outside option. Hence, a worker's outside option is worse when bargaining with a large firm and so wages are lower. Moreover, the outside option depends on both the size of her own employer and the overall distribution of employment shares in the labor market (market structure). Naturally, the outside option is worse if the overall distribution of employment is more concentrated.

This model generates a theory of market power which corresponds closely to the "lay" intuition of how market power operates: if there is a single large employer, then workers do not have other options: the firm implicitly says, where else are you going to work? Importantly, this merely affects the terms-of-trade but not, to a first order, quantities. This property implies that more market power does not lead to "underemployment," as the standard labor supply model would emphasize.

We show that the overall extent of competition is summarized by a particular concentration index which is closely related to the Hirschman-Herfindahl Index (HHI). As such, our model provides a novel microfoundation for the HHI and for work (e.g., Azar, Marinescu, and Steinbaum (2020)) that relates wages to concentration as measured by the HHI. The intuition for why such a concentration index emerges is simply that in a random search setting the sum of squared market shares captures the ex-ante probability of twice encountering the same firm.

We then extend the model to accommodate a second dimension of heterogeneity, productivity, which allows us to match additional features of the micro-data, such as the positive size-wage gradient. In the richer model, we can separate the effects of employment concentration and productivity concentration.

To ground our theory empirically, we show some evidence on the basic idea in our model and quantify its strength. Our empirical setting is Austria from 1997-2015. The empirical implementation faces the basic challenge of market definition: what counts as a labor market? We build on Nimczik (2018) to define labor markets based on worker flows. Formally, we cluster firms on the basis of worker flows, where our model of clustering is a stochastic block model. This data-driven notion makes market definition an empirical question, rather than an *a priori* choice such as geography or industry. We view these data-driven boundaries as complementary to standard boundaries and also report results for the latter.

The basic idea in our model is simply that workers cannot "escape" big employers and are likely to re-encounter them in the future. Firms do not compete with these future re-encounters because outside options are truly outside the firm. In our model, an on-equilibrium version of a re-encounter is to see workers return to firms after having been employed elsewhere. Aggregating this idea to the market level, a high HHI implies a high likelihood of re-encounters. We define the re-encounter rate to be the probability of these re-encounters relative to the probability of moving twice. This re-encounter rate is fundamentally a firm-level measure and so does not depend on market definition. Hence, we can use it to assess whether the level of concentration implied by any given market definition is matched by worker behavior, and thus whether it delivers a measure of concentration that is empirically plausible.

Empirically, we show that more concentrated markets indeed have higher re-encounter rates. Moreover, the magnitudes are surprisingly similar to what we would expect based on a stylized version of our model, and are especially similar in the data-driven labor markets. Thus, we view the evidence from the re-encounter rate as supportive of the basic random search perspective on what would be distinctive about a more concentrated labor market, as well as our use of the data-driven labor markets.

We then consider three quantitative exercises to illustrate the potential magnitudes of size-based labor market power. Our first exercise replaces firms with a continuum of infinitesimally small firms which eliminates size-based market power and hence allows us to quantify its wage consequences. The median market experiences an increase in the labor share of 2.4%. The average labor share rises by 10%, which reflects a highly skewed distribution where a few markets that are almost monopsonistic experience very large wage gains.

We then revisit this exercise in an extended model that allows for on-the-job search. On-the-job search is an interesting extension because it increases the competition for workers since workers can escape an employer. Adding on-the-job search leaves the median gains nearly unchanged, while reducing the average gains. The reason is that with on-the-job search large employers now face additional competition and so cannot markdown wages as much. This force is particularly strong in extremely concentrated markets. Nonetheless, we present the theory (and empirical results) in a setting without on-the-job search because it allows us to derive and employ closed-form expressions that clearly elucidate the key mechanisms.

Our second exercise shows that, through the lens of the baseline model, changes in concentration have contributed to the observed decline in the Austrian labor share. From 1997 to 2015, movements in concentration reduced the Austrian labor share by over one percentage point, which is about forty percent of the observed change. About half of this effect comes from the increasing concentration of productivity in large firms.

Our third exercise evaluates the labor market consequences of mergers (Naidu, Posner, and Weyl (2018) and Marinescu and Hovenkamp (2019)). To do so, we simulate the merger of the two largest employers in each labor market and re-compute wages at all employers. On average, wages at merging firms decline by seven percent. Crucially, the mergers have large spillovers to all other employers who, recognizing the reduction in competition, reduce their wages by about three percent. Interestingly, our model implies non-linear effects of concentration on wages so that mergers have particularly large effects in markets that are already highly concentrated.

Relationship to the literature: Besides the literatures already discussed, our paper is conceptually related to Stole and Zwiebel (1996). In that paper, firms manipulate size to affect workers' wages, and so it is similar to our paper in finding a connection between size and wages. The key difference is that in Stole and Zwiebel (1996) firms manipulate size to affect workers' inside option (the marginal product of the match), whereas in our model, size affects workers' outside options.

Our paper is also related to models of imperfect competition in the posting tradition of Burdett and Mortensen (1998), such as Manning (2003) and Gouin-Bonenfant (2020).[1] One difference is that these models have a continuum of firms and so do not share the notion of size-driven market power studied in this paper. More broadly, Manning (2003) terms this the "dynamic monopsony" model because it provides a microfoundation for the upward-sloping labor curve (to the firm) of

[1] See also Webber (2015) and Webber (Forthcoming).

Robinson (1933), and so generates the same tight link between prices and quantities: firms that pay less are smaller.

Our paper joins a literature that emphasizes variation in outside options in generating wage variation. Some examples include Beaudry, Green, and Sand (2012), Caldwell and Danieli (2021), Schubert, Stansbury, and Taska (2020), and Arnoud (2018) (see Jaeger et al. (2020) for a dissent). The key novelty is that we emphasize the role of employer size in affecting outside options.

We are not the first paper to consider the role of finiteness in search models. Menzio and Trachter (2015) consider a large firm and a continuum of small firms in the product market. Analogously, Burdett (2012) considers one (non-strategic) large firm (the public sector) in the context of the Burdett and Mortensen (1998) model. There is also a literature on market power in the directed search literature, e.g., Galenianos, Kircher, and Virag (2011). In the context of this literature, our mechanism is distinct. Similarly, Zhu (2012) studies an over-the-counter market where when a seller recontacts a buyer the buyer updates negatively about the quality of the seller's good; this adverse-selection-like channel is not the operative mechanism in our model.

Outline: This paper proceeds as follows. Section 1 presents the baseline model and analyzes its implications for wages. Section 2 extends the model to include productivity heterogeneity and analyzes the implications for wages and pass-through of productivity shocks to wages. Section 3 presents some institutional background, introduces the matched employer-employee data from Austria that we use, discusses how we define labor markets using worker flows, and describes how we parameterize the model. Section 4 presents some stylized facts. First, it documents the empirical importance of the granularity that we emphasize in the model: namely, that workers are likely to reencounter employers, and are especially likely to do so in more concentrated labor markets. Second, it shows aggregate trends in labor share and concentration in Austria. Section 5 presents our quantitative results about the role of levels and trends in market structure in explaining levels and trends in wages. Section 6 presents our merger simulations. Section 7 concludes.

1 Granular search

In this section, we develop a partial equilibrium random search model in which workers apply to job openings that are distributed across a finite number of firms. Wages are set through Nash-bargaining and we introduce our key idea: granular employers exert market power by not competing with themselves.

We characterize the relevant concentration index capturing market structure and the mapping to average wages as well as the firm size-wage gradient. In Section 2, we extend the framework to allow for heterogeneous productivity across firms.

1.1 Set-up

We study a discrete time economy populated by a measure one of infinitely lived homogeneous workers. Workers are either employed, producing a flow output of one unit of the economy's single, homogeneous good, or workers are unemployed. The common discount factor is $0 < \beta < 1$.

An employed worker experiences a separation shock at rate $\delta > 0$. In this event, the worker flows back into unemployment. An unemployed worker receives flow value $b < 1$.

Firms are granular and control a positive measure of vacancies. Because there is exogenous job destruction and no on-the-job search, the vacancy share also corresponds to the employment share. There are N distinct firms. The probability that a particular job opening is at firm i is given by time-invariant f_i and so $\sum_{i=1}^{N} f_i = 1$. In a slight abuse of language, we often refer to the firm's market share, f_i, as the firm's size.

Matching: For each job opening, firm i pays a per period fixed cost c_i. The process which pairs unemployed workers with job openings is governed by an urn-ball matching function. Each period, u unemployed workers send one application (balls) towards v vacancies (urns). This matching process is subject to coordination frictions and so some vacancies receive no applications while others may receive multiple. Standard arguments imply that the number of applications a vacancy receives in a period is exponentially distributed.

If a firm receives multiple applications, then it follows up on a randomly chosen one. Subsequently, the firm and the worker bargain over the wage. Specifically, there is continuous Nash bargaining over the wage where $\alpha \in [0, 1]$ denotes the bargaining power of workers. We assume that all job openings have strictly positive surplus so that the job finding rate is given by $\lambda \equiv \frac{v}{u}(1 - e^{-\frac{u}{v}})$ (see, e.g., Shimer (2005)).

Given that firms sometimes receive multiple applications, one natural question is why we assume the firm cannot have the multiple applicants compete for the job opening. The same issue arises in Blanchard and Diamond (1994, pg. 425). They invoke a standard no-commitment assumption to rule out this competition. In particular, the no-commitment assumption means that as soon as the other applicants lose contact with the firm, the hired worker would seek to renegotiate the contract. Similarly, Blanchard and Diamond (1994) also implicitly assume that there are no side payments so that the firm cannot extract the value of the match to the worker in an up-front payment. We follow them here and make both assumptions.

Finally, we assume that firms with multiple job openings treat them in isolation from each other. As a consequence, they cannot consolidate the applications across vacancies, which would give large employers even more market power.

Worker value functions: We let U denote the value of unemployment while W_i denotes the value of a worker employed at firm i. Formally, U satisfies

$$U = b + \beta\left(\lambda \sum_i f_i W_i + (1-\lambda)U\right). \tag{1}$$

Next period the worker receives an offer with probability λ. This offer is from firm i with probability f_i in which case the worker receives value W_i. If the worker does not receive an offer, then she remains unemployed.

In commonly adopted models of wage setting in frictional labor markets, a key determinant of wages is a worker's outside option, namely the value of unemployment. In markets with intense demand side competition, workers find other jobs rapidly which is encoded in the outside option and raises the wage. Suppose employer i and a potential hire were using equation (1) to determine a worker's outside option. Then granular firms would compete with themselves: when bargaining with a particular firm, the worker would effectively claim the same firm's future vacancies as an outside option.

Our key departure is that a firm can remove itself from a worker's outside option, thus preventing competition with itself. To do so, suppose the firm and the worker fail to find an agreement and the worker applies to a job opening controlled by the same employer in the future. In the event that the vacancy received multiple applications, the firm can break the tie by hiring one of the other applicants. This tie-breaking rule allows the employer to (partially) remove its own job openings from the outside option of the worker in the wage bargain. Importantly, this strategy is costless to the firm since it only applies to situations where workers are rationed and the firm never gives up an opportunity to produce. If a deviating worker happens to be the sole applicant to one of the firm's job openings, then the firm rationally hires the worker. Thus, this mechanism operates through off-equilibrium payoffs and the parties never fail to reach agreement.

To make the analysis tractable, we make a particular assumption on the duration of this disagreement "punishment." We assume that, as soon as a job opportunity arises at some other employer j, the worker gets released from the punishment state by firm i. This restriction substantially reduces the state space since it cuts the histories the agents have to keep track of.

In order for the punishment to have bite, we assume that workers cannot direct their applications away from firm i. That is, a worker applies to firm i with probability f_i, no matter what the chances are that she will be hired. This assumption is consistent with an interpretation of the search process as one where workers randomly encounter job openings and is a natural benchmark. More broadly, it captures the idea that jobs are imperfect substitutes in the search process.

In a slight abuse of notation, we denote by U_i the continuation value of the worker in the event of a trade breakdown with firm i, which satisfies

$$U_i = b + \beta\left(\lambda \sum_{j\neq i} f_j W_j + \underline{\lambda} f_i W_i + (1-\lambda(1-f_i) - \underline{\lambda} f_i)U_i\right). \tag{2}$$

This equation states that, after disagreement with employer i, a worker's probability of meeting and subsequently working for any other employer j are unaltered. Moreover, the value of working for employer j does not depend on the worker's history. However, if the worker applies to a vacancy controlled by i, then she only gets hired if she is the only applicant, which happens at rate $\underline{\lambda} \equiv e^{-\frac{u}{v}}$. With complementary probability $1 - \lambda(1 - f_i) - \underline{\lambda} f_i$ the worker remains unemployed. Critically, if employer i is larger, then rejecting i's offer leads to a larger reduction in the job finding rate and so the outside option when bargaining is worse.

We note that equation (2) does not require commitment power for the firm since it is costless for the firm to select another applicant. It only imposes that the firm "recognizes" a worker under punishment.

Let w_i denote the wage firm i pays under the Nash bargaining solution. The value of working for firm i then satisfies

$$W_i = w_i + \beta\Big(\delta U + (1 - \delta)W_i\Big). \tag{3}$$

This equation says that the value of being employed at firm i is the wage at firm i plus a continuation payoff, which weights the probability of the job being exogenously destroyed and entering unemployment or remaining employed. Importantly, following an exogenous breakdown of an employment spell, a worker is free to return to another vacancy posted by the same employer. Thus, the outside option when bargaining and the value of unemployment following a job spell differ.[2]

Discussion of punishment: Before we discuss the plausibility of the punishment, it is important to re-iterate what it implements: it makes the outside option of a worker truly *outside*, namely, the outside option refers to jobs outside the employer with which she is bargaining. In a granular search context where there is a positive probability of re-encountering the same firm in the future, this outcome seems natural. In contrast, the alternative assumption that somehow a worker threatens a firm with itself in the wage bargain seems very unnatural. Key for this paper is the outcome of the micro-foundation: firms do not compete with themselves.

We now provide some suggestive evidence that our micro-foundation is plausible and approximates real-world behavior and institutions.

First, for our mechanism to work, firms need to keep track of past applicants, in particular those they have bargained with. We now discuss three pieces of evidence which suggest that firms have the technology to remember job applicants: First, both in the U.S. and in Austria, there are legal requirements to store job applications; e.g., in the U.S., the Civil Rights Act of 1964 requires that firms store job applications for at least a year. Second, online advice suggests that it is common for employers to retrieve information about its past interactions with an applicant.[3] Third, we

[2] This assumption is not central to our mechanism and it is feasible to solve the model with the assumption that workers who exogenously lose their jobs enter state U_i, rather than U. But a firm would hurt itself by carrying out this punishment. In equilibrium, a firm that promised to "punish" its exogenously displaced workers by not hiring them would have to pay higher wages to compensate workers for the worse prospects in case of job loss.

[3] "Many organizations use applicant tracking systems to manage their recruiting efforts, and the system will

examined 200 job applications by sampling the stock of jobs on indeed.com in early April 2020. We found that over half of job applications ask whether a worker has previously worked at an employer, and almost 10 percent asked whether a worker had previously applied.[4] In sum, it is plausible that employers can remember past applicants, especially within the fairly short duration of an unemployment spell as required by our model.

Second, our mechanism posits that the threat to not hire re-applicants is credible. This threat plays out in the event of trade breakdown which only happens off-equilibrium. Hence, the common belief that this could occur would be sufficient to establish credibility. Online job boards are filled with questions about applying to employers previously turned down and re-applying for jobs one was turned down for. Among other things, they suggest that being "blacklisted" occurs.[5] Similarly, one common piece of advice on job boards is that it is important to provide a good reason why circumstances have changed if one wants to re-apply to the same firm.[6] Consequently, the fact that the duration of the punishment in our micro-foundation is limited to within an unemployment spell makes it unlikely that the worker's circumstances have changed and, hence, unlikely for the worker to apply again (let alone to be successful if they did).

Taken together, this evidence suggests that claiming an employer's other job openings as an outside option is implausible: workers that have been turned down for jobs (or turned down jobs) are not necessarily welcomed back; and firms have the informational requirements to be able to credibly keep track of workers and deny the worker this part of her outside option.

Firm value functions: Firm i values the bilateral relationship with each of its workers at J_i satisfying

$$J_i = 1 - w_i + \beta(1-\delta)J_i. \tag{4}$$

This equation says that the value to firm i of filling the vacancy is the flow output of the match less the wage, and, in the event that the job is not exogenously destroyed, the job continues. Note that this equation reflects the assumption discussed below that the job has no continuation value

show the recruiter that you have applied previously. That fact isnt going to slide under the radar." https://www.themuse.com/advice/ask-an-honest-hr-professional-reapply-for-a-job-after-rejection (last accessed, April 23, 2020).

[4] A detailed description of our sampling procedure on indeed.com can be found in Appendix D. In Austria, online job applications are less prevalent and less detailed than in the U.S. Nevertheless, sampling 60 applications on monster.at in April 2020, we found that 24 percent of all applications asked for previous employment at the same employer.

[5] E.g., "Personal experience with this exact thing...has resulted in me being"blacklisted" with a company here in town - and that was over 3 years ago" https://workplace.stackexchange.com/questions/19359/re-applying-to-a-company-after-declining-a-job-offer (last accessed April 23, 2020).

[6] For example, "No, it's not wrong if it's a job you really want and can convince the employer that the reason you turned down the job previously was not because of the employer or the job." https://www.quora.com/Is-it-wrong-to-reapply-to-a-position-you-previously-declined (last accessed April 23, 2020). Similarly, "For that reason [because employers typically know who previously applied], its best to be direct and include a cover letter that mentions that youve applied before and also highlights why youre a stronger candidate now." https://www.themuse.com/advice/ask-an-honest-hr-professional-reapply-for-a-job-after-rejection (last accessed, April 23, 2020).

after an exogenous separation (i.e., $V_i = 0$). In turn, we have that a job opening has value

$$V_i = -c_i + \beta(1 - e^{-\frac{u}{v}})J_i. \tag{5}$$

To keep a vacancy open, firm i pays fixed cost c_i. The term in parentheses captures the probability that the job opening receives at least one application this period. In equilibrium, trade never breaks down and the match is always formed.

Surplus and wage determination: The joint net value of forming a match ("surplus") is given by

$$S_i \equiv W_i - U_i + J_i. \tag{6}$$

In words, once the firm has followed up on one of the applications, the pair can form a match or not: if the match forms, then the worker is in state W_i and the firm moves into state J_i. In turn, under disagreement, the worker moves into state U_i while the firm has no continuation value.

We adopt the axiomatic Nash bargaining solution to the bargaining problem. In this case, the wage implements a surplus split such that the net value of forming the match to the worker is

$$\alpha S_i = W_i - U_i, \tag{7}$$

while the net value of forming the match to employer i is

$$(1-\alpha)S_i = J_i. \tag{8}$$

Throughout, we already anticipate the result that in equilibrium workers are willing to work for all firms i. That is $S_i \geq 0 \, \forall i$.

Discussion of the entry condition: We are interested in the role of size as a source of labor market power. We therefore simply read the f_i off the data and study its consequences for wages rather than exploring its origins. We also follow the convention in the Diamond-Mortensen-Pissarides literature and close the model by imposing a standard implication of a free entry condition.

In particular, we impose that $V_i = 0, \forall i$ by picking the c_i to make equation (5) hold. This inversion procedure defines a flexible function that relates the cost of creating vacancies to size.[7] By construction, firms are indifferent across points on the cost schedule, which rationalizes our posited equilibrium.

We revisit this point in the context of the extended model in Section 2 and then again when we conduct model-based exercises in Section 5.

[7]There is plenty of direct firm-level survey evidence that vacancy and hiring costs per vacancy increase with firm size, see e.g. Barron and Bishop (1985, Table 3) for the U.S., Blatter, Muehlemann, and Schenker (2012, Table 6) for Switzerland, and Kiarsi and Muehlemann (2020, Table 5) for Germany.

Summary: Our model combines three conceptual ideas so that concentration of employment affects wages. First, competition for workers affects wages through the bargaining/outside option channel. Second, for workers, random search and the imperfect substitutability of job openings in the search process implies that the ability of large employers to remove their own jobs from the outside option is functional in depressing wages. Third, the urn-ball matching function implies that in most situations firms view job applicants as perfect substitutes. This substitutability introduces the important asymmetry in the model: workers value the possibility of a future encounter with the firm, but the firm does not (and, hence, it is costless to the firm to rule out a future match).

This asymmetry between firms and workers is shared with the "classical" monopsony set-up (in the terminology of Hemphill and Rose (2018)) of Robinson (1933) and its descendants where firms view workers as perfect substitutes (sometimes this perfect substitutes assumption only occurs within worker "type"), and the worker's idiosyncratic preferences make firms imperfect substitutes.[8] Thus, while the assumption that firms view workers as perfect substitutes is a strong one, it is shared with—and central to—the other dominant approach to modeling firm market power in the labor market. Relaxing this assumption by allowing workers to differ in how "granular" they are and thus studying two-sided market power is a fascinating question that we leave to future research.

1.2 A Concentration Index

We are interested in the mapping between market structure – in particular, employment concentration – and equilibrium wages. Concentration is frequently measured via the HHI. But concentration has no inherent cardinality so the right choice of units depends on the question and model at hand. This subsection presents a particular concentration index that shares many similarities with the HHI and turns out to be the right way to summarize market structure in our model. That is, the concentration index this subsection introduces will govern wages according to our model as we show below.

Let $f^k \equiv \sum_i f_i^k$ such that $f^1 = 1$ and f^2 is the HHI index for employment shares in our labor market with $0 \leq f^2 \leq 1$. The following is the relevant concentration index in our environment.

Definition 1. *Let $\tau \equiv \alpha \frac{\beta(\lambda - \underline{\lambda})}{1-\beta(1-\lambda)} \in (0, \alpha)$. Define concentration as*

$$\mathcal{C} \equiv \frac{\sum_{k=2}^{\infty} \tau^{k-2} f^k}{1 + \tau \sum_{k=2}^{\infty} \tau^{k-2} f^k}.$$

This concentration index turns out to be the model-relevant measure of market structure, which we demonstrate in Proposition 1 below. Why does the model generate a concentration index? Briefly, random search implies that workers re-encounter firms.

The first summand in this expression is exactly the HHI. It captures the (ex-ante) probability that a worker's second match is the same as its first and, therefore, not competition. The reason all

[8] Empirically, we find that 17% of the overall wage variation (in 2015) is explained by our 368 data-driven labor markets. This compares to 38% of the variance that is explained by the 39,798 firms. Thus, the data-driven labor markets go a long way towards segregating workers by skill.

the higher-order terms appear is that the worker may re-encounter the same employer several times in a row. The τ weights the higher-order terms and emerges because these encounters happen in the future and so are appropriately discounted. In particular, τ summarizes how costly punishment is for workers (given the firm size distribution and the size of the current employer): it is increasing in the share of surplus that a worker gives up when under punishment (α), and in the strength of the punishment ($\lambda - \underline{\lambda}$; i.e., the probability of matching with an employer and there being multiple applicants).[9]

This concentration index is different from—yet very closely related to—the standard HHI. It is closely related to the HHI in that the first element of the sum terms is simply f^2, the HHI. What differs is the presence of the higher order terms which we just explained. In addition, the index is increasing in τ and hence depends on model parameters. As perceived by the worker, concentration increases when punishment becomes more costly. Therefore, in principle, concentration as measured through the lens of our model and the HHI might differ.[10] However, we find that the HHI and $\mathcal{C}$ are very similar in the Austrian data, both in terms of level and trends.

Our index also shares the same bounds as the HHI: in the limit with atomistic employers, we have that $\mathcal{C} = 0$, just like the HHI. In the limit of a single monopsonistic employer, we have that $\mathcal{C} = 1$, just like the HHI.[11]

1.3 Concentration, Average Surplus, and Wages

We now state the structural mapping from $\mathcal{C}$ to wages. Define $\omega_i \equiv \frac{w_i - b}{1-b}$ to be the worker share of flow surplus at firm i (recall that all firms produce flow output of 1), which we refer to as *compensation*. Let $\bar{\omega} \equiv \sum_i f_i \omega_i$ denote mean compensation, which is an affine transformation of mean wages and hence shares its comparative statics. Our first result is the following:

Proposition 1. *The equilibrium relationship between (employment-weighted) mean compensation and concentration is:*

$$1 - \bar{\omega} = (1-\alpha)\,\frac{1-\beta\,(1-\delta)}{1-\beta\Big(1-\lambda\alpha\,\underbrace{[1-\mathcal{C}]}_{\textit{wedge 1}}-\delta\,\underbrace{[1-\tau\mathcal{C}]}_{\textit{wedge 2}}\Big)}. \tag{9}$$

[9] Going forward, we use the approximation $\tau \approx \alpha\frac{\beta\lambda}{1-\beta(1-\lambda)}$ to avoid clutter. This effectively ignores the possibility that a worker under punishment is the sole applicant which is empirically unlikely (see, e.g., Davis and Samaniego (2019)). This approximation is accurate in the model, for $\lambda = 0.093$ we obtain $\underline{\lambda} = 0.00002$. We derive our main theoretical results under the exact model and only impose the approximation at the very end of the proofs so the reader can find the exact expressions in the appendix. When we implement our framework quantitatively we work with the exact expressions.

[10] In Appendix A we present an example of two economies where these two measures present different rankings. One economy consists of a monopsonist with a competitive fringe, and another consists of all equal-sized firms. By choosing the relative size of the monopsonist in comparison to the equal-sized firms, we can make these two measures move in opposite direction. The reason is that $\mathcal{C}$ places more weight on the largest firm (the monopsonist) than the HHI.

[11] To see these bounds, note that $f^k = 0\ \forall k \geq 2$ in case of perfect competition while $f^k = 1\ \forall k \geq 2$ in the case of a monopsonist.

Proof. See Appendix B.1. □

The denominator in this expression shows that size-based market power introduces two wedges into the wage equation, which reflect the two mechanisms by which increases in concentration decrease wages. In a static setting, the worker would receive a share α of net output, and so $1 - \bar{\omega} = 1 - \alpha$. In a dynamic setting, the worker's share is increased through competition for workers: the parties recognize that the worker has other options, which is the $\lambda\alpha$ term.

The reason for the first wedge is that concentration reduces competition: granular employers do not compete with themselves. So a worker's outside option—which encodes competition—is reduced relative to the atomistic benchmark. Hence, as concentration increases, mean wages fall because workers have deflated outside options.

The reason for the second wedge is that size-based market power inflates the inside option. By reaching an agreement, the pair increases the worker's continuation value in unemployment from U_i to U: the worker has the possibility of returning to the firm. Anything that makes the inside option more attractive relative to the outside option reduces competition and shifts resources towards employers. The strength of this second wedge is decreasing in τ: if unemployment spells are long because the job finding rate, λ, is low, then the worker's return to the firm is further in the future and so it is a less important consideration in wage-setting.

Proposition 1 provides a structural relationship between average wages and market structure. As a consequence, given a set of parameters $\{\beta, \delta, \alpha, \lambda, b\}$, it allows us to directly assess the quantitative contribution of empirically observed employment concentration (and changes therein) to average wages. Given those parameters, measuring $\mathcal{C}$ empirically does not require any more information than the HHI.

We conclude with an important corollary to Proposition 1:

Corollary 1. *Average wages are monotonically decreasing and strictly concave in concentration $\mathcal{C}$.*

Proof. Follows from the definition of ω and differentiation. □

This result provides a theoretical foundation for a negative relationship between concentration—as measured by $\mathcal{C}$— and average wages. Furthermore, the strict concavity is a cautionary note on aggregation: the literature on trends in aggregate concentration often aggregates local concentration measures in a weighted linear fashion (e.g., Rinz (2020)). But if the mapping between concentration and the outcome of interest is non-linear at the local level, then the aggregated trends may be misleading. In our empirical analysis, we find that there are periods where concentration measured as a simple weighted linear aggregate index fell, but using the model we find that concentration changes depressed wages (compare Figures 4a and 2). The non-linearity in the model is the culprit.

1.4 Concentration and Firm-Level Wages

In the previous section, we related market-wide mean pay to concentration. The model also has implications for firm-level wages w_i. We are particularly interested in the relationship between firm-level wages w_i, concentration $\mathcal{C}$, and the size of the individual employer i, f_i.

We summarize our key findings in Proposition 2:

Proposition 2. *Firm-specific relative wages are fully characterized by*

$$\frac{1-w_i}{1-w_j} = \frac{1-\tau f_j}{1-\tau f_i}.$$

Proof. See Appendix B.2. □

Proposition 2 implies that wages are monotonically decreasing in employer size f_i. All else equal, firms with more market power pay a lower wages.

The combination of Proposition 1 and 2 implies that firm-level wages are monotonically decreasing in $\mathcal{C}$ at all employers. To make this more concrete, suppose that two firms merge and market-level concentration increases, then wages at all non-merging firms decrease and profits rise. A surprising implication of Proposition 2 is that relative profits are independent of market structure: wages at the non-merging firms move in a way that leaves the ratio of firm profits unchanged (recall that $1 - w_i$ is the flow profit of firm i).

The proposition also reveals that the profit-size gradient steepens as τ increases. The reason is that τ summarizes how costly punishment is for workers and hence how important the mechanism is. For example, if the job finding rate, λ, is high, then from the firm's perspective the ability to cut itself out of the worker's outside option and shield itself from competition is more powerful precisely because competition for workers is more intense.

Proposition 2 emphasizes that market power affects wages purely through size, which is a distinct mechanism from the typical "markdown" mechanism embedded in monopsony-style models. In those models, the variation in wages fundamentally derives from variation in the elasticity of labor supply to the firm (here, in matches with positive surplus, the elasticity of labor supply to each firm is zero).

2 Heterogeneous Productivity

The model presented in the previous section has the virtue of simplicity. But it has a pair of stark and counterfactual implications: size perfectly predicts wages, and wages are decreasing in firm size. To generate the imperfect relationship between size and wages observed in the data, in this section we add productivity heterogeneity to the model.

This extension allows us to separate the two ways employment shares affect labor market outcomes: first, through the pure size distribution already studied in the previous section. And, second, through how size and productivity are correlated. Our model yields a clean decomposition between the two and hence lets us separately quantify the consequences of each dimension. Underlying this decomposition is the result that the model generates size-dependent pass-through of productivity with less pass-through at larger firms. Thus, holding aggregate productivity constant, worker wages are lower when productivity is concentrated in larger firms. Hence, if the firms with large market shares are more productive firms, then market structure has larger effects on wages than pure employment concentration suggests.

2.1 Concentration, Average Surplus, and Wages

Let p_i denote output per worker at firm i. As before, let $f^k \equiv \sum_i f_i^k$ and define $p^k \equiv \sum_i p_i f_i^k$ such that p^1 is the employment weighted average output produced by a match. We also define $\tilde{p}_i = p_i - b$ and $\tilde{p}^k \equiv \sum_i (p_i - b) f_i^k$ to be *net* output and the employment weighted average *net* output. The definition of $\mathcal{C}$ is unchanged. We note that, with heterogeneous productivity, not all matches may have positive surplus. Our exposition imposes, however, that all matches are formed, a feature that will be guaranteed by our calibration strategy.

The entry condition is satisfied in the extended model in the same way as in the baseline model. Here, the inversion involves picking a c_i that is (p_i, f_i) specific. As before, this cost schedule renders firms indifferent across points on the cost schedule, which rationalizes our posited equilibrium.

The following is the productivity counterpart of $\mathcal{C}$, namely a productivity-weighted concentration index:

Definition 2. *Define productivity-weighted concentration as*

$$\mathcal{C}^P \equiv \frac{\sum_{k=2}^{\infty} \tau^{k-2} \tilde{p}^k}{\tilde{p}^1 + \tau \sum_{k=2}^{\infty} \tau^{k-2} \tilde{p}^k}.$$

This index is identical to $\mathcal{C}$ except the employment shares are productivity-weighted. It shares the same properties as $\mathcal{C}$ discussed above. Next, we relate $\mathcal{C}$ and $\mathcal{C}^P$.

Definition 3. *Define the wedge between concentration and productivity-weighted concentration as*

$$\mathcal{P} \equiv \left[\mathcal{C}^P - \mathcal{C}\right] \left(1 + \frac{\tau \sum_{k=2}^{\infty} \tau^{k-2} \tilde{p}^k}{\tilde{p}^1}\right).$$

This wedge has two key properties. First, it is equal to zero if p_i is identical across firms. Second, the wedge is positive when the weighted covariance between size and productivity is positive. In particular, we show in Appendix B.3 that the sign of $\mathcal{P}$ is the same sign as $\sum_i \frac{f_i(\tilde{p}_i - 1)}{1 - \tau f_i}$, which is the weighted covariance between size and (normalized) productivity, where the weights are $\frac{1}{1-\tau f_i}$, and so are increasing in size.

The object $\mathcal{P}$ effectively measures to what extent productivity is correlated with size. If size and productivity are positively correlated, then effective concentration is higher than implied through a simple measure of employment concentration. Put differently, market structure can depress wages either because employment grows more concentrated or because productivity and size become more correlated (the latter case is the "superstar" firms effect of Autor et al. (2020)). $\mathcal{P}$ separates these forces.

We now relate concentration to wages in this richer environment. Denote by $\bar{\omega}^*$ average worker compensation in the homogeneous firms benchmark presented in Proposition 1. Similar to before let $\bar{\omega} \equiv \frac{\bar{w}-b}{p^1-b} = \frac{\bar{w}-b}{\tilde{p}^1}$ be the fraction of the average net flow output that goes to workers. Let $\hat{\tau} \equiv \tau \left(1 + \frac{\beta\lambda}{(1-\beta(1-\delta))}\right) > 0$. Our key result is summarized in the following proposition:

Proposition 3. *The equilibrium relationship between compensation and concentration satisfies:*

$$1 - \bar{\omega} = (1 - \bar{\omega}^*) \left(1 + \hat{\tau}\mathcal{P}\right). \tag{10}$$

Proof. See Appendix B.4. □

Proposition 3 naturally extends the results in Proposition 1 to the heterogeneous firms case. It shows that average compensation is given by exactly the same expression as in the baseline case up to an additional wedge $\hat{\tau}\mathcal{P}$. This wedge is positive if productivity positively covaries with employment. It reflects the fact that workers' outside options deteriorate if, given a distribution of employment, productivity shares become more concentrated. The reason is that pass-through is lower at larger firms as we discuss further below. We also have that:

Corollary 2. *Average wages are monotonically decreasing and strictly concave in concentration $\mathcal{C}$ and $\mathcal{P}$.*

Proof. Follows from differentiating. □

This result extends Corollary 1 to the heterogeneous firms case: there is a negative relationship between the concentration of employment shares as measured by $\mathcal{C}$ and wages. What is new is that increases in productivity concentration as measured by $\mathcal{P}$ also depress wages.

2.2 Concentration, Pass-Through, and Firm-Level Wages

We now extend our previous results on firm-level wages to the heterogeneous productivity case. To that end, it is useful to define $\Pi \equiv \frac{\beta\lambda(1-\alpha)}{1-\beta+\beta(\lambda+\delta)}(b - \bar{w})$. Importantly, Π depends only on the mean wage and parameters. It is linearly decreasing in the mean wage and, as such, an affine transformation of $1 - \bar{\omega}$ as defined in Proposition 3. As a consequence, it is simply another way of summarizing market power that is useful in the following result:

Proposition 4. *Firm level wages w_i satisfy*

$$(1 - \tau f_i)\,(p_i - w_i) = (1 - \alpha)\,(p_i - b) + \Pi. \tag{11}$$

Proof. See Appendix B.5. □

To interpret this result, note that $p_i - w_i = (1 - \alpha)(p_i - b)$ is the solution to the static Nash bargain. Suppose market structure changes, leading to a decline in the mean wage $\bar{w}$ and an increase in Π. This change affects employers market-wide, even those with unchanged size. In this case, wages at all firms fall. The multiplier $(1 - \tau f_i)$ is the size mark-down. It again reflects the fact that larger firms have more power to shape workers' outside options.[12]

The previous proposition also shows that, all else equal, more productive firms pay higher wages. The following corollary records the coefficient that governs the pass-through from productivity levels to wage levels:

Corollary 3. *The firm-level productivity pass-through coefficient* $(\frac{\partial w_i}{\partial p_i})$ *is:*

$$\frac{\alpha - \tau f_i}{1 - \tau f_i}.$$

Proof. Follows from rearranging and differentiating the equation in Proposition 4. □

This expression shows that the model generates size-dependent pass-through of productivity to wages.[13] We can see that the pass-through coefficient is maximized at α at the smallest firms in the economy. This pass-through reflects the fact that firms and workers divide the surplus, and the worker share is given by α. As the firm's size-based market power increases, the pass-through rate declines. In the monopsonistic limit, the pass-through coefficient can be arbitrarily close to zero when workers are patient and unemployment spells are short for the same reasons discussed above in the context of Proposition 1.

Another important aspect of the corollary is the implication that firm level pass-through in levels is independent of the overall market structure. Hence, market level concentration matters for the level of wages, but not for relative wages across employers.

This corollary revealed a tight connection between pass-through and worker bargaining power, α. The next corollary shows the relationship between worker bargaining power and the effect of changes in concentration on wages:

Corollary 4. *The elasticity of wages with respect to concentration becomes smaller in magnitude as worker bargaining power* (α) *increases.*

Proof. See Appendix B.6. □

This corollary shows that, all else equal, variation in concentration matters more when worker bargaining power is low. The reason is that, when bargaining power is low, wages are primarily determined by the outside option which is precisely what concentration affects. As a consequence, lower pass-through of productivity shocks to wages suggests a more important effect of concentration on wages. Some recent evidence is consistent with this corollary: Benmelech, Bergman, and Kim (2020) and Qui and Sojourner (2019) find that union density—which one might think

[12] We can also use Proposition 4 to express relative wages in a form similar to Proposition 2,

$$(1 - \tau f_i)(p_i - w_i) - (1 - \alpha)(p_i - b) = (1 - \tau f_j)(p_j - w_j) - (1 - \alpha)(p_j - b). \tag{12}$$

This expression nests Proposition 2.

[13] One can think of this derivative as a cross-sectional wage-productivity gradient. To interpret it literally as a pass-through coefficient one needs to implicitly also change c_i to keep $V_i = 0$.

of as proxying worker bargaining power—appears to reduce the effects of concentration on wages. Over the relevant parts of the parameter space, an analogous result also holds for λ: as the job finding rate rises, variation in concentration affects wages less. The intuition is analogous: a high job finding rate increases the effective bargaining position of workers and so outside options matter less for wages.

These two mechanisms suggest that it is ambiguous whether our mechanism would be stronger or in the U.S. or Austria. Institutional differences (e.g., union coverage) suggest that worker bargaining power is higher in Austria than in the U.S., which would lead to larger effects of concentration on wages in the U.S. On the other hand, the job finding rate is higher in the U.S. which effectively increases worker bargaining power and so would suggest larger effects in Austria than the U.S.

We conclude by noting that Proposition 4 implies that wages decrease when firms increase their size. One way firms can increase their size is to merge, which we discuss quantitatively below.

3 Data, institutional background, and measurement

In this section we introduce the institutional setting and the data we use. We then discuss how we define a labor market and how we define and measure variables and parameters in the data.

3.1 Institutional Setting

Wage setting in Austria is characterized by a combination of institutional regulation and flexibility. By law, all private sector employers are obliged to belong to an economic chamber. Wage negotiations are primarily conducted on the industry-by-occupation level between the economic chambers and unions representing the workers. Collective agreements regulate working hours, conditions, and wage floors and are binding for the vast majority of work contracts.

Despite the high prevalence of collective bargaining, the institutional setting leaves substantial flexibility for wage variation across firms and workers and hence bargaining at the worker-firm level. Firms regularly offer higher wages than the negotiated wage floors. Leoni and Pollan (2011) document that on average manufacturing wages exceed the bargained floors by about 20 percent over our sample period. As a result, wage dispersion between firms, even within the same industry, is large (e.g., see Borovickova and Shimer (2020) and Jaeger et al. (2020)). While wages are relatively flexible (Arpaia and Pichelmann (2007)), labor mobility is relatively low (Bachmann, Bechara, and Vonnahme (2020)). Nevertheless, we show below that a substantial fraction of job switchers cross industry and regional boundaries. This motivates our focus on the definition of labor markets in Section 3.3.

3.2 Matched employer-employee data

We use the Austrian labor market data base (AMDB) that covers the universe of private sector employment in Austria. For 1997 to 2015, the AMDB provides daily information on employment and unemployment spells, reports annual wages (including base pay and bonus payments) for each worker-firm combination, and contains some worker characteristics (age, gender, nationality) and firm characteristics (industry, geographical location, age). The notion of an employer in the dataset is closer to a firm than an establishment.[14] We construct an annual panel where, for each year, our sample consists of all workers aged 20-60 that have a regular job in a firm on August 1st. Regular jobs are defined as blue- and white-collar jobs that last for at least 30 days and exclude marginal work, apprenticeships, or subsidized work. Table A1 summarizes the order in which we impose sample restrictions and the effect these restrictions have on our sample sizes. Panel A of Table 1 shows some summary statistics on workers and firms in our sample in 2015.

3.3 Market definition

We consider several different market definitions. Following the literature, we consider markets based on observable features of firms such as industry and geography. In particular, we examine concentration within industry (NACE) by region (NUTS-3) cells.[15] Industry by regions cells are most similar to definitions commonly employed in the literature (e.g., Lamadon, Mogstad, and Setzler (2020) and Berger, Herkenhoff, and Mongey (2021)).

As we document below, a large share of worker flows cross industry and regional boundaries.[16] Pre-defined categorizations therefore do not necessarily capture the set of reasonable potential employers for a given worker. Likewise, a commensurately long literature discusses whether human capital is industry-, occupation-, or task-specific (e.g., Neal (1995), Kambourov and Manovskii (2009), and Gathmann and Schonberg (2010)).

To address these concerns, we use as our primary definition of a labor market a data-driven notion that clusters firms based on observed worker flows. This definition corresponds to the model in the sense that in the model a labor market is a set of firms where a worker would plausibly go following a spell of unemployment. We follow Nimczik (2018) and estimate a stochastic block model on the network of worker flows. The model assumes that worker mobility is driven by unobserved markets and backs out the assignment of each firm to an unobserved market.

To pick the number of markets, we maximize the penalized likelihood of the objective function. Our main choice for regularization is the minimum description length criterion, which penalizes the likelihood with the amount of "information" needed to describe the model (i.e., a particular functional form on the number of parameters). A Bayesian interpretation is that this approach is equivalent to maximizing the posterior probability using uniform priors over the number of markets (i.e. finding the mode of the posterior distribution of the parameters, see, e.g., (Peixoto, 2017)).[17]

[14] Fink et al. (2010, pg. 5) contrast the number of employer IDs in the AMDB with the number of firms in the Austrian firm register. The AMDB has more units than the firm register but the difference is small. As a consequence, the authors conclude that employers in the AMDB are mostly firms.

[15] There are on average about 440,000 people per commuting zone in the U.S.; there are on average about 250,000 people per NUTS-3 region.

[16] For the importance of cross-industry flows in the U.S., see Bjelland et al. (2011), especially Figure 7 documenting that over half of employer-to-empoyer flows are across 11 super-sectors (which are coarser than 1 digit NAICS industries).

[17] To see the equivalence, let A be the observed $N \times N$ matrix of transitions between firms, $z = \{z_i\}$ be the assignment of firms to one of K markets for $i = 1, \ldots, N$, and let the $K \times K$ matrix M denote transitions between

This approach leads us to 376 labor markets. Throughout, we report results for the 368 labor markets that are populated from 1997 to 2015. For comparison, our 2-digit industry by region definition implies over five times as many distinct labor markets. We refer readers to Nimczik (2018) for complete details, but in Appendix C we provide a basic sketch of what we do.

We maintain fixed labor market boundaries over time for conceptual and practical reasons. Conceptually, this allows us to compare our results to industry times region boundaries, where a firm is also assigned to a single market over time. Practically, this allows us to quantify the consequences of changing market concentration in a simple fashion. In Appendix C, we show that our data-driven markets cross industry and region boundaries, and present some summary statistics which suggest that data-driven markets are more "isolated" than traditional industry-region markets.

3.4 Parameters and variables

The two key variables that we extract from the matched employer-employee data are firm size and wages. We supplement this with information on the aggregate labor share from KLEMS data. The model also depends on 6 parameters: $\{b, \lambda, \underline{\lambda}, \delta, \alpha, \beta\}$. We treat our model as a monthly model and take annual averages of the labor market parameters (λ, $\underline{\lambda}$, and δ). We discuss how we combine the variables and parameters to back out firm-level productivity p.

To the extent that the respective empirical moments can be measured at the market level and over time, we choose market-time-specific parameters. We denote a market by m and time by t. We measure year-specific values for these parameters and variables because we want to speak to the evolution of concentration and their contribution to wages over time. We recognize that the model imposes a steady state with time-invariant employment and productivity shares. We believe that the resulting discrepancies are small because the model is known to have fast-moving state variables and because of the high-persistence of firm-level employment and wages.

Firm market share f_{it}: We employ the following measure of firm market share f_{it}: We count the number of regular employees in a given firm on August 1st of each year. We then divide it by the total number of employees in the relevant market. This measure has the virtue of simplicity and comparability to previous studies that have computed employment-based HHI (e.g., Azar, Marinescu, and Steinbaum (2020), Benmelech, Bergman, and Kim (2020) and Rinz (2020)). We also report our main results when we measure f_{it} as the share of new hires from unemployment.

Wages, w_{it}: The wage data contains annual earnings (regular pay plus bonus pay) of each employer-employee relation as well as the number of days in that person-firm-year record. Wages are censored at the social security contribution limit which varies by year. We compute average

markets. The posterior probability of observing the data A given parameters is $P(z, M|A) = \frac{P(A|z,M)P(z,M)}{P(A)}$. The numerator can be expressed as $\exp(-\Sigma)$ where $\Sigma = -\ln P(A|z, M) - \ln P(z, M)$ is the description length. The first term in the description length is the negative log likelihood of the model given parameters z and M. The second term is the penalization term that measures the number of bits necessary to describe the model parameters.

daily salaries by dividing annual earnings by the number of days worked and convert these to real wages using the consumer price index provided by Statistik Austria with 2000 as base year. The data does not provide any information on working hours and whether workers are part-time or full-time employed. In order to restrict the analysis to likely full-time workers, we drop all observations with earnings below a minimum daily wage of 32.71 Euros.[18]

To estimate firm-level wages, we view the firm-wage as the fixed effect in a two-way fixed effect (Abowd, Kramarz, and Margolis (1999)) regression. Because we want to be able to have a year-specific estimate of the firm effect, we implement a "time-varying" AKM decomposition (Engbom and Moser (2020) and Lachowska et al. (2020)) where we interact the firm fixed effect with a year indicator.[19] This procedure allows us to purge the firm wages of observable and unobservable differences in worker composition.

The firm effects are identified up to scale. We convert the (log) firm effects to levels and pick the scale such that the implied total earnings align with the data. The reason we work in levels is that our bargaining model pre-supposes that utility is transferable and so the natural unit in our model is the wage in levels, not logs (see, e.g., Kline et al. (2019, pg. 1352-1353) for a related discussion). We are also interested in quantifying the impact of size-based market power on the labor share in national income, a statistic which is computed in levels rather than logs.

We report sensitivity to considering alternative measures of the wage, including a measure of the wage without residualizing, as well as an alternative way of residualizing the wage. See Figure A2 for the firm-level distribution of wages under these three definitions.

Productivity p_{it}: We use Proposition 4 to back out firm-level productivity. Given variables that we discussed above and parameters that we discuss below, the Proposition implies one equation in one unknown per firm and so we can use the model to recover firm-level productivity. Figure A3 shows the productivity distribution implied by our estimates. We provide three pieces of evidence to document that the inferred productivity distribution reflects plausible values. First, the log 90 to log 10 gap is 0.601, which compares to 0.651 *within* 4-digit SIC industries in the U.S. reported in Syverson (2004, Table 1). Second, we can use the fact that the firm-level productivity process is not constrained in any way and assess the persistence of firm-level productivity. Table A4 reports one-year persistence rates obtained from regressions of productivity (and other measures) on one-year lags. The regression coefficients indicate a high degree of persistence that is comparable to or even higher than what Foster, Haltiwanger, and Syverson (2008, Table 3) find in U.S. data. Third, over time aggregate productivity as backed out from our model rose by 35% in real terms between 1997 and 2015 which closely matches the 32% increase in aggregate value added (and gross output) in the 2017 release of the KLEMS data (O'Mahony and Timmer (2009), see also

[18] Austria has no universal minimum wage. The vast majority of employers and employees however are covered by collective bargaining contracts, which introduced a monthly minimum wage of 1167 Euros in 2009, equivalent to a daily wage of 32.71 Euro in 2000.

[19] The additional covariates in our AKM decomposition are a third-order polynomial in age, fully interacted with gender and nationality where the linear term is normalized to be constant above age 40, a second-order polynomial in tenure, also fully interacted with gender and nationality, and an indicator for censored wages.

http://www.euklems.net/).

Labor share: We use the KLEMS data to measure the time-varying labor share in Austria. The labor share is defined as aggregate payments to labor over aggregate value-added for all industries in Austria.

Job finding rate λ_{mt}: We measure market and time specific parameters λ_{mt} by calculating the share of workers unemployed in market m in month s who are employed in month $s+1$. We measure unemployment rates by destination and say a worker is unemployed in market m if her spell ends with a job in market m. We then compute λ_{mt} as the yearly average of monthly rates. Across years, the employment-weighted average of the job finding rate drops from 16 percent to 10 percent (see Figure A4). There is also substantial heterogeneity in the monthly job finding rates across markets. In 2015, the 25th to 75th percentile ranges from 7 to 12 percent. For a small number of market-years, there are no unemployed workers who find a job. In these cases, we use the average job finding rate for the same market in all other years.

Likelihood of being the only applicant $\underline{\lambda}_{mt}$: Let $\theta \equiv \frac{v}{u}$. The urn-ball matching function implies a unique value of θ_{mt} associated with a λ_{mt}, which in turn implies $\underline{\lambda}_{mt}$. That is, the rate at which workers exit unemployment dictates the probability of being the only applicant for a job. Given that workers exit unemployment at a very sluggish pace, the implied median value of $\underline{\lambda}_{mt}$ is 0.00002. There is some heterogeneity in $\underline{\lambda}_{mt}$ across markets with a large right tail so that the average is 0.00065.

Job destruction rate δ_{mt}: We measure market and time specific parameters δ_{mt} by computing the share of workers who are employed in a firm in market m in month s and are unemployed in month $s+1$ and then compute yearly averages. In 2015, the monthly unemployment inflow rate measured this way is 0.9 percent.

Using standard mass balance arguments, the steady state unemployment rate is given by $u = \frac{\delta}{\lambda+\delta}$. If we compute market-month specific steady state unemployment rates associated with the market-month specific flows we measure and then aggregate we match the increase in Austrian unemployment from about 7 to 9 percent (Statistik Austria) over our sample period quite precisely.

Worker bargaining power and flow value of unemployment α_t and b_{mt}: We jointly calibrate workers' bargaining power and the flow value of unemployment to match two targets: First, we target the time-varying aggregate labor share. Second, we set those parameters such that the least productive firm in a market pays the reservation wage or, equivalently, just breaks even. As a consequence, all matches have (weakly) positive surplus. This strategy gives us a time-varying, country-wide α_t, and a market-time specific b_{mt}.

Intuitively, α_t governs the "split of the pie" and, as such, the share of income going to workers. In turn, b_{mt} determines the "size of the pie" and, as such, whether there is non-negative surplus in all matches: if we see firms with vastly different pay co-exist in the market, then b_{mt} must be low for all matches to have non-negative surplus.

Importantly, because we match the aggregate labor share, the remaining output gets fully absorbed by the c_i. We can thus no longer interpret c_i as a vacancy creation cost in the standard sense. Instead, we view c_i as also capturing the fixed and variable cost of (pre-installed) capital that is complementary to a worker, similar to Acemoglu and Shimer (1999).

This strategy gives us an α of 0.44 in 2015, and an employment-weighted mean value of b of -180, where the units are Euros per day (adjusted to the year 2000) (Figure A5 shows how these vary over time). This compares to a mean daily wage of 77 Euros. Why is our b so negative? Intuitively, we are asking our model to match the empirical extent of residual wage dispersion. As Hornstein, Krusell, and Violante (2011) emphasize, in a benchmark search model, unemployment must be very painful for workers to rationally accept the lowest paying jobs in the economy. How plausible is our α? We use Corollary 3 to convert our α into measures of pass-through and find a mean value (across firms and markets) of 0.40. There is limited evidence on pass-through of productivity shocks to wages in levels; for example, the central estimate in Kline et al. (2019, Table 8, Panel A, Column 1b) is 0.29, but this masks substantial heterogeneity between incumbents and new hires that our model does not capture (the value for incumbents is 0.61; see Table 8, Panel A, Column 4b). Kramarz (2017, Table 9.3) finds a coefficient of 0.53. Below, we consider extensive sensitivity for α and b.

Time discount β: There is no information in the data that informs this parameter, and so we follow standard convention and set β so that the annual discount factor is 0.95. On a monthly basis this gives us $\beta = 0.95^{1/12} = 0.9957$.

Aggregation: We compute measures market-by-market, and then report results on an employment-weighted basis. For computing the labor share, we aggregate in the way national accounts do and we compute the economy-wide wage bill over economy-wide productivity; that is, letting s_{mt} be the employment share of market m at time t, we compute $LS_t = \frac{\sum_m s_{mt}\bar{w}_{mt}}{\sum_m s_{mt}p^1_{mt}}$. Independent of market definition, a maintained assumption is that labor markets are isolated islands. Furthermore, we keep the boundaries of labor markets fixed throughout our sample for reasons that we discussed above (namely, to mimic the time-invariance of industry x region boundaries, and to simplify the exercises which aim at quantifying changes over time).

Summary Statistics: Table 1 provides summary statistics on the main variables (Panel A) and summarizes our parameter values (Panel B). The average daily wage in the sample is 77 Euros, the average worker is 40 years old, 16 percent of the sample are immigrants, and the average job tenure is almost eight years. The average market has about 5000 workers and around 100 firms.

4 Motivating Facts: Re-encounters and aggregate trends

We start our empirical analysis by providing some motivating facts. First, we demonstrate that the key implication of granularity can be observed in the data: Workers re-encounter the same firm multiple times during their career. In line with the predictions from our model, this occurs more often in more concentrated labor markets. Second, we show that aggregate trends that are prevalent in many countries can also be observed in the Austrian data: The labor share declined over the past decades and wage growth is rather low.

4.1 Granularity and Re-encounters

Our granular search model builds on the premise that with granular firms—in contrast to the atomistic textbook model—workers might re-encounter the same firm multiple times during their career. As a consequence, size leads to labor market power because workers cannot "escape" big firms. Firms recognize that workers will likely encounter other jobs controlled by the same firm and firms exercise labor market power by not competing with their own jobs, thus reducing a worker's outside option. The re-encounters that support our micro-foundation—where, in some situations, a firm would refuse to hire a worker—are not recorded in our data and, moreover, only occur off-equilibrium in our model.[20] So to build the case for the empirical plausibility of our mechanism, we start by examining the more general prediction that workers may return to a previous non-atomistic employer after having spent time at another employer. Through the lens of our model, the extent to which workers return to the same employer is an (inverse) measure of competition for workers.

In this section, we show that re-encounters frequently occur, and occur more often in more concentrated (higher HHI) labor markets. In addition, we use a simplified version of a random search model to show that the strength of this co-movement is quantitatively plausible. Finally, we show that this re-encounter probability suggests that the data-driven market definition best captures the actual level of concentration and the associated degree of competition for workers.

A stylized model of granular search: To fix ideas, consider a stylized three-period random search setup with granular firms. Suppose that a worker is employed at some firm in period 1, 2, and 3, and that the identity of these employers is drawn in an i.i.d. fashion from an invariant distribution: the probability of drawing firm j is f_j.

The mobility pattern that we are interested in is "aba" moves, where a worker is employed at firm a in period 1, spends time at another firm b in period 2, and returns to a in period 3. The basic idea of granularity is that returning to a is increasingly likely as a's market share, f_a, grows. We contrast this probability with the frequency of "ab$\cancel{b}$" moves, where a worker is at firm a in period 1 and at some other firm b in period 2. Then the worker moves from period 2 to 3, and this

[20] Fernandez and Fernandez-Mateo (2006) and Fernandez and Mors (2008) have data on applications to a single employer over time and find that about 25 percent of all applications to these firms are from people who applied multiple times to the same firm.

includes moves to *any* firm besides her period 2 employer, "$\not b$" (including a).[21]

We define the firm-level re-encounter rate r_a as the fraction of "ab$\not b$" that are "aba" moves. Put simply, we record events where a worker leaves a firm to another firm and then moves again. The re-encounter rate is then the share of the second moves which are back to the original employer and is a measure of concentration revealed by worker flows.

In this model, this revealed measure is closely related to the HHI. To see why, consider the special case of N equal-sized firms. In this case, the HHI is given by $\sum_a f_a^2 = \frac{1}{N}$. In turn, the average re-encounter rate is $R = \sum_a f_a r_a = \frac{1}{N-1}$.[22]

The re-encounter rate can be measured at the firm-level and so, like size (but not market share), it can be computed without defining a firm's market. As a consequence, we can construct a country-wide measure of concentration—the employment-weighted average of the firm-level re-encounter rates—that is revealed by worker flows and is market-definition agnostic.

In contrast, the HHI depends on market definition: a firm's employment share depends on market definition. In light of the tight connection between HHI and re-encounters, this gives us a natural way to assess the choice of market definition: Does the degree of concentration measured by the employment-weighted average of market-level HHIs correspond to the revealed (by re-encounters) concentration level?

There are at least two mechanisms not in the model which would generate a disconnect between the HHI and the re-encounter rate. First, suppose workers separate because of revelations of match quality. In this case, we would expect fewer re-encounters than predicted by the model. In contrast, if workers retain contacts or human capital at their old firms then one would expect a higher re-encounter rate than predicted by the model. While these mechanisms suggest that the level of the measure might be biased, the co-movement between the HHI and the re-encounter rate that we document below is not naturally generated by these mechanisms. Thus, we find the evidence we present below suggestive that a key feature of a more concentrated labor market is a higher rate of re-encounters.

Empirical implementation: We make several choices in defining and measuring the re-encounter event. In order to not interpret seasonal employment as return moves, we only look at a worker's employer on August 1st (and we measure employer size on August 1st). To minimize the role of recalls, we require that workers spend two years away from a (with potentially two different intermittent employers).[23] Hence, relative to the stylized model where we looked at a span of three

[21] These re-encounters are consistent with our model. Specifically, either of two assumptions we made in the model is sufficient to generate such re-encounters. The first is that a worker enters state U when she loses her job exogenously and thus can be rehired by the same firm. The second is that a worker only remains in state U_i (under punishment) until she encounters another employer; thereafter, she could be rehired by the same firm. Hence, even if we assumed that an exogenously separated worker entered state U_i, then this assumption would allow her to return to a after being employed by b.

[22] The gap between the HHI and the revealed measure arises because for a worker to move from b to $\not b$ it has to be the case that she leaves b. If b is large, then there is a positive probability that she does not leave b and so this inflates the revealed measure relative to the HHI. As the special case suggests, this gap is empirically fairly small.

[23] Specifically, the recall literature tends to focus on workers who return to the same employer *within an unemployment spell.* Here, we focus on workers who spend a significant amount of time employed at a different firm, so

years, empirically we look at a span of four years. Since job mobility is a rare event and yearly measures of the firm-level re-encounter rate are noisy, we pool all job mobility across the sample period for each firm.[24]

Empirical results: Column (1) of Table 2 shows the employment-weighted average HHI in the economy. Columns (2) and (3) show the resulting re-encounter rate in Austria and its relationship to the HHI. In contrast to the HHI, the empirical re-encounter rate does not depend on market definition.

The average re-encounter rate is 0.09 in our sample: of workers who move twice, almost ten percent of them return to their original employer. For our baseline market definition, the HHI is quite similar: 0.11. Thus, for this market definition, the tight theoretical link between HHI and the re-encounter rate holds.

Column (3) shows that more concentrated markets according to the revealed concentration measure are also more concentrated according to the HHI. The coefficient from a market-level regression of HHI on the revealed concentration measure is positive in all market definitions and very close to one in our baseline market definition. The takeaway is that revealed concentration closely tracks the HHI. Workers who work in more concentrated labor markets as measured by the HHI more frequently return to their previous employers.[25]

To more precisely understand the quantitative predictions of the stylized model and to compare it to the data, Table 2 shows the relationship between the HHI and a re-encounter rate that we simulate using the model in section 4.1 and the empirical f_a (Columns (4) and (5)). The results for the simulated and actual re-encounter rate are quite similar, suggesting that the tight theoretical connection we have emphasized holds. It also implies that the relationship between the re-encounter rate and the HHI that we derived in the special case of equal-sized firms also holds under the actual firm-size distribution.

Looking across Table 2, the link between HHI and the re-encounter rate is particularly tight when we use our baseline market-definition of data-driven markets. Column (2) shows that in industry $\times$ region market definitions the HHI is above the re-encounter rate. In contrast, in data-

the moves we register are unlikely to be recalls. Katz and Meyer (1990) censor unemployment spells at a year when considering the possibility of recalls. Fujita and Moscarini (2017) primarily study recalls that occur within 6 months are leaving an employer. Using Austrian data, Nekoei and Weber (2015, pg. 143) find that the 95th percentile of the duration of the expected recall hire date is 121 days after separation. Similarly, using Austrian data Pichelmann and Riedel (1992) show that in 1985 the mean duration of unemployment spells ending in a recall was 91 days.

[24] We need a total of four years of data to measure the re-encounter rate because we require two years at a different employer. Hence, we measure re-encounters where the base year is 1997 to 2012. For comparability to how we construct the re-encounter rate, for this section only we construct the HHI by using a firm-level employment number that is the total of employment on August 1st from 1997 to 2012. Because we average over many years, the level of concentration is lower than when we use a single year of data to define firm-level employment.

[25] In Appendix Table A3, we show that our results are quite robust to a wide variety of reasonable perturbations. First, we consider a one-year gap (as opposed to a two-year gap). Naturally, we find higher levels of re-encounters, but the broad patterns are similar. Similarly, we restrict to firms that do not shrink from year t to year $t+3$ and find slightly higher levels of re-encounters, but similar cross-sectional results. Our third and fourth perturbations are to consider year-by-year definitions of the re-encounter rate. Here we find lower levels, and weaker cross-sectional relationships (consistent with the role of noise), but the broad comparisons across market definitions are similar.

driven markets they are quite similar. Similarly, column (3) shows by far the strongest co-movement between the re-encounter rate and the HHI for our baseline market definition.

The bottom line is that, consistent with the importance of granularity in the labor market, we find that re-encounters are an important feature of the data: workers frequently return to their previous employers. Crucially for us, they do so more often when they work in markets that look concentrated through the lens of a standard concentration measure.

Discussion: This tight relationship between concentration and re-encounters might be unsurprising and appear mechanical. This is, however, exactly the intuitive appeal of the mechanism we develop. Our mechanism posits that workers and firms in more concentrated labor markets are aware of the higher probability of re-encounters, and take this into account when setting wages.

4.2 Aggregate trends

Figure 1 shows that over our sample period the labor share has declined and wage growth has been slow. The top panel shows that the labor share has declined over our sample period by about three percentage points. This overall pattern masks a u-shape, where in the mid-2000s the labor share had declined by over five percentage points from its level at the start of the sample period. The bottom panel shows that real wages rose slowly over the sample period. The annualized real wage growth is under half a percentage point a year.

Figure 2 shows that concentration in Austria is low, has followed a u-shaped pattern from 1997-2015, and that these patterns are not sensitive to the particular concentration measure. The figure shows four different measures of concentration: HHI, wage-bill HHI (emphasized by Berger, Herkenhoff, and Mongey (2021)), our concentration index ($\mathcal{C}$) and our productivity-weighted concentration index ($\mathcal{C}^P$). In terms of levels, simply reading the nature of competition off of the HHI would suggest that on average the Austrian labor market is not very concentrated. The threshold for a market to be considered "moderately concentrated" according to U.S. antitrust authorities is 0.15 and all the concentration measures are always below this number.[26] While it is logically possible for our model-based concentration index to depart in important ways from the HHI, the gap is small in practice. Reflecting the positive size-wage correlation in our data (see Figure A6), the wage bill HHI is always higher than the HHI, and our productivity-weighted concentration index ($\mathcal{C}^P$) is higher than our concentration index most of the time. All four measures show similar trends of a u-shape.

In the Appendix, we present some alternative ways of summarizing these trends. First, in Figure A7 we weight markets equally, rather than weighting by employment. Reflecting the fact that smaller markets tend to be more concentrated, the figure shows higher levels than in the weighted version. There is still a u-shape, though the shape of the u differs. Second, in Figure A8 we consider alternative market definitions with combinations of regions and 2-, 3-, and 4-digit

[26] See `https://www.justice.gov/atr/herfindahl-hirschman-index`.

industries. Naturally, the level of concentration is lower for market definitions that generate fewer markets.

5 Quantification of the model: the effect of size-based market power on the labor share

Propositions 1 and 3 suggest a simple approach to thinking about the strength of market power. Specifically, these propositions imply that quantifying the force of our mechanism just requires picking a small number of parameters along with information about the firm-size and -productivity distribution. Indeed, through the lens of our model we can use the data to pin down parameters and variables in an internally consistent way. With the calibrated model, we can quantify the effects of size-based market power.

We begin by exploring the nonlinear impacts of concentration on wages. Our first exercise then considers the effect on wages of shifting from the existing market structure to the atomistic benchmark. Our second exercise uses the model to quantify how the observed evolution of market structure from 1997 to 2015 has affected wages in Austria.

Implementation: Model-based accounting

Throughout this section, we use Proposition 3 to do accounting exercises. The Proposition shows that average wages are a function of a vector of market-level parameters, $\Xi_{mt} = \{\beta, \alpha_t, \delta_{mt}, \lambda_{mt}, \underline{\lambda}_{mt}\}$, employment concentration, $\mathcal{C}_{mt}$, and productivity concentration $\mathcal{P}_{mt}$: $\bar{w}(\mathcal{C}_{mt}, \mathcal{P}_{mt}; \Xi_{mt})$, where all of these objects vary across markets (m) and time (t).[27] The proposition therefore implies a simple way of quantifying the impact of changes in these objects. We proceed as follows: we keep Ξ_{mt} at the observed values and vary either or both of the two concentration indices to compute the changes in wages associated with concentration changes.

In this paper, we are interested in the question of the effect of market structure on various outcomes. Market structure, however, is fundamentally an equilibrium outcome. So it is not possible to have primitive shocks that only change market structure while leaving other determinants of wages unchanged. Hence, there are two alternatives to use the model to gauge the impact of market structure.

The first is to consider the following thought experiment: Compare an observed labor market with a counterfactual market where the employment-weighted productivity distribution is identical but all firms are atomistic and so there is no size-based market power. Here, to change market structure we are moving around the entry cost schedule, which is typically taken as a technology and thus fixed across counterfactuals. The benefit of doing so is that the difference in average wages

[27] Combining equations (9) and (10) and the definition of $\bar{\omega}$:

$$\bar{w}(\mathcal{C}_{mt}, \mathcal{P}_{mt}; \Xi_{mt}) \equiv (p^1_{mt} - b_{mt}) \left[1 - (1 + \hat{\tau}_{mt}\mathcal{P}_{mt})(1 - \alpha_t) \frac{1 - \beta(1 - \delta_{mt})}{1 - \beta\left(1 - \lambda_{mt}\alpha_t[1 - \mathcal{C}_{mt}] - \delta_{mt}[1 - \tau_{mt}\mathcal{C}_{mt}]\right)}\right] + b_{mt}.$$

between these two markets isolates the effect of market structure on wages through the lens of our model.

An alternative way of dealing with the fact that it is not possible to engineer a primitive shock that only affects market structure would be to hold the cost schedule constant but assume that firms and workers do not take granularity into account in setting wages (e.g., Berger, Herkenhoff, and Mongey (2021) pursue this approach). This alternative additionally picks up the fact that the employment-weighted productivity distribution might be different in the counterfactual. Our approach isolates the impact of the observed market structure by contrasting it with a different alternative: One where the employment-weighted productivity distribution is the same but all firms are atomistic. Both approaches shed light on the question of the effect of market structure on wages.

5.1 The nonlinear relationship between the labor share and concentration

We begin by highlighting the nonlinear relationship between labor share and concentration in our model. In particular, all changes in concentration are not the same: a given change in concentration from a high initial value of concentration has a larger effect on wages than from a lower initial value.

To illustrate the effects of these nonlinearities quantitatively, we consider what happens to the labor share as we move concentration from the atomistic limit 0 to the monopsonistic limit 1.[28] Figure 3a shows, consistent with Corollary 1, that wages are decreasing in concentration. But for a given increase in concentration, this decrease is small at low levels of concentration and becomes much more dramatic at high-levels of concentration. Put differently, as Panel B shows, the elasticity of wages to concentration grows (in magnitude) as concentration increases. This figure explains why the average effect (across markets) of eliminating market power differs from the median.

5.2 Effects of levels of concentration: the atomistic benchmark

As mentioned above, we quantify the change in wages from moving to the atomistic benchmark. To do so, in each market-year we first isolate the role of productivity concentration by computing $\bar{w}(\mathcal{C}_{mt}, 0; \Xi_{mt})$. To isolate the role of pure employment concentration, we then compute $\bar{w}(0, 0; \Xi_{mt})$. We hold average productivity p^1_{mt} constant.

Figure 4a shows that moving to the atomistic limit increases the labor share by 7 to 11 percent. Put differently, the model suggests that the concentration of employment and productivity in Austria depresses wages by about 10 percent.

The figure shows that employment concentration accounts for the bulk of this increase: the existing productivity-size relationship depresses wages by merely one to two percent while the remainder is accounted for by employment concentration. The relative magnitude of the two effects can be anticipated from Figure 2 which shows that $\mathcal{C}$ and $\mathcal{C}^P$ are quantitatively similar, implying a limited role for size-productivity covariance.

This suggests that the forces we model potentially redistribute a large share of aggregate income

[28] We do this exercise in all labor markets to average over the parameter values.

from workers to employers. The average effect, however, is driven by a few markets with extremely large effects. As we document in Table 3, markets at the 95th percentile experience an increase in the labor share that is almost an order of magnitude larger than in the median market. This reflects the nonlinearities discussed in the previous subsection and results in a median increase of the labor share of 2.4% (in 2015), which is smaller than the mean of 10%. We stress these nonlinearities since the tail vanishes with the introduction of on-the-job search, leading to substanitally smaller mean effects as we show in the next subsection.

Our baseline results use the data-driven labor market boundaries. Table 4 considers alternative industry times region market definitions and alternative definitions of size and wages. Naturally, concentration and size-based market power increase as we draw the boundaries of the labor market more narrowly. The results are not very sensitive to changing the definition of firm-level wages. If we consider only new hires from unemployment to compute size and wages, the change in the labor share is cut in half, anticipating our results with on-the-job search below. Finally, the wage impact of size-based market power appears higher for women than for men.

Panel A of Figure 5 shows that eliminating market power would increase inequality; equivalently, it is higher-earnings workers who experience the largest losses from employer market power. Panel B of Figure 5 shows that the re-encounter rate follows a similar pattern. Specifically, the most highly paid workers are nearly twice as likely to re-encounter their previous employers (conditional on moving twice) than the lowest paid workers. Thus, the re-encounter rate supports the view that size-based market power has substantial distributional consequences.

5.2.1 On-the-Job Search

This section considers the effects of market power in an extension of our baseline model that allows for on-the-job search. We do so because on-the-job search naturally introduces an additional form of competition for workers that mitigates the impact of the outside option channel. Furthermore, our baseline calibration strategy leads to very low values of the flow value of unemployment, b. The introduction of on-the-job search leads to considerably higher values of b as discussed in Hornstein, Krusell, and Violante (2011). The higher value of b means that there is less surplus from the match hence less room for market power to redistribute surplus. We relegate all details to Appendix E and here just verbally describe the setting.

Employed workers sample a random outside job offer (from the same exogenous distribution as the unemployed) with probability λ_e while employed. We maintain the assumption that wages are set according to the Nash-bargaining solution where unemployment is the outside option of the worker. We then calibrate this extended model to match the same targets. The additional parameter λ_e is calibrated so as to match market-specific job-to-job transition rates that are consistent with our model in that they are up the ladder defined by firm-specific wages. The vacancy shares f_i—which no longer correspond to employment shares—are picked so as to match the empirically observed employment shares. The rest of the implementation mimics our strategy for the baseline. In order to measure the consequences of market power, we then compute the labor share in a counterfactual situation that mimics our approach from the baseline. Specifically, we ask what wages would occur if the vacancy shares where distributed across atomistic employers without adjusting the entry margin, i.e. leaving the distribution of vacancies across job productivity unaltered.

In this extended setting, market power creates a new inefficiency. In an efficient model with on-the-job search, firms are ordered on the job ladder according to their productivity p_i, which is the case in a model with constant markdowns. But in our setting, markdowns depend on size and so a small firm with lower productivity might pay a higher wage than a larger firm with higher productivity because it has less market power. As a consequence, eliminating market power comes with aggregate productivity gains. The reason for aggregate gains is different than in models driven by labor supply elasticities where aggregate employment expands and workers are reallocated; here, it is just that workers get reallocated to more productive employers along the job ladder.[29]

We present our results in Table A5. Panel A reports the observed job-to-job transition rate and the re-calibrated parameters. The most important change relative to the baseline is the higher value for b. Panel B presents the change in the labor share, in wages, and in productivity that results from removing size-based market power. The results indicate that even with on-the-job search and the associated possibility to leave employers with high market power, there are positive changes in wages and the labor share from removing the mechanism. They are, however, lower than in our baseline model. While the difference to the baseline is small for the median market (2.1% rather than 2.4%), the average change in the labor share reduces to 3.8% (from 10% in the baseline).

There are two basic reasons we find smaller effects with this extension. First, the flow value of unemployment, b, is higher. As a consequence, a model with on-the-job search finds less surplus from the match. Hence, changing market power has less of an effect on wages. Second, as emphasized in Figure 3a, the effect of eliminating market power in the baseline model is particularly high in markets with very high levels of concentration. In these markets, on-the-job search substantially improves the outside option of workers who face a large employer. Nonetheless, the basic forces we have highlighted throughout are still at play and still lead to substantial losses for workers.

The final row of Table A5 quantifies the inefficiency generated by size-based market power. Reallocation of workers towards more productive firms (rather than towards firms with less market power) raises aggregate productivity by 0.1 percent on average. This effect on productivity drives a wedge between changes in wages and the labor share, though it is quantitatively very small. In a few markets, the efficiency effect even dominates the wage effect and leads to a decline in the labor share.

[29]For related reasons, market power here does not map into the labor supply elasticity. The labor supply elasticity to a firm depends on its location on the ladder, but in this model two firms can pay the same—and share a location on the ladder—while having different markdowns.

5.3 Quantifying the effects of changes in concentration on the labor share

We are next interested in the effects of the observed changes in market structure from 1997 to 2015 on wages. We again proceed in two steps. In the first, we compute $\bar{w}(\mathcal{C}_{mt}, \mathcal{P}_{m97}; \Xi_{mt})$ for all market years (note that 1997 is the first year in our sample). The differences between this implied alternative and the actual evolution of employment weighted average wages then isolates the role of changes in productivity concentration over time. In a second step, we compute $\bar{w}(\mathcal{C}_{m97}, \mathcal{P}_{m97}; \Xi_{mt})$ for all markets and years and again take employment weighted averages. This captures the role of changes in both employment and productivity concentration over time and so contrasting the first alternative wage series with the second isolates the role of employment concentration alone.

Figure 4b shows that changes in market structure over time substantially contributed to the decline in the Austrian labor share. The first exercise shows that changes in the covariance between size and productivity have reduced the labor share over our sample period by about 0.75 percent. The second exercise shows that, over the entire sample period, shifts in employment concentration reduced the labor share by about as much as shifts in productivity shares. Taken together, size-based market power thus reduced the Austrian labor share by about 1.5 percent over our sample period, which can explain over one third of the overall decline depicted in Figure 1a.

There are two things worth emphasizing about the patterns in this figure. First, as before, the time path is not a simple monotone transformation of the path of the concentration measures displayed in Figure 2. This finding emphasizes that in the context of our model it is not sufficient to compute a weighted linear average of local concentration to infer the contribution of trends in local concentration to trends in labor share. Second, one appealing feature of our framework is that we can separate the effect of changes in concentration from changes in productivity-weighted concentration, which turn out to have different temporal patterns. Moreover, this separation allows us to quantify the "superstar" firm effect of Autor et al. (2020), and here it turns out to contribute to roughly a one percentage point decline in the labor share.

We now ask how these results depend on market definition. We report the results in Table 5. Compared with the role of market definition in the atomistic benchmark, the results here are more sensitive to the choice of market definition. Nonetheless, we view our findings as overall very consistent given the wide range of market definitions we consider. The effect of changes in concentration is much less sensitive to variation in the wage measure and the size measure.

6 Merger simulation

Our model is about how market structure maps into market power in the labor market and, as such, is a natural laboratory to think through the wage effects of mergers. This exercise allows us to connect with an evolving literature on the labor market consequences of mergers. For instance, Naidu, Posner, and Weyl (2018), Marinescu and Hovenkamp (2019), and Shapiro (2019) argue that antitrust authorities should consider the labor market implications of mergers.

We use our model to simulate the effects of a set of hypothetical mergers on labor market outcomes. In our model, the impact of mergers depends not only on the size of the merging firms, but also on the size-distribution of the remaining firms in the market. Moreover, mergers affect wages at all firms in a market, including at non-merging firms.

We simulate mergers as follows. In each labor market in 2015, we merge the two largest employers. We initially assume that the combined employer has the employment-weighted average productivity of the two constituent firms, and explore alternatives below. In each market, this implies a new concentration of employment shares, $\hat{\mathcal{C}}_{m15}$, and a new employment-productivity relationship, $\hat{\mathcal{P}}_{m15}$.[30]

We then compute post-merger wages in two steps. First, we compute new market-wide average wages $\bar{w}(\hat{\mathcal{C}}_{m15}, \hat{\mathcal{P}}_{m15}; \Xi_{m15})$. Second, we use Proposition 4 to compute the associated changes in firm-level wages (note that the Π in equation (11) contains $\bar{w}$ which we re-compute in step one). This allows us to compute the impact on wages at both the merging and non-merging firms.[31]

Panel A of Table 6 shows that these hypothetical mergers would lead to a large increase in concentration. On average, the largest firm has a 21 percent market share and the second largest firm has a 10 percent market share (at the median, these numbers are 15 and 8 percent). Hence, these mergers would, on average, increase the HHI by 0.05 from the average level of 0.12.

This change reduces wages by almost seven percent. As before, the average effect is significantly larger than the median effect, again highlighting that the force we model here becomes particularly powerful in markets which are already highly concentrated. Importantly, Panel A of Table 6 shows that there are large spillovers to the remaining firms in the market with wages at non-merging firms declining by 2.5 percent on average. All market participants recognize the reduction in demand-side competition associated with the merger and consequently lower wages.

The last row of Panel A emphasizes that our model features pure rent extraction: size-based market power shifts the distribution of match surplus. Hence, when firms merge, wages change without employment changing. In contrast, in standard models of monopsony, quantities and prices are tightly linked: firms reduce wages by reducing employment. In our model, a merger combines the market shares of two firms with no other changes. Naturally, real-world mergers are endogenous and typically entail other changes. In the nascent literature evaluating the labor market effects of mergers, the paper with the strongest research design finds negative effects on wages but no effects on employment (Prager and Schmitt (2021, Table 2)). Other papers find more mixed results: He and le Maire (2020, Footnote 22) finds no employment effects, while Arnold (2020) finds negative employment effects.

Panel B emphasizes the nonlinearity in the model. We show the wage effects of increasing $\mathcal{C}$ by 0.025 (i.e., the median increase in HHI in mergers) at various levels of concentration and averaging

[30] We again adjust the vacancy cost schedule in the background such that the newly formed firm and all other firms make zero profits ex post. It is not ex ante clear how one should model the drivers of a merger in the first place. Our exercise motivates the merger by a shock to the entry/capital cost structure that renders two previously viable employers unprofitable but allows them to stay in business upon merging. This procedure mimics the spirit of our other exercises.

[31] We drop the 13 markets where there are fewer than three firms because in these markets it is not possible to compute the wage effects on non-merging firms.

over the effects across all markets. As can be anticipated from Figure 3a, the effects of the same change in concentration depend on the initial level of concentration.

Panel C emphasizes the importance of the productivity level at the merged firm. If the newly created firm has the maximum (rather than the average) of the merging firms' productivity, then the market-wide wage decline is a quarter to a half as large. Similarly, we ask how large a productivity increase would be required to keep market-wide wages constant. If the merged firms get the average productivity, then in the median market this productivity increase is almost five percent.

Table A6 shows how the effects of our hypothetical mergers depend on labor market definition. Not surprisingly, the finer the market definitions the larger the wage reductions following mergers.

7 Discussion

This paper develops a new model of market power in the labor market. Unlike traditional models which operate through firms restricting quantities to reduce wages, our model is one of endogenous (effective) bargaining power where market structure affects the division of surplus. Our model is built from a novel feature of the labor market that we document: in more concentrated labor markets, workers are more likely to re-encounter the same employers. The key mechanism in our model is that the possibility of these re-encounters endows firms with size-based market power since outside options are truly outside the firm: firms do not compete with their own vacancies. Hence, a worker's outside option is worse when bargaining with a larger firm, and wages depend on market structure. Specifically, wages are lower in more concentrated labor markets.

The link to employer size means that the model provides a new micro-foundation for an equilibrium relationship between market structure—in particular, concentration—and wages. The model provides a natural intuition for why a concentration index includes the sum of squared market shares. Under random search, it captures the probability that an unemployed worker encounters the same firm two times in a row. The possibility of this second encounter generates market power.

To illustrate the quantitative magnitudes implied by our model, we calibrate the model and consider three quantitative exercises. We implement our framework in Austrian matched employer-employee data. We complement standard definitions of labor markets with data-driven labor markets based on worker flows. Our model suggests that size-based market power depresses Austrian wages by about ten percent, and that changes in market structure have contributed to the decline in the labor share. In our third quantitative exercise, we simulate mergers, which have large effects: even workers at non-merging suffer substantial wage losses.

The model could be extended in a variety of directions. For example, one could endogenize the size distribution. Similarly, one could analyze non-compete clauses or unions, or any shock that affects the distribution of employment and productivity across firms. Empirically, developing evidence about the way that size-based market power affects labor markets is a high priority. More broadly, it is likely the case that the mechanism developed in this paper operates alongside other forms of imperfect competition. Thus, developing models that combine various forms of imperfect competition as well as testing between these various models would be an exciting avenue for future research on imperfect competition in the labor market.

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Table 1: Summary statistics and parameter values

	Average	Median	25th	75th
Panel A. Summary Statistics				
Workers				
Age	40.48	41	31	50
Share Female	0.43			
Share Austrian	0.84			
Tenure in Days	2869.71	1855	600	4474
Daily Wage	76.54	72.99	56.13	98.06
Share with Censored Wage	0.16			
Worker per market	4952.23	3303	1996	5967
Number of Workers	1,819,998			
Firms				
w_i	76.80	76.13	72.93	80.82
Employment	45.87	13	8	29
Hires	12.99	4	2	10
Hires from u	7.41	2	1	6
Firms per market	107.97	87	39.25	139.25
Number of Firms	39,798			
Panel B. Parameters				
λ_m	0.098	0.093	0.070	0.119
$\underline{\lambda}_m$	0.00065	0.00002	0.00000	0.00023
δ_m	0.009	0.008	0.005	0.012
α	0.4360			
b_m	-180.02	-158.04	-261.72	-100.07
β	0.9957			
Panel C. Average pass-through coefficients				
Productivity	0.4010	0.4230	0.4100	0.4289

Notes: All statistics are for 2015 and when there are market-specific parameters these reflect employment-weighted averages. Panel A reports summary statistics on workers and firms in our sample. On the firm level, w_i is the (time-varying) firm effect from an AKM wage decomposition normalized to daily wages in Euros (2000) for firm i. Firm size is measured on August 1st. We also measure size as the number of total yearly hires or hires from unemployment. Panel B reports parameter values. For market- and time-specific parameters λ, $\underline{\lambda}$, δ, and b, it reports employment-weighted summary statistics. λ, $\underline{\lambda}$ and δ are at a monthly frequency. b is in the same units as wages. Panel C reports the average pass-through of productivity changes to wages.

Table 2: Relationship between revealed concentration and HHI

		Data			Simulations		
	HHI	Level	Reg. coef. (se)	Adj. R^2	Level	Reg. coef. (se)	Adj. R^2
Baseline (368)	0.11	0.09	0.98 (0.144)	0.11	0.10	0.83 (0.028)	0.70
Alternative market definitions							
2-digit industries × region (1838)	0.15	0.09	0.36 (0.064)	0.02	0.17	0.84 (0.006)	0.92
3-digit industries × region (3615)	0.24	0.09	0.33 (0.052)	0.01	0.25	0.73 (0.009)	0.63
4-digit industries × region (5384)	0.30	0.09	0.29 (0.043)	0.01	0.31	0.65 (0.009)	0.47

Notes: This Table reports levels of concentration and regression results for the relationship between the HHI and the average re-encounter rate. Column (1) reports the HHI for various market definitions. Columns (2) and (3) show the level of the average empirical re-encounter rate in the Austrian data and its relationship to the HHI. The coefficient is for the following regression,

$$HHI_m = \beta_0 + \beta_1 R_m + \epsilon_m,$$

where R_m is the average re-encounter rate in market m. Columns (4) and (5) show the level of the average re-encounter rate simulated from the three-period model and its relationship to the HHI estimated in the same regression.

Table 3: Heterogeneity of effects of market structure across markets

	Average	Median	5th	25th	75th	95th
Panel A. Concentration measures						
HHI	0.120	0.053	0.012	0.030	0.102	0.691
$\mathcal{C}$	0.124	0.056	0.012	0.030	0.107	0.729
$\mathcal{C}^{\mathcal{P}}$	0.124	0.056	0.012	0.030	0.110	0.589
$\mathcal{P}$	0.002	0.001	-0.001	0.000	0.003	0.023
Panel B. %Δ in labor share in the atomistic benchmark						
$\mathcal{P} = 0$	1.3	0.2	-0.1	0.0	0.6	4.3
$\mathcal{P} = \mathcal{C} = 0$	10.0	2.5	0.5	1.3	5.0	22.2

Notes: This Table reports how a variety of measures vary across markets. All measures are calculated for the year 2015. The average column reflects employment-weighted averages. The remaining columns report results for employment-weighted quantiles of the markets. Panel A shows the distribution of the Hirschman-Herfindahl index (HHI), our concentration index $\mathcal{C}$, our productivity-weighted concentration index $\mathcal{C}^{P}$, and our productivity-concentration weighted wedge $\mathcal{P}$. In Panel B, we compute the distribution of the change in the labor share due to moving to the atomistic benchmark by setting $\mathcal{P} = 0$ or $\mathcal{P} = \mathcal{C} = 0$, and then report quantiles of this distribution across markets.

Table 4: Sensitivity of increase in labor share in atomistic benchmark in 2015

	%Δ labor share	
	$\mathcal{P}=0$	$\mathcal{C}=\mathcal{P}=0$
	(1)	(2)
Baseline (368, $\alpha=0.44$, $\bar{b}$ =-180)	1.29	9.96
Panel A. Alternative market definitions		
2-digit industries $\times$ region (1838, $\alpha=0.39$, $\bar{b}$ =-137)	1.79	11.55
3-digit industries $\times$ region (3615, $\alpha=0.36$, $\bar{b}$ =-88)	2.59	16.18
4-digit industries $\times$ region (5384, $\alpha=0.36$, $\bar{b}$ =-69)	3.12	20.10
Panel B. Alternative wage and size definitions		
w_i median raw wage at i (368, $\alpha=0.51$, $\bar{b}$ =-259)	1.86	12.98
w_i mean raw wage at i (368, $\alpha=0.49$, $\bar{b}$ =-237)	1.77	12.29
w_i median residualized wage at i (368, $\alpha=0.48$, $\bar{b}$ =-227)	1.78	12.61
f_i and w_i only from u (mean wage) (365, $\alpha=0.45$, $\bar{b}$ =-161)	0.64	5.84
f_i and w_i only men (mean wage) (368, $\alpha=0.52$, $\bar{b}$ =-304)	1.44	10.22
f_i and w_i only women (mean wage) (368, $\alpha=0.53$, $\bar{b}$ =-210)	2.39	19.01

Notes: This Table reports the sensitivity of the effects of moving to the atomistic benchmark to market definition, and alternative definitions of wages and employer size. The first row shows our baseline results where we use 368 data-driven labor markets. We consider two quantitative exercises: setting $\mathcal{P}$ to zero and setting $\mathcal{P}$ and $\mathcal{C}$ to zero and report the percent increase in the labor share in these exercises. In each row we recalibrate the model. In parentheses, we report the number of markets, α, and $\bar{b}$ (in units of euros per day). Panel A considers alternative market definitions. Panel B considers alternative definitions of the firm-level wage, where our baseline results use time-varying AKM firm effects. We consider raw wages unadjusted for worker composition and residualized wage measures. It also considers alternative definition of f_i based on share of new hires from unemployment in year t and explores heterogeneity with respect to gender.

Table 5: Effects of changes in market structure on the labor share

	Contribution of	
	$\mathcal{P}$ and $\mathcal{C}$	$\mathcal{P}$
	(1)	(2)
Baseline (368)	-0.87	-0.47
A. Alternative market definitions		
2-digit industries × region (1838)	0.30	-0.59
3-digit industries × region (3615)	-0.47	-0.70
4-digit industries × region (5384)	-1.53	-1.00
Panel B. Alternative wage and size definitions		
w_i median wage at i (368)	-1.04	-0.77
w_i mean wage at i (368)	-0.88	-0.71
w_i median residualized wage at i (368)	-1.19	-0.65
f_i and w_i only from u (mean wage) (365)	-1.22	-0.17
f_i and w_i only men (mean wage) (368)	-0.22	-0.42
f_i and w_i only women (mean wage) (368)	-2.06	-0.97

Notes: This Table reports the percentage point change in the labor share explained by changes in $\mathcal{P}$ and $\mathcal{C}$ from 1997 to 2015 in our baseline market definition, as well as various alternative market definitions. The numbers in the baseline row correspond to the last point (scaled by the level of the labor share to convert to percentage points) in Figure 4b. The remaining rows report the parallel exercise for other market definitions (Panel A) or wage and size definitions (Panel B). Our baseline results use time-varying AKM firm effects. We consider raw wages unadjusted for worker composition and residualized wage measures. Panel B also considers alternative definition of f_i based on share of new hires from unemployment in year t and explores heterogeneity with respect to gender.

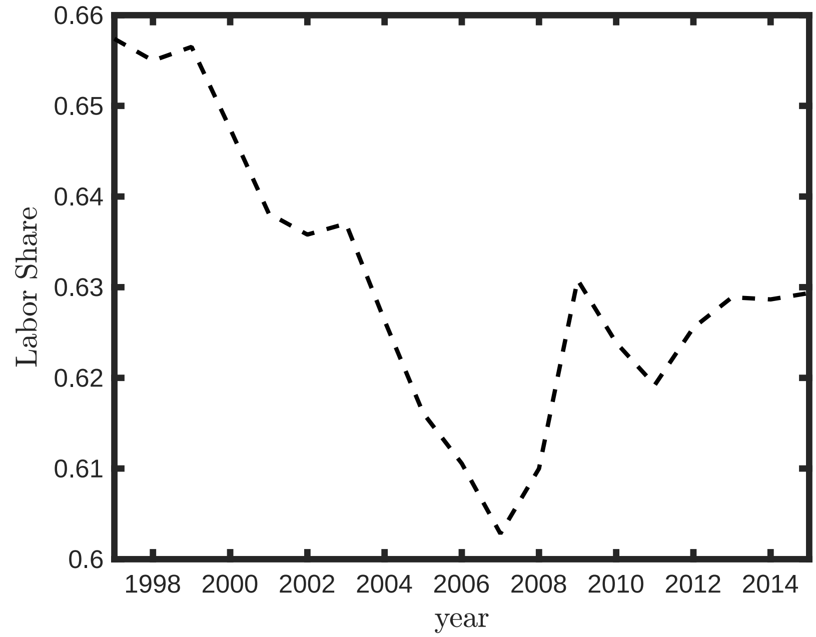
Table 6: Merger simulation

	Average	Median	25th	75th
Panel A. Distribution of effects				
Δ HHI	0.046	0.025	0.013	0.058
Market share largest firm	0.21	0.15	0.09	0.25
Market share 2nd largest firm	0.10	0.08	0.05	0.12
%Δ wages at merging firms	-6.8	-3.4	-6.8	-2.2
%Δ wages at non-merging firms	-2.5	-0.7	-1.9	-0.3
%Δ market-wide wages	-4.6	-1.3	-3.8	-0.7
%Δ employment	0.0	0.0	0.0	0.0
Panel B. %Δ market-wide wages of a merger that increases $\mathcal{C}$ by 0.025				
From $\mathcal{C}$ = 0.030 (25th)	-1.1			
From $\mathcal{C}$ = 0.108 (75th)	-1.3			
From $\mathcal{C}$ = 0.250	-1.8			
From $\mathcal{C}$ = 0.500	-4.6			
From $\mathcal{C}$ = 0.600	-8.5			
From $\mathcal{C}$ = 0.650	-13.7			
Panel C. Alternative assumptions on the productivity of the merged firms				
%Δ market-wide wages with $p_{new} = \max\{p_1, p_2\}$	-2.8	-0.3	-2.1	0.8
%$\Delta\, p_{new}$ to implement $\Delta\bar{w} = 0$ (compared to max prod)	2.3	1.0	-3.4	5.3
%$\Delta\, p_{new}$ to implement $\Delta\bar{w} = 0$ (compared to avg. prod)	8.1	4.5	3.0	8.7

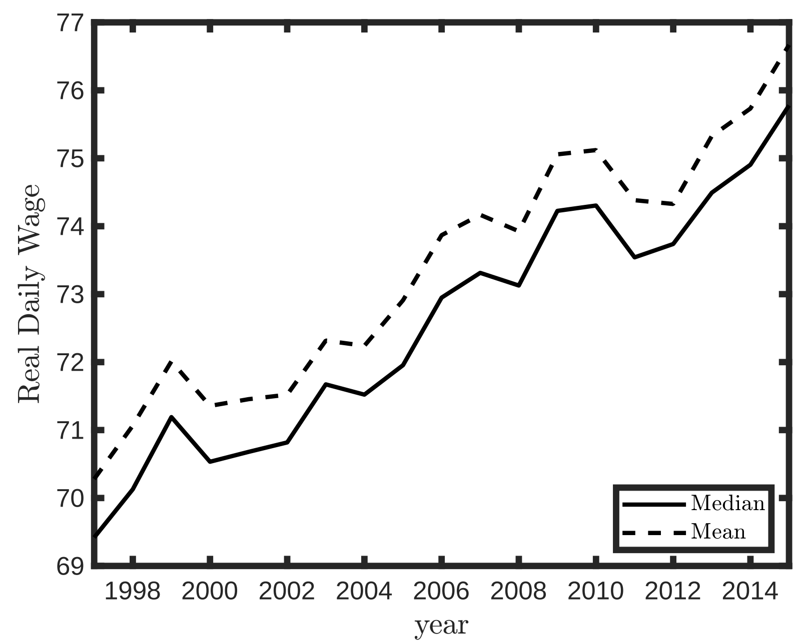
Notes: Panels A of this Table reports the effects of combining the two largest employers in each data-driven labor market in 2015. We report results for the 356 markets where there are more than two firms. Panel A reports employment-weighted statistics,. Panel B reports the effects of increasing $\mathcal{C}$ from various levels by 0.025. We average over markets and leave the size-productivity correlation unchanged. Panel C computes wage changes when the new firm in each merger has the maximum productivity of the merging firms (rather than the average). It then reports the percent increase in productivity at the merging firms required to hold wages constant following the merger.

Figure 1: Trend in labor market aggregates in Austria

(a) Labor Share

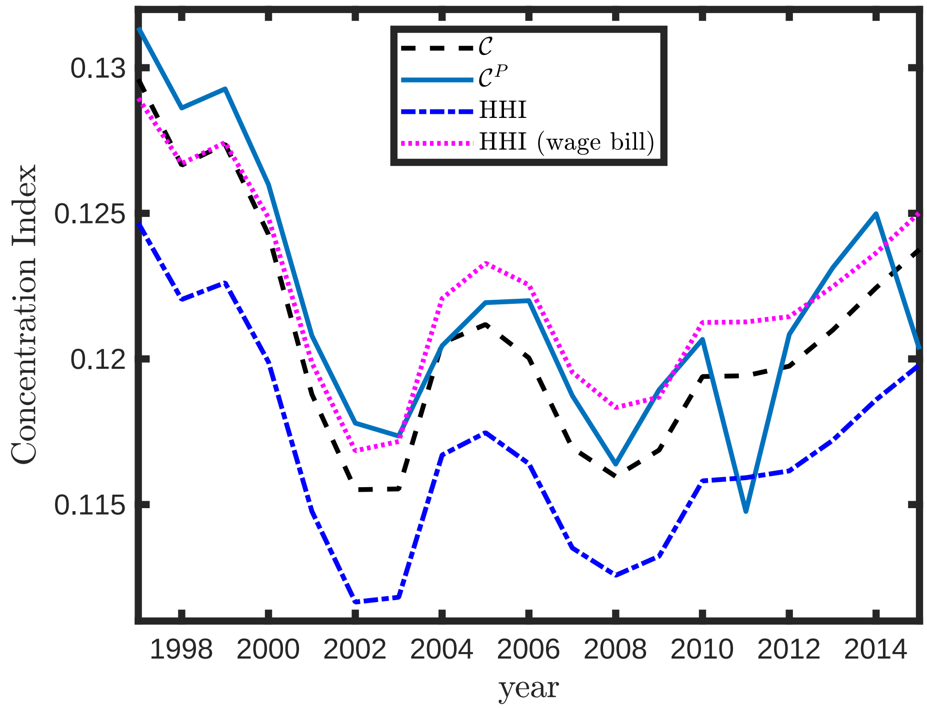


(b) Real Daily Wages



Notes: Panel A of this Figure plots the labor share in Austria based on KLEMS data for the sample period from 1997 to 2015. The labor share is defined as aggregate compensation over aggregate value added for all industries in Austria. Panel B plots employment-weighted median and mean of real daily earnings in our sample using the CPI from Statistic Austria with base year 2000 as the deflator.

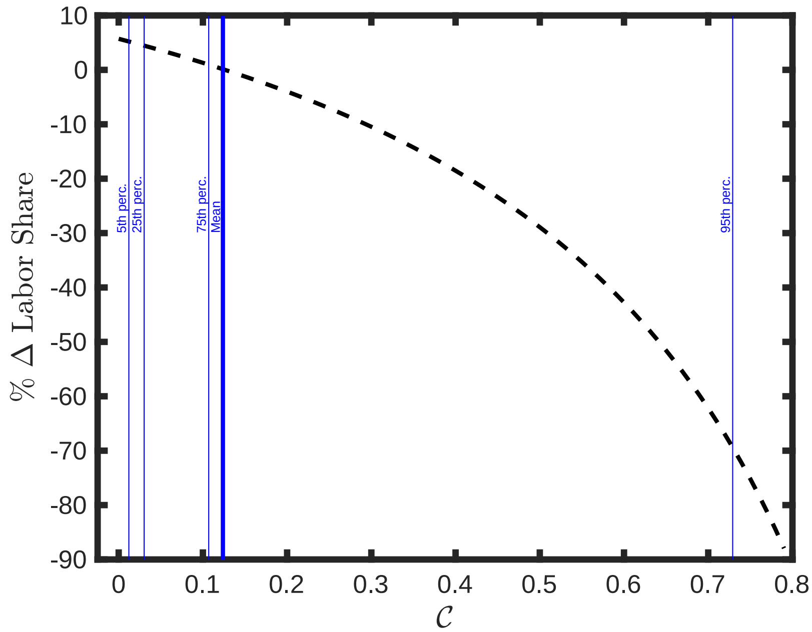
Figure 2: Trends in labor market concentration



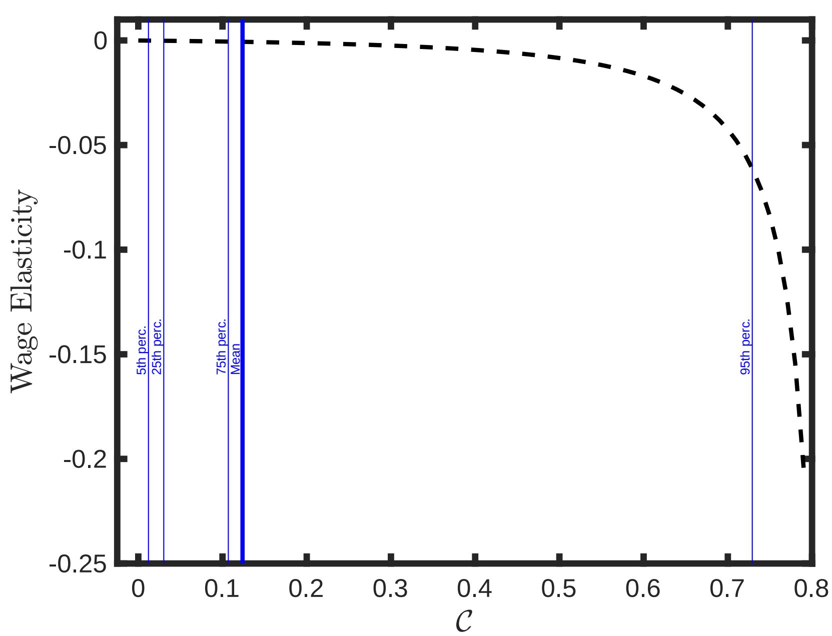
Notes: This Figure plots concentration indexes $\mathcal{C}$, $\mathcal{C}^P$, HHI and wage-bill HHI from 1997 - 2015. The figure displays employment-weighted averages over all 368 data-driven labor markets.

Figure 3: Nonlinear effects of concentration on the labor share and wage elasticity

(a) Effect of moving to atomistic benchmark



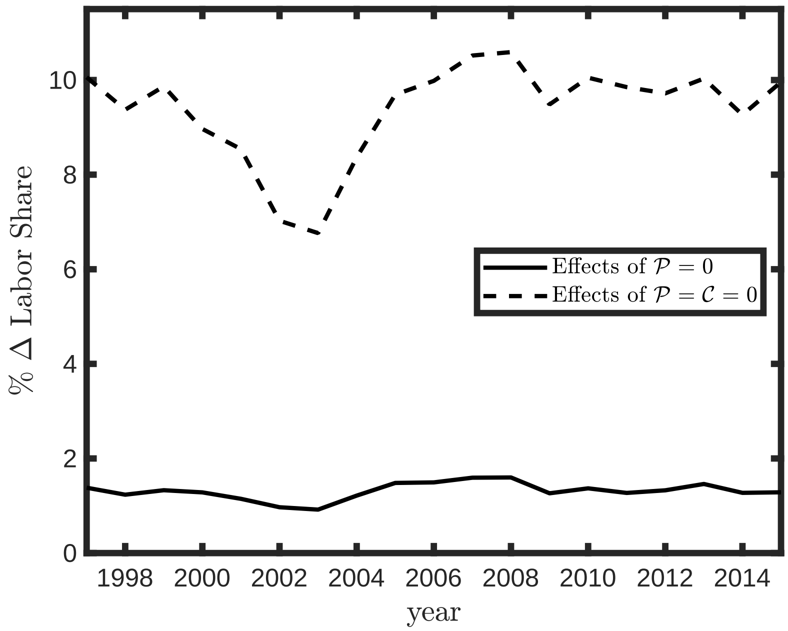
(b) Elasticity of wages with respect to $\mathcal{C}$



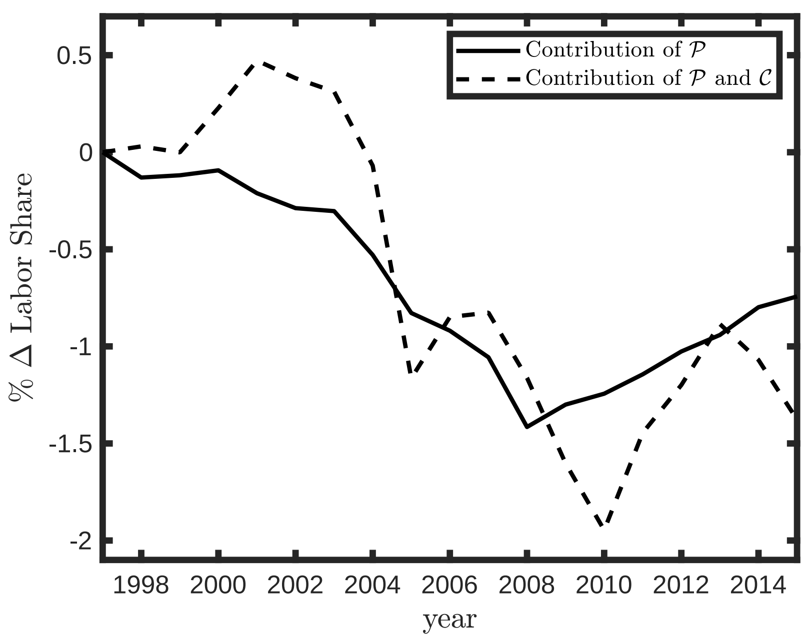
Notes:. This Figure documents nonlinearities in the effect of concentration on the labor share and wages. Panel (a) reports the effect on the aggregate labor share when moving each market from the observed level of concentration in the data over the support of $\mathcal{C}$. The thick dashed lines show the average value of $\mathcal{C}$ in our data in 2015, and the thin dashed lines show the 5th, 25th, 75th and 95th percentiles. Panel (b) shows that the elasticity of wages with respect to $\mathcal{C}$ varies with $\mathcal{C}$. We compute the arc-elasticity of wages with respect to concentration using a one-percent change in $\mathcal{C}$ at different levels of $\mathcal{C}$.

Figure 4: Labor share accounting exercises

(a) Change in labor share in atomistic benchmark



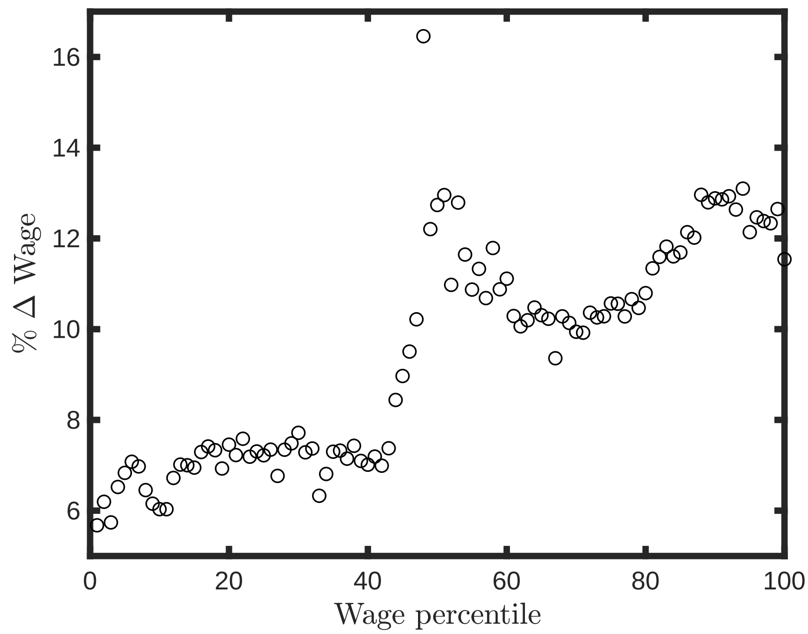
(b) Change in labor share over time



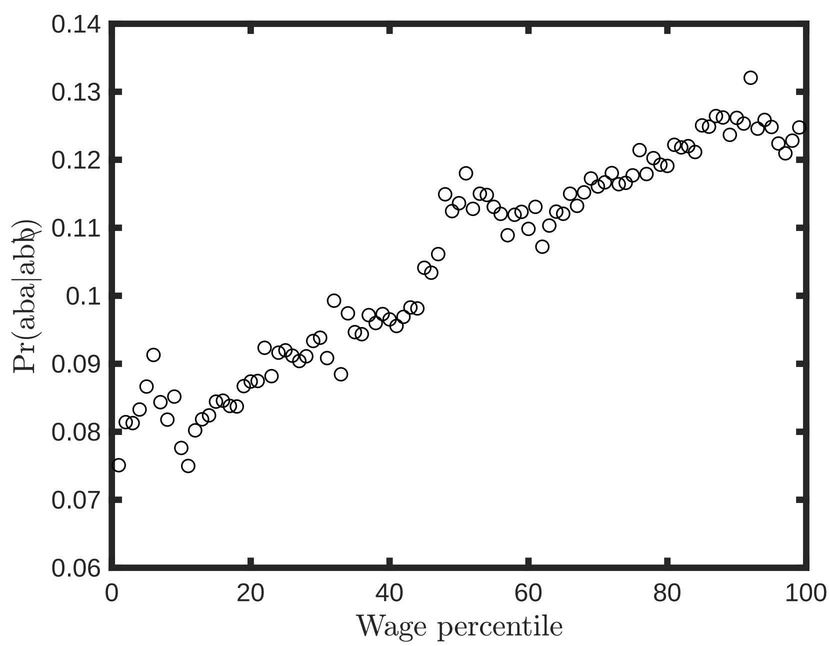
Notes: This Figure reports changes in labor share due to changes in concentration. It reports the change relative to the actual evolution of the labor share ($\frac{\bar{w}}{p^1}$) in percent. We report changes in the employment-weighted averages across the 368 data-driven labor markets. The top panel moves the economy to the atomistic benchmark in two steps: First, we compute $\bar{w}(\mathcal{C}_{mt}, 0; \Xi_{mt})$, then we compute $\bar{w}(0, 0; \Xi_{mt})$. In the bottom panel, we compute $\bar{w}(\mathcal{C}_{mt}, \mathcal{P}_{m1997}; \Xi_{mt})$, and then we compute $\bar{w}(\mathcal{C}_{m1997}, \mathcal{P}_{m1997}; \Xi_{mt})$.

Figure 5: Distributional impact of moving to the atomistic benchmark

(a) Change in wages



(b) Re-encounter probability



Notes: Panel A of this Figure shows how the percent change in wages implied by moving to the atomistic benchmark varies over the distribution of individual-level wages. We bin raw wages from 2015 (below the social security contribution cap) into percentiles and compute average wage changes within each bin. We compute the percent wage change as the wage change at the worker's employer. Panel B shows how the re-encounter probability varies with individual-level wages. We proceed analogously to Panel A except that the firm-level object is the re-encounter probability at the worker's firm.

A Example where $\mathcal{C}$ and HHI switch positions

In this Appendix, we describe two model economies. The ordering of the concentration of these economies according to $\mathcal{C}$ is different than the ordering according to HHI.

Relationship between the two economies: Choose c_1 such that $c_1 = \sqrt{c_2} - \epsilon$.

Economy 1: monopsonist with a competitive fringe:

- c_1 share of employment at the first firm;
- $\frac{1-c_1}{n-1}$ of employment at the remaining $n-1$ firms, where we let $n \to \infty$.

Economy 2: equally-sized, but finite number of firms:

- c_2 share of employment at each of the $\frac{1}{c_2}$ firms.

HHI in these two economies: For the first one:

$$c_1^2 + \frac{(1-c_1)^2}{n-1} \approx c_1^2,$$

where the $\approx$ relies on $n \to \infty$.

For the second one:

$$\frac{1}{c_2} c_2^2 = c_2.$$

Now $c_1^2 = (\sqrt{c_2} - \epsilon)^2 \approx c_2 - \epsilon < c_2$, so the second economy is more concentrated when measured using HHI.

$\mathcal{C}$ in these two economies: We now consider the $k > 2$ terms.

For the first economy:

$$c_1^k + (n-1)(\frac{1-c_1}{n-1})^k = c_1^k + \frac{(1-c_1)^k}{(n-1)^2} \approx c_1^k,$$

where the $\approx$ relies on taking $n \to \infty$.

For the second economy:

$$\frac{1}{c_2} c_2^k = c_2^{k-1}.$$

For $k > 2$ the first economy is now more concentrated. To see this note that

$$c_1^k = (\sqrt{c_2} - \epsilon)^k \approx c_2^{k/2} - \epsilon^k.$$

Because for $k > 2$ we have $\frac{k}{2} < k - 1$, $c_2 < 1$ and ϵ is small,

$$c_2^{k/2} - \epsilon^k > c_2^{k-1}.$$

Hence, for small enough ϵ the first economy will be more concentrated according to $\mathcal{C}$. Intuitively, $\mathcal{C}$ places more weight on the largest firm than HHI (in the limit, only the largest share), and so the monopsonist with the competitive fringe is more concentrated according to $\mathcal{C}$ than HHI.

B Omitted proofs

B.1 Proof of Proposition 1

Proof. Now:

$$\begin{aligned} U_i &= b + \beta[\lambda \sum_{j \neq i} f_j W_j + \underline{\lambda} f_i W_i + (\lambda - \underline{\lambda}) f_i U_i + (1-\lambda) U_i] \\ U_i &= b + \beta[U_i + \lambda \sum_{j \neq i} f_j (W_j - U_i) + \underline{\lambda} f_i (W_i - U_i)]. \end{aligned} \tag{A1}$$

From equations (7), (3), and (2)

$$\begin{aligned} \alpha S_i = (W_i - U_i) &= w_i + \beta[\delta U + (1-\delta) W_i] - b - \beta[U_i + \lambda \sum_{j \neq i} f_j (W_j - U_i) + \underline{\lambda} f_i (W_i - U_i)] \\ &= w_i + \beta \alpha S_i - \beta[\delta \alpha S_i)] - b - \beta[\lambda \alpha S^1 - (\lambda - \underline{\lambda}) f_i \alpha S_i + \lambda \sum_j f_j (U_j - U_i)] + \beta \delta (U - U_i) \\ (1 - \beta(1-\delta)) \alpha S_i &= w_i - b + \beta(\lambda - \underline{\lambda}) f_i \alpha S_i - \beta \lambda [\alpha S^1 + \sum_j f_j (U_j - U_i)] + \beta \delta (U - U_i), \end{aligned} \tag{A2}$$

where we define $S^k \equiv \sum_i f_i S_i^k$ so that $S^1 \equiv \sum_i f_i S_i$ and we used the fact that:

$$\begin{aligned} \sum_{j \neq i} f_j (f_i S_i - f_j S_j) &= \sum_{j \neq i} f_j (f_i S_i - f_j S_j) + f_i (f_i S_i - f_i S_i) \\ &= \sum_j f_j (f_i S_i - f_j S_j). \end{aligned}$$

Now, we obtain two expressions for $(U_j - U_i)$ and $(U - U_i)$ in order to re-write equation (A2) above. We start with $(U_j - U_i)$. Note that

$$\begin{aligned} U_k &= b + \beta[U_k + \lambda \sum_{j \neq k} f_j (W_j - U_k) + \underline{\lambda} f_k (W_k - U_k)] \\ &= b + \beta[U_k + \lambda W^1 - \lambda f_k W_k - \lambda(1 - f_k) U_k + \underline{\lambda} f_k (W_k - U_k)] \\ (1 - \beta(1-\lambda)) U_k &= b + \beta[\lambda W^1 - \lambda f_k W_k + \lambda f_k U_k + \underline{\lambda} f_k (W_k - U_k)] \\ (1 - \beta(1-\lambda)) U_k &= b + \beta[\lambda W^1 - (\lambda - \underline{\lambda}) f_k \alpha S_k] \end{aligned}$$

where to go from the first line to the second line we use $\sum_i f_i = 1$ and define $W^1 \equiv \sum_j f_j W_j$. Hence,

$$(U_j - U_i) = \frac{\beta(\lambda - \underline{\lambda})\alpha}{(1 - \beta(1-\lambda))} [f_i S_i - f_j S_j]. \tag{A3}$$

Now, recall, from (1), that $U = b + \beta[\lambda \sum_i f_i W_i + (1-\lambda)U]$. Then, note that:

$$U - U_i = \beta[\lambda W^1 + (1-\lambda)U] - \beta[U_i + \lambda \sum_{j \neq i} f_j(W_j - U_i) + \underline{\lambda} f_i(W_i - U_i)]$$

$$(1 - \beta(1-\lambda))(U - U_i) = \beta(\lambda - \underline{\lambda}) f_i \alpha S_i$$

$$\beta\delta(U - U_i) = \beta\delta \frac{\beta(\lambda - \underline{\lambda})}{(1 - \beta(1-\lambda))} f_i \alpha S_i. \tag{A4}$$

Plug(A4) and (A3) into (A2) to get

$$(1 - \beta(1-\delta))\alpha S_i$$

$$= w_i - b + \beta(\lambda - \underline{\lambda}) f_i \alpha S_i - \beta\lambda[\alpha S^1 + \frac{\beta(\lambda - \underline{\lambda})\alpha}{(1 - \beta(1-\lambda))} \sum_j f_j[f_i S_i - f_j S_j]] + \beta\delta \frac{\beta(\lambda - \underline{\lambda})}{(1 - \beta(1-\lambda))} f_i \alpha S_i$$

$$(1 - \beta(1-\delta))\alpha S_i = w_i - b - \beta\lambda\alpha S^1 + \beta\lambda \frac{\beta(\lambda - \underline{\lambda})\alpha}{(1 - \beta(1-\lambda))} S^2 + \frac{1 - \beta(1-\delta)}{1 - \beta(1-\lambda)} \beta(\lambda - \underline{\lambda}) f_i \alpha S_i, \tag{A5}$$

where we used $S^k \equiv \sum_i f_i^k S_i$.

Combine (5), (4), and the normalization that $V_i = 0$ to get that:

$$w_i = 1 - (1 - \beta(1-\delta))(1-\alpha) S_i. \tag{A6}$$

Hence, combine (A6) and (A5)

$$(1 - \beta(1-\delta)) S_i = 1 - b - \beta\lambda\alpha S^1 + \beta\lambda \frac{\beta(\lambda - \underline{\lambda})\alpha}{(1 - \beta(1-\lambda))} S^2 + \frac{1 - \beta(1-\delta)}{1 - \beta(1-\lambda)} \beta(\lambda - \underline{\lambda}) f_i \alpha S_i. \tag{A7}$$

Recall again that $\tau = \frac{\beta(\lambda - \underline{\lambda})\alpha}{1 - \beta(1-\lambda)}$, $S^k \equiv \sum_i f_i^k S_i$, and that $f^k \equiv \sum_i f_i^k$, to rewrite (A7) as

$$(1 - \beta(1-\delta)) S^k = f^k \left[1 - b - \beta\lambda\alpha S^1 + \beta\lambda \frac{\beta(\lambda - \underline{\lambda})\alpha}{(1 - \beta(1-\lambda))} S^2\right] + (1 - \beta(1-\delta))\tau S^{k+1}. \tag{A8}$$

Evaluate (A8) at $k = 1, 2, 3, ...$ and to get

$$(1 - \beta(1-\delta)) S^1 = f^1 \left[1 - b - \beta\lambda\alpha S^1 + \beta\lambda \frac{\beta(\lambda - \underline{\lambda})\alpha}{(1 - \beta(1-\lambda))} S^2\right] + (1 - \beta(1-\delta))\tau S^2$$

$$(1 - \beta(1-\delta)) S^2 = f^2 \left[1 - b - \beta\lambda\alpha S^1 + \beta\lambda \frac{\beta(\lambda - \underline{\lambda})\alpha}{(1 - \beta(1-\lambda))} S^2\right] + (1 - \beta(1-\delta))\tau S^3$$

$$(1 - \beta(1-\delta)) S^3 = f^3 \left[1 - b - \beta\lambda\alpha S^1 + \beta\lambda \frac{\beta(\lambda - \underline{\lambda})\alpha}{(1 - \beta(1-\lambda))} S^2\right] + (1 - \beta(1-\delta))\tau S^4.$$

Note that, for $k = 1$, we can use $f^1 = 1$ and the definition of τ to write

$$(1 - \beta(1-\delta)) S^1 = 1 - b - \beta\lambda\alpha S^1 + \beta(\lambda - \underline{\lambda})\alpha \frac{1 - \beta + \beta(\delta + \lambda)}{(1 - \beta(1-\lambda))} S^2. \tag{A9}$$

Hence:

$$(1-\beta(1-\delta))S^1 = \left[1-b-\beta\lambda\alpha S^1 + \beta\lambda\frac{\beta(\lambda-\underline{\lambda})\alpha}{(1-\beta(1-\lambda))}S^2\right]\left[f^1+\tau f^2+\tau^2 f^3....\right] \tag{A10}$$

$$(1-\beta(1-\delta))S^2 = \left[1-b-\beta\lambda\alpha S^1 + \beta\lambda\frac{\beta(\lambda-\underline{\lambda})\alpha}{(1-\beta(1-\lambda))}S^2\right]\left[f^2+\tau f^3+\tau^2 f^4....\right]. \tag{A11}$$

Define

$$F \equiv \left(f^2 + \left(\frac{\lambda}{\lambda+r}\right)f^3 + \left(\frac{\lambda}{\lambda+r}\right)^2 f^4 + ...\right) = \sum_{k=2}^{\infty}\tau^{k-2}f^k \tag{A12}$$

to get that, directly from equations (A10) and (A11)

$$S^2 = S^1\frac{F}{1+\tau F} = S^1\mathcal{C}. \tag{A13}$$

Plug this into equation (A9) to get that mean surplus is given by

$$S^1 = \frac{1-b}{\left[(1-\beta(1-\delta))+\beta\lambda\alpha\right] - \tau\left[1-\beta(1-\delta)+\beta\lambda\right]\mathcal{C}}. \tag{A14}$$

This is where we use the approximation that $\underline{\lambda}\approx 0$. As a consequence,

$$\tau \approx \alpha\frac{\beta\lambda}{1-\beta(1-\lambda)}$$

and so

$$S^1 = \frac{1-b}{\left[(1-\beta(1-\delta))+\beta\lambda\alpha\right] - \left[\lambda+\frac{\beta\lambda\delta}{1-\beta(1-\lambda)}\right]\alpha\beta\mathcal{C}}$$

or

$$S^1 = \frac{1-b}{1-\beta\left(1-\lambda\alpha\underbrace{[1-C]}_{\text{wedge 1}}-\delta\underbrace{\left[1-\alpha\mathcal{C}\left(\frac{\beta\lambda}{1-\beta\left(1-\lambda\right)}\right)\right]}_{\text{wedge 2}}\right)}. \tag{A15}$$

Sum across i in equation (A6) to get

$$\begin{aligned}
w^1 &= 1-(1-\beta(1-\delta))(1-\alpha)S^1\\
(1-\alpha)(1-\beta(1-\delta))\frac{1-b}{1-\beta\Big(1-\lambda\alpha\left[1-\mathcal{C}\right]-\delta[1-\tau\mathcal{C}]\Big)} &= 1-w^1\\
(1-\alpha)\frac{1-\beta(1-\delta)}{1-\beta\Big(1-\lambda\alpha\left[1-\mathcal{C}\right]-\delta[1-\tau\mathcal{C}]\Big)} &= 1-\bar{\omega} \qquad \text{(A16)}
\end{aligned}$$

where the second line uses (A15) and the third line divides by $1-b$ and uses the definition of $\bar{\omega}$. $\square$

B.2 Proof of Proposition 2

Proof. Start with (A5) and use the exact definition of $\tau = \frac{\beta\lambda - \underline{\lambda}\alpha}{1-\beta(1-\lambda)}$ to get

$$
\begin{aligned}
(1-\beta(1-\delta))\alpha S_i &= w_i - b - \beta\lambda\alpha S^1 + \beta\lambda\frac{\beta(\lambda-\underline{\lambda})\alpha}{(1-\beta(1-\lambda))}S^2 + \frac{1-\beta(1-\delta)}{1-\beta(1-\lambda)}\beta(\lambda-\underline{\lambda})f_i\alpha S_i \\
(\alpha - \tau f_i)S_i &= \frac{w_i - b}{1-\beta(1-\delta)} + \frac{1}{1-\beta(1-\delta)}\Big(-\beta\lambda\alpha S^1 + \beta\lambda\tau S^2\Big).
\end{aligned} \tag{A17}
$$

Use equation (A6) to add $(1-\alpha)S_i = \frac{1-w_i}{1-\beta(1-\delta)}$ on both sides to get

$$
(1-\tau f_i)S_i = \frac{1-b}{1-\beta(1-\delta)} + \frac{1}{1-\beta(1-\delta)}\Big(-\beta\lambda\alpha S^1 + \beta\lambda\tau S^2\Big).
$$

Plug in for S_i using $S_i = \frac{1-w_i}{(1-\alpha)(1-\beta(1-\delta))}$ and observe that the right hand side is a constant to get that

$$
\frac{1-w_i}{1-w_j} = \frac{1-\tau f_j}{1-\tau f_i}. \tag{A18}
$$

□

B.3 Properties of $\mathcal{P}$

Proof. Note that:

$$
\begin{aligned}
\mathcal{C}^P &= \frac{\sum_{k=2}^{\infty}\tau^{k-2}\tilde{p}^k}{\tilde{p}^1 + \tau\sum_{k=2}^{\infty}\tau^{k-2}\tilde{p}^k} \times \frac{\tilde{p}^1}{\tilde{p}^1} \\
&= \frac{\sum_{k=2}^{\infty}\tau^{k-2}\tilde{p}^k/\tilde{p}^1}{1+\tau\sum_{k=2}^{\infty}\tau^{k-2}\tilde{p}^k/\tilde{p}^1}.
\end{aligned} \tag{A19}
$$

We have that:

$$
\mathcal{C}^P - \mathcal{C} = \frac{\sum_{k=2}^{\infty}\tau^{k-2}\tilde{p}^k/\tilde{p}^1}{1+\tau\sum_{k=2}^{\infty}\tau^{k-2}\tilde{p}^k/\tilde{p}^1} - \frac{\sum_{k=2}^{\infty}\tau^{k-2}f^k}{1+\tau\sum_{k=2}^{\infty}\tau^{k-2}f^k}. \tag{A20}
$$

Forming a common denominator, the sign of $\mathcal{C}^p - \mathcal{C}$ depends on the sign of $\sum_{k=2}^{\infty}\tau^{k-2}\tilde{p}^k/\tilde{p}^1 - \sum_{k=2}^{\infty}\tau^{k-2}f^k$. So now let us sign this component:

$$
\begin{aligned}
\sum_{k=2}^{\infty}\tau^{k-2}\tilde{p}^k/\tilde{p}^1 - \sum_{k=2}^{\infty}\tau^{k-2}f^k &= \sum_{k=2}^{\infty}\tau^{k-2}(\tilde{p}^k/\tilde{p}^1 - f^k) \\
&= \sum_i\sum_{k=2}^{\infty}\tau^{k-2}f_i^k(\tilde{p}_i/\tilde{p}^1 - 1) \\
&= \frac{1}{\tau^2}\sum_i\sum_{k=1}^{\infty}\tau^k f_i^k(\tilde{p}_i/\tilde{p}^1 - 1) - \frac{1}{\tau^2}\sum_i \tau f_i(\tilde{p}_i/\tilde{p}^1 - 1) \\
&= \frac{1}{\tau^2}\sum_i(\tilde{p}_i/\tilde{p}^1 - 1)\frac{\tau f_i}{1-\tau f_i} - \frac{1}{\tau}(\tilde{p}^1/\tilde{p}^1 - 1).
\end{aligned} \tag{A21}
$$

Note that ${}^{\tilde{p}^1}/_{\tilde{p}^1} - 1 = 0$. So we have:

$$
\begin{aligned}
\sum_{k=2}^{\infty} \tau^{k-2} {}^{\tilde{p}^k}/_{\tilde{p}^1} - \sum_{k=2}^{\infty} \tau^{k-2} f^k &= \frac{1}{\tau^2} \sum_i ({}^{\tilde{p}_i}/_{\tilde{p}^1} - 1) \frac{\tau f_i}{1 - \tau f_i} \\
&= \frac{1}{\tau} \sum_i \frac{f_i({}^{\tilde{p}_i}/_{\tilde{p}^1} - 1)}{1 - \tau f_i}. \qquad \text{(A22)}
\end{aligned}
$$

Since $\sum_i f_i {}^{\tilde{p}_i}/_{\tilde{p}^1} = 1$, the numerator is the *weighted* empirical covariance between f_i and ${}^{\tilde{p}_i}/_{\tilde{p}^1}$ (note that $\sum_i f_i({}^{\tilde{p}_i}/_{\tilde{p}^1} - 1) = \sum_i (f_i - \bar{f})({}^{\tilde{p}_i}/_{\tilde{p}^1} - 1)$), where the weights are $\frac{1}{1-\tau f_i}$, so we place more weight on the larger firms. □

B.4 Proof of Proposition 3

Proof. Recall that, under heterogeneous productivity, the output per worker at firm i is given by p_i. Hence, the equivalent of equation (4) is

$$J_i = p_i - w_i + \beta(1-\delta)J_i.$$

This equation, together with (8), gives us the equivalent of (A6) under heterogeneous productivity:

$$w_i = p_i - (1 - \beta(1-\delta))(1-\alpha)S_i. \qquad \text{(A23)}$$

Now, we proceed in exactly the same fashion as in the proof of Proposition 1. The proof is unaltered up to equation (A5).

$$(1 - \beta(1-\delta))S_i = p_i - b - \beta\lambda\alpha S^1 + \beta\lambda \frac{\beta(\lambda - \underline{\lambda})\alpha}{(1 - \beta(1-\lambda))} S^2 + \frac{1 - \beta(1-\delta)}{1 - \beta(1-\lambda)} \beta(\lambda - \underline{\lambda}) f_i \alpha S_i. \qquad \text{(A24)}$$

Thus, proceeding identically to the proof of Proposition 1, we combine (A23) and (A24) to obtain the counterpart to equation (A8):

$$(1 - \beta(1-\delta))S^k = \tilde{p}^k + f^k \left[-\beta\lambda\alpha S^1 + \beta\lambda \frac{\beta(\lambda - \underline{\lambda})\alpha}{(1 - \beta(1-\lambda))} S^2 \right] + \frac{1 - \beta(1-\delta)}{1 - \beta(1-\lambda)} \beta(\lambda - \underline{\lambda})\alpha S^{k+1} \qquad \text{(A25)}$$

where $\tilde{p}^k \equiv \sum_i f_i^k (p_i - b)$ is the employment weighted average (net) productivity.

Evaluate (A25) at $k = 1, 2, 3, ...$ to get

$$
\begin{aligned}
(1 - \beta(1-\delta))S^1 &= \tilde{p}^1 + f^1 \left[-\beta\lambda\alpha S^1 + \beta\lambda \frac{\beta(\lambda - \underline{\lambda})\alpha}{(1 - \beta(1-\lambda))} S^2 \right] + \frac{1 - \beta(1-\delta)}{1 - \beta(1-\lambda)} \beta(\lambda - \underline{\lambda})\alpha S^2 \\
(1 - \beta(1-\delta))S^2 &= \tilde{p}^2 + f^2 \left[-\beta\lambda\alpha S^1 + \beta\lambda \frac{\beta(\lambda - \underline{\lambda})\alpha}{(1 - \beta(1-\lambda))} S^2 \right] + \frac{1 - \beta(1-\delta)}{1 - \beta(1-\lambda)} \beta(\lambda - \underline{\lambda})\alpha S^3 \\
(1 - \beta(1-\delta))S^3 &= \tilde{p}^3 + f^3 \left[-\beta\lambda\alpha S^1 + \beta\lambda \frac{\beta(\lambda - \underline{\lambda})\alpha}{(1 - \beta(1-\lambda))} S^2 \right] + \frac{1 - \beta(1-\delta)}{1 - \beta(1-\lambda)} \beta(\lambda - \underline{\lambda})\alpha S^4.
\end{aligned}
$$

Importantly, for $k = 1$, we can also write

$$(1-\beta(1-\delta))S^1 = \tilde{p}^1 - \beta\lambda\alpha S^1 + \beta(\lambda - \underline{\lambda})\alpha\frac{1-\beta+\beta(\delta+\lambda)}{(1-\beta(1-\lambda))}S^2. \tag{A26}$$

Now start the substitution

$$(1-\beta(1-\delta))S^1 = \tilde{p}^1 + f^1\Big[-\beta\lambda\alpha S^1 + \beta\lambda\tau S^2\Big] + \tau\Big(\tilde{p}^2 + f^2\Big[-\beta\lambda\alpha S^1 + \beta\lambda\tau S^2\Big] + (1-\beta(1-\delta))\tau S^3\Big). \tag{A27}$$

If we keep substituting, then we get:

$$(1-\beta(1-\delta))S^1 = \Big(\tilde{p}^1 + \tau\tilde{p}^2 + \tau^2\tilde{p}^3 + ...\Big) + \Big[-\beta\lambda\alpha S^1 + \beta\lambda\tau S^2\Big]\Big(f^1 + \tau f^2 + \tau^2 f^3 + ...\Big). \tag{A28}$$

Proceeding identically for S^2 gives

$$(1-\beta(1-\delta))S^2 = \Big(\tilde{p}^2 + \tau\tilde{p}^3 + \tau^2\tilde{p}^4 + ...\Big) + \Big[-\beta\lambda\alpha S^1 + \beta\lambda\tau S^2\Big]\Big(f^2 + \tau f^3 + \tau^2 f^4 + ...\Big). \tag{A29}$$

Define

$$P \equiv \Big(\tilde{p}^2 + \tau\tilde{p}^3 + \tau^2\tilde{p}^4 + ...) = \sum_{k=2}^{\infty}\tau^{k-2}\tilde{p}^k \tag{A30}$$

and let, as previously, $F \equiv \sum_{k=2}^{\infty}\tau^{k-2}f^k$. This gives, directly from equations (A28) and (A29)

$$S^2 = S^1\frac{F}{1+\tau F} - \frac{1}{1-\beta(1-\delta)}\left[\left(\tilde{p}^1 + \tau P\right)\frac{F}{1+\tau F} - P\right] = S^1\mathcal{C} - \frac{1}{1-\beta(1-\delta)}\left[\left(\tilde{p}^1 + \tau P\right)\mathcal{C} - P\right]. \tag{A31}$$

Note that

$$\begin{aligned}\left(\tilde{p}^1 + \tau P\right)\mathcal{C} - P &= \left(\tilde{p}^1 + \tau P\right)\mathcal{C} - P\frac{\tilde{p}^1 + \tau P}{\tilde{p}^1 + \tau P} \\ &= \left(\tilde{p}^1 + \tau P\right)(\mathcal{C} - \mathcal{C}^P) \\ &= \tilde{p}^1\left(1 + \frac{\tau P}{\tilde{p}^1}\right)(\mathcal{C} - \mathcal{C}^P) \\ &= -\tilde{p}^1\mathcal{P}\end{aligned}$$

and so A31 becomes

$$S^2 = S^1\mathcal{C} + \frac{1}{1-\beta(1-\delta)}\tilde{p}^1\mathcal{P}. \tag{A32}$$

Plug this into equation (A26) to get

$$S^1 = \frac{\tilde{p}^1\left(1 + \tau\frac{1-\beta(1-(\delta+\lambda))}{1-\beta(1-\delta)}\mathcal{P}\right)}{1-\beta(1-(\delta+\lambda\alpha)) - \tau\mathcal{C}(1-\beta(1-(\delta+\lambda)))}. \tag{A33}$$

Define S^{1*} to be the employment weighted mean surplus from the homogeneous firm case given in (A15). Use the definition of $\hat{\tau}$ and the steps leading from (A14) to (A15) to get that

$$S^1 = S^{1*}\frac{\tilde{p}^1}{1-b}\left(1+\hat{\tau}\mathcal{P}\right). \tag{A34}$$

Integrate across equation (A23) to get

$$(1-\beta(1-\delta))(1-\alpha)\frac{S^1}{\tilde{p}^1} = 1-\bar{\omega}$$

and thus, plugging in the previous expression

$$(1-\beta(1-\delta))(1-\alpha)\frac{S^{1*}}{1-b}\left(1+\hat{\tau}\mathcal{P}\right) = 1-\bar{\omega}$$

and so the result is immediate from comparison with (A16). □

B.5 Proof of Proposition 4

Proof. Equations (A5) and (A17) also hold in the extension with heterogeneous productivity.

$$\begin{aligned}(1-\beta(1-\delta))\alpha S_i &= w_i - b - \beta\lambda\alpha S^1 + \beta\lambda\frac{\beta(\lambda-\underline{\lambda})\alpha}{(1-\beta(1-\lambda))}S^2 + \frac{1-\beta(1-\delta)}{1-\beta(1-\lambda)}\beta(\lambda-\underline{\lambda})f_i\alpha S_i \\ (\alpha-\tau f_i)S_i &= \frac{w_i-b}{1-\beta(1-\delta)} + \frac{1}{1-\beta(1-\delta)}\Bigg(-\beta\lambda\alpha S^1 + \beta\lambda\tau S^2\Bigg).\end{aligned} \tag{A35}$$

Use equation (A23) to add $(1-\alpha)S_i = \frac{p_i-w_i}{1-\beta(1-\delta)}$ on both sides of (A17) to get

$$(1-\tau f_i)S_i = \frac{p_i-b}{1-\beta(1-\delta)} + \frac{1}{1-\beta(1-\delta)}\Bigg(-\beta\lambda\alpha S^1 + \beta\lambda\tau S^2\Bigg).$$

Plug in for S_i once more to get

$$(1-\tau f_i)\left(p_i-w_i\right) = (1-\alpha)\left(p_i-b\right) + (1-\alpha)\Bigg[-\beta\lambda\alpha S^1 + \beta\lambda\tau S^2\Bigg]. \tag{A36}$$

To characterize the term in squared brackets use, from equation (A26),

$$(1-\beta(1-\delta)+\beta\lambda\alpha)S^1 = \tilde{p}^1 + \tau(1-\beta+\beta(\delta+\lambda))S^2.$$

Rewrite as

$$\beta\lambda\Bigg[\tau S^2 - \frac{1-\beta((1-\delta)+\beta\lambda\alpha}{1-\beta+\beta(\delta+\lambda)}S^1\Bigg] = -\tilde{p}^1\frac{\beta\lambda}{1-\beta+\beta(\delta+\lambda)}$$

and so

$$
\begin{aligned}
\beta\lambda\left[\tau S^2-\alpha S^1-\frac{(1-\alpha)[1-\beta(1-\delta)]}{1-\beta+\beta(\delta+\lambda)}S^1\right] &= -\tilde{p}^1\frac{\beta\lambda}{1-\beta+\beta(\delta+\lambda)}\\
\beta\lambda\left[\tau S^2-\alpha S^1\right] &= -\tilde{p}^1\frac{\beta\lambda}{1-\beta+\beta(\delta+\lambda)}+\beta\lambda\frac{(1-\alpha)[1-\beta(1-\delta)]}{1-\beta+\beta(\delta+\lambda)}S^1\\
\beta\lambda\left[\tau S^2-\alpha S^1\right] &= -\frac{\beta\lambda}{1-\beta+\beta(\delta+\lambda)}\left[\tilde{p}^1-S^1(1-\beta(1-\delta))(1-\alpha)\right].
\end{aligned}
$$

Use this to replace the term in squared brackets in (A36) and plug in for $S^1=(p^1-\bar{w})\frac{1}{(1-\beta(1-\delta))(1-\alpha)}$ to get that

$$
\begin{aligned}
(1-\tau f_i)(p_i-w_i) &= (1-\alpha)(p_i-b)-\frac{\beta\lambda(1-\alpha)}{1-\beta+\beta(\delta+\lambda)}\left[\tilde{p}^1-(p^1-\bar{w})\right]\\
(1-\tau f_i)(p_i-w_i) &= (1-\alpha)(p_i-b)-\frac{\beta\lambda(1-\alpha)}{1-\beta+\beta(\delta+\lambda)}(\bar{w}-b),
\end{aligned}
$$

which completes the proof.

□

B.6 Proof of Corollary 4

Proof. The proof proceeds in a few steps:

1. First, establish that $\frac{\partial\bar{w}}{\partial\mathcal{C}}\frac{\mathcal{C}}{\bar{w}}<0$.
2. Second, establish that $\frac{\partial^2\bar{\omega}}{\partial\mathcal{C}\partial\alpha}\frac{\mathcal{C}}{\bar{w}}>0$.
3. Combined, these steps imply that $\frac{\partial\bar{w}}{\partial\mathcal{C}}\frac{\mathcal{C}}{\bar{w}}$ becomes smaller in magnitude when α increases.

Establish that $\frac{\partial\bar{w}}{\partial\mathcal{C}}\frac{\mathcal{C}}{\bar{w}}<0$ To keep notation more compact, it is helpful to note that:

$$
\bar{w}=\bar{\omega}(1-b)+b \tag{A37}
$$

Then:

$$
\frac{\partial\bar{w}}{\partial\mathcal{C}}=(1-b)\frac{\partial\bar{\omega}}{\partial\mathcal{C}}. \tag{A38}
$$

And:

$$
\begin{aligned}
\frac{\partial\bar{w}}{\partial\mathcal{C}}\frac{\mathcal{C}}{\bar{w}} &= \frac{\partial\bar{\omega}}{\partial\mathcal{C}}\frac{(1-b)\mathcal{C}}{\bar{\omega}(1-b)+b}\\
&= \frac{\partial\bar{\omega}}{\partial\mathcal{C}}\frac{\mathcal{C}}{\bar{\omega}+\frac{b}{1-b}}.
\end{aligned} \tag{A39}
$$

Note that:

$$
\frac{\partial\bar{\omega}}{\partial\mathcal{C}}=\frac{-(1-\alpha)\tau[1-\beta(1-\delta)][1-\beta(1-\delta)+\beta\lambda]}{\left(\left[(1-\beta(1-\delta))+\beta\lambda\alpha\right]-\left[1-\beta(1-\delta)+\beta\lambda\right]\tau\mathcal{C}\right)^2}<0. \tag{A40}
$$

Hence, combining (A39), (A40) and the fact that $\frac{\mathcal{C}}{\bar{w}} > 0$, we have

$$\frac{\partial \bar{w}}{\partial \mathcal{C}} \frac{\mathcal{C}}{\bar{w}} < 0. \tag{A41}$$

Establish that $\frac{\partial^2 \bar{\omega}}{\partial \mathcal{C} \partial \alpha} \frac{\mathcal{C}}{\bar{w}} > 0$ Now:

$$\begin{aligned} \frac{\partial \frac{\partial \bar{w}}{\partial \mathcal{C}} \frac{\mathcal{C}}{\bar{w}}}{\partial \alpha} &= \frac{\partial \frac{\partial \bar{\omega}}{\partial \mathcal{C}}}{\partial \alpha} \frac{\mathcal{C}}{\bar{\omega} + \frac{b}{1-b}} - \frac{\partial \bar{\omega}}{\partial \mathcal{C}} \frac{\partial \bar{\omega}}{\partial \alpha} \frac{\mathcal{C}}{(\bar{\omega} + \frac{b}{1-b})^2} \\ &= \frac{\mathcal{C}}{\bar{\omega} + \frac{b}{1-b}} \left(\frac{\partial^2 \bar{\omega}}{\partial \mathcal{C} \partial \alpha} - \frac{\partial \bar{\omega}}{\partial \mathcal{C}} \frac{\partial \bar{\omega}}{\partial \alpha} \frac{1}{(\bar{\omega} + \frac{b}{1-b})} \right). \end{aligned} \tag{A42}$$

Note that:

$$\begin{aligned} \frac{\partial \bar{\omega}}{\partial \alpha} &= \frac{\left(\left[1 - \beta(1-\delta)) + \beta\lambda\alpha \right] - \left[1 - \beta(1-\delta) + \beta\lambda \right] \tau\mathcal{C} - (\alpha - \tau\mathcal{C})\beta\lambda \right) \left[1 - \beta(1-\delta) + \beta\lambda \right]}{\left(\left[(1 - \beta(1-\delta)) + \beta\lambda\alpha \right] - \left[1 - \beta(1-\delta) + \beta\lambda \right] \tau\mathcal{C} \right)^2} \\ &= \frac{(1 - \tau\mathcal{C})[1 - \beta(1-\delta)][1 - \beta(1-\delta) + \beta\lambda]}{\left(\left[(1 - \beta(1-\delta)) + \beta\lambda\alpha \right] - \left[1 - \beta(1-\delta) + \beta\lambda \right] \tau\mathcal{C} \right)^2} > 0. \end{aligned} \tag{A43}$$

Now we can consider the cross-partial:

$$\begin{aligned} \frac{\partial^2 \bar{\omega}}{\partial \mathcal{C} \partial \alpha} =& \left(\left[(1 - \beta(1-\delta)) + \beta\lambda\alpha \right] - \left[1 - \beta(1-\delta) + \beta\lambda \right] \tau\mathcal{C} + 2\beta\lambda(1-\alpha) \right) \\ & \times \frac{\tau[1 - \beta(1-\delta)][1 - \beta(1-\delta) + \beta\lambda]}{\left(\left[(1 - \beta(1-\delta)) + \beta\lambda\alpha \right] - \left[1 - \beta(1-\delta) + \beta\lambda \right] \tau\mathcal{C} \right)^3} > 0. \end{aligned} \tag{A44}$$

Plugging (A40), (A43), and (A44) into (A42), we have that $\frac{\partial^2 \bar{\omega}}{\partial \mathcal{C} \partial \alpha} \frac{\mathcal{C}}{\bar{w}} > 0$.

Conclude Since $\frac{\partial \bar{w}}{\partial \mathcal{C}} \frac{\mathcal{C}}{\bar{w}} < 0$ and $\frac{\partial^2 \bar{\omega}}{\partial \mathcal{C} \partial \alpha} \frac{\mathcal{C}}{\bar{w}} > 0$, we have that when α increases the elasticity decreases in magnitude.

$\square$

C Data-driven labor markets

C.1 Definition

We assume that each firm $i = 1, \dots, N$ in the economy is in one of K labor markets. An $N \times 1$ vector z denotes the assignment of firms to markets with $z_i \in \{1, \dots, K\}$. We assume that worker flows between firms are driven by the latent markets. In particular, a $K \times K$ matrix M summarizes transition probabilities between labor markets where the typical element $M_{mm'}$ indicates how likely a firm in market m experiences a transition of one of its workers to a firm in market m'.

The dependence of worker flows between firms i and j on market assignments is then

$$E[A_{ij}] = M_{z_i z_j} \gamma_j^+ \gamma_i^- , \tag{A45}$$

where the number of worker transitions from i to j , A_{ij}, depends on the markets of firms i and j, z_i and z_j, the transition probability between these markets, and the firm-level parameters γ_j^+ and γ_i^- which measures the propensity of firm j to hire workers and the propensity of workers to leave firm i.

Based on the observed $N \times N$ matrix of worker transitions between firms, we estimate the parameters of equation (A45) by a computational approximation to maximum likelihood. An important tuning parameter is the number of markets to consider, K. A higher number of labor markets increases the flexibility of the stochastic block model to describe the data where in the limit of $K = N$ each firm represents its own market. This additional flexibility comes with the threat of overfitting.

To guide the trade-off between model complexity and flexibility, we rely on a regularization approach where we pick the number of labor markets to maximize the penalized likelihood of the objective function. In our baseline, we choose parameters by minimizing the description length of the model. The description length is given by the difference between the log-likelihood and the information (entropy) of the model. The log-likelihood of the stochastic block model can be written $\log \mathcal{L} = \sum_{m,m'} E_{mm'} \log \frac{E_{mm'}}{d_m^+ d_{m'}^-}$, where $E_{mm'}$ denotes the number of transitions between markets m and m' and d_m^+ and $d_{m'}^-$ denote the number of incoming links in market m and outgoing links in market m', respectively.[32] The information can be written $\frac{K(K+1)}{2} \log E + N \log K$, where E denotes the total number of worker flows.

Minimizing the description length leads us to 376 labor markets out of which 368 are populated throughout the entire sample period. In a robustness check, we use modularity maximization as an alternative regularization approach, which yields a coarser classification into 9 labor markets. Fixing K, we estimate the partition that maximizes the log-likelihood and then evaluate the different variants according to the modularity score. The modularity score, $Q = \frac{1}{2E} \sum_{ij} (A_{ij} - \frac{d_i d_j}{2E}) \mathbf{1}\{z_i = z_j\}$, compares the share of transitions *within* a market to the share of expected within-market transitions in a null model that keeps the number of links constant for each firm but generates links uniformly at random (ignoring the market structure).

For the purposes of estimating the model, we only use employment-to-employment transitions. An EE transition is defined as a change of the firm with at most 30 days of non-employment between the two spells and at least one year of tenure in the old and the new job. Spurious transitions due to firm renamings, mergers or spin-offs are excluded using cutoffs on worker flows.

[32] For a derivation of this result see, e.g., Nimczik (2018).

C.2 Comparison to industry-region markets

We find that the data-driven labor markets frequently cross the boundaries of regions and (4-digit) industries. For each labor market, we compute the share of employment that is in the "dominant" industry or region, which is the industry or region accounting for the largest share of employment in the labor market. If a data-driven labor market lies completely within an industry or region, then this share is 1. Instead, Figure A1 shows that there are many low values of this measure, indicating that most labor markets have a large fraction of employment outside the dominant industry or region. The top panel shows that the average share of the dominant region is below 0.6 (there are 35 regions compared to 368 data-driven labor markets). The bottom panel shows that labor markets are even less well-described by 4-digit industry.

Data-driven labor markets are more isolated islands than labor market definitions based on industry or industry-region in the following two senses: The first column of Table A2 shows that, relative to defining a labor market by industry or industry-region, a larger share of transitions happens within the data-driven labor markets. That said, the absolute level is fairly low: about 40 percent of transitions are within the data-driven labor markets. For context, when we look at 2-digit industry $\times$ region, only 25 percent of transitions are within these labor markets.

A second metric which adjusts for mechanical effects due to the number of markets is the modularity score, which is the excess share of within-market transitions over a null model of random transitions. The last column of the table shows that the modularity score for the data-driven markets far exceeds the modularity score obtained when employing standard industry-region labor market definitions.

D Sampling procedure on indeed.com

We visited indeed.com on several occasions between April 7th and April 18th 2020. The vacancies we sampled were posted between March 20th and April 18th.

The website classifies job ads into 6 job types: full-time, part-time, contract, temporary, commission, and internship. These categories are not mutually exclusive and it is common for a position to be open both as part-time and full-time, for example. We did not consider job postings that were classified exclusively as contract, temporary, commission, or internship. That is, we required jobs to be either part-time or full-time.

We searched for jobs using the "relevance" criterion which is the default algorithm the website uses to list jobs from its stock. Most jobs were selected in the order at which they appeared and no further "researcher intervention" occurred. However, because we sampled jobs in the midst of the Covid-19 pandemic, the composition of jobs was dominated by cashiers, delivery drivers, warehouse helpers, and sales representatives. In order to partially offset this, we skipped some of the jobs in those categories and instead selected among the ones that appeared right after.

If two jobs looked very similar but one of them was posted by a company that had received at least one review from website users, we chose the job from the reviewed company and considered the other a phantom vacancy.

Crucially, all vacancies were sampled before we reviewed the information requested in the application form. We filled out application forms for each of the 200 jobs we sampled but did not submit any actual applications.

About half of the firms redirected us to their own websites where we filled a customized application form. About half of the firms use a semi-automatic application form provided by the software company Workday, which includes a predefined set of questions and also allows firms to include firm-specific questions. A few firms asked only for resumes.

We recorded each case where the employer asked whether the applicant had previously worked for the employer and, correspondingly, each case where the employer asked whether the applicant had previously applied to the employer.

E On-the-Job Search

Without loss, order firms by the wage they pay. We first relate the vacancy shares to the empirically observed employment shares.

E.1 Job finding rate

Let f_i firm i's vacancy share which is not directly observable and let g_i be it's employment share which is observed. We have that $\sum_i f_i = 1$ and $\sum_i g_i = 1$. Let F_i be $\sum_{j=1}^{i} f_j$ and $G_i = \sum_{j=1}^{i} g_j$. Then, the following flow balance has to hold at the firm level.

$$f_i(u\lambda + (1-u)G_{i-1}(1-\delta)\lambda_e) = g_i(1-u)(\delta + (1-\delta)\lambda_e(1-F_i)) \tag{A46}$$

The left hand side is the inflow of new workers into firm i. These are the unemployed that draw i and those employed at less attractive employers that don't lose their job (note the implicit timing assumption) and then draw i. The right hand side is the outflow. These are the ones that lose their job and those of the survivors that end up sampling an offer from a more attractive firm.

Denote the (observed) job-to-job transition rate by $\mathcal{X}$ which satisfies

$$\mathcal{X} = \lambda_e \sum_{i=1}^{N} (1-F_i)\, g_i.$$

These equations, jointly with the unemployment rate $u = \frac{\delta}{\delta+\lambda}$ can then be used to solve for the f_i and λ_e.

E.2 Surplus

The value function for employment at i now is

$$W_i = w_i + \beta\left(\delta U + (1-\delta)\left(W_i + \lambda_e \sum_{j>i} f_j(W_j - W_i)\right)\right)$$

We use $\alpha S_i = W_i - U_i$ to get that

$$\alpha S_i = w_i + \beta[\delta U + (1-\delta)(W_i + \lambda_e \sum_{j>i} f_j(W_j - W_i))] - b - \beta[U_i + \lambda \sum_{j\neq i} f_j(W_j - U_i) + \underline{\lambda} f_i(W_i - U_i)]$$

Proceeding in exactly the same fashion as in Appendix B.1, we get the following expression for surplus,

$$[(\alpha-\tau f_i)(1-\beta(1-\delta)(1-\lambda_e \bar{P}_i))]S_i = w_i - b - \beta\lambda\alpha S^1 + \beta\lambda\tau S^2 + \beta(1-\delta)\lambda_e \sum_{j>i} f_j(S_j(\alpha-\tau f_j)) \tag{A47}$$

where τ is defined as before. We solve this equation numerically.

E.3 Calibrating the value of leisure b with on-the-job search

As before, we calibrate b such that the lowest observed $\underline{w}$ equals the reservation wage. To do so, note that the value of being unemployed equals the value of being employed at the reservation wage,

$$W\left(\underline{w}\right) = U. \tag{A48}$$

Using this, it is straightforward to show that

$$W\left(\underline{w}\right) = \underline{w} + \beta((1-(1-\delta)\lambda_e)W(\underline{w}) + (1-\delta)\lambda_e\bar{W}). \tag{A49}$$

where $\bar{W} \equiv \sum_i f_i W_i$ is the employment weighted average value of employment. The value of unemployment is

$$U = b + \beta\left(\lambda\bar{W} + (1-\lambda)U\right). \tag{A50}$$

Now, equate (A49) and (A50) and solve for b to get

$$b = \underline{w}\frac{1-\beta(1-\lambda)}{1-\beta(1-\lambda_e(1-\delta))} + \bar{W}\frac{\beta\left[(1-\beta)(\lambda_e(1-\delta)-\lambda)\right]}{1-\beta(1-\lambda_e(1-\delta))}. \tag{A51}$$

Use the definition of $\bar{W}$ to get,

$$\begin{aligned}\bar{W} &= \sum_i f_i w_i + \beta(\delta\sum_i f_i U + (1-\delta)\sum_i f_i W_i + (1-\delta)\sum_i f_i \sum_{j>i}\lambda_e f_j(W_j - W_i)) \\ &= \bar{w} + \beta\delta W(\underline{w}) + \beta(1-\delta)\bar{W} - \beta(1-\delta)\left[\sum_i f_i S_i(\alpha-\tau f_i)\lambda_e\bar{P}_i - \sum_i f_i\sum_{j>i}\lambda_e f_j(S_j(\alpha-\tau f_j))\right]\end{aligned}$$

where the second equation proceeds as in Appendix B.1 and the derivation of (A47). Expressing $W(\underline{w})$ in terms of $\bar{w}$ and $\bar{W}$, we have an expression that implicitly defines $\bar{W}$ in terms of observables and surplus only. Solve for $\bar{W}$ and plug back into (A51) to obtain an expression that relates b to observables and surplus only which guarantees that the lowest paying firm pays the reservation wage. This can then be jointly solved with the expression for surplus in (A47).

E.4 Backing out productivity p_i and calibrating α

As before, we construct the p_i such that the value function of the firm is satisfied,

$$J_i = (1-\alpha)S_i = p_i - w_i + \beta(1-\delta(1-\lambda_e\bar{P}_i))(1-\alpha)S_i. \tag{A52}$$

Given p_i for each firm i in market m, we can compute average productivity p_m^1 for each market. Then, we compute the labor share as $\frac{\sum_m \bar{w}_m emp_m}{\sum_m p_m^1 emp_m}$ and calibrate α such that this equals the labor share from the KLEMS data.

E.5 Counterfactual

We compare the w_i found in the data with counterfactual wages w_i' that prevail if all firms are atomistic but the distribution of employment is unchanged. To mimic our approach in the baseline case, we keep all parameters $\{f_i, \lambda, \underline{\lambda}, \lambda_e, \delta, \alpha, \beta, b\}$ unchanged but order firms by p_i which reflects the new job ladder. We compute a new distribution of firm sizes, g_i' from the flow-balance equation (A46). This does pick up productivity effects that arise from the re-ordering of the job ladder but still does not pick up a potential feedback into the vacancy shares f_i, just like in our baseline exercise. Now, we compute the surplus S_i' in the counterfactual. We have $S_i' = W_i' - U + J_i' - V_i'$. We maintain $V_i' = 0$, that is we implicitly adjust the c_i as before. Plugging in, it is straightforward to verify that

$$S_i' = p_i - b + \beta(1-\delta)S_i' - \beta\lambda\alpha S'^1 + \beta(1-\delta)\lambda_e\alpha\left(\sum_{j>i} f_j\left(\alpha S_j' - S_i'\right)\right). \tag{A53}$$

The last term reflects the gains from on-the-job search. If successful, the worker continues with a fraction α of the next surplus but the current match is destroyed. This equation can be directly solved for all the S_i'. To compute counterfactual wages, again use the (unchanged) value function of the firm satisfying (A52).

F Additional Tables and Figures

Table A1: Sample Size and Construction

	Person/year	Firm/year
Total number of observations	2,857,835	236,142
Impose daily wage threshold (32.71 Euro)	2,525,519	192,952
Impose firm-size threshold ($\geq$ 5 employees)	2,290,285	65,285
Restrict to largest connected set	1,858,871	39,827
Restrict to markets with at least one firm in each year	1,819,998	39,798

Notes: This Table reports sample sizes for the year 2015. The total number of observations includes all employment spells of workers aged 20-60 that are present on August 1, 2015 and last for at least 30 days. In the second row, we subtract all spells where the average daily wage for the spell is below a minimum daily wage of 32.71 Euros. In the third row, we subtract spells in firms that employ fewer than 5 employees on August 1st. The fourth row shows the number of observations that are in the largest connected set based on employer-to-employer transitions.

Table A2: Share of transitions within markets

	Share of within-market transitions				Modularity score
	Average	Median	25th	75th	
Data-driven Labor Markets (368)	0.41	0.52	0.07	0.62	0.41
Alternative market definitions					
States (9)	0.76	0.75	0.75	0.85	0.60
NUTS3-regions (35)	0.60	0.71	0.43	0.77	0.49
2-digit Industries (80)	0.40	0.39	0.25	0.52	0.36
3-digit Industries (255)	0.34	0.35	0.19	0.47	0.32
4-digit Industries (538)	0.30	0.31	0.14	0.42	0.29
2-digit Industries × Regions (1838)	0.25	0.24	0.12	0.34	0.24
3-digit Industries × Regions (3615)	0.21	0.18	0.05	0.30	0.21
4-digit Industries × Regions (5384)	0.18	0.14	0.03	0.28	0.18

Notes: This Table reports summary statistics on the share of within-market transitions among all employer-employer (EE) transitions between the firms in our sample. An EE transition is defined as a change of the firm with at most 30 days of non-employment between the two spells and at least one year of tenure in the old and the new job. The first set of columns shows the share of EE transitions. The last column shows the modularity score, which is the excess share of within-market transitions over a null model of random transitions.

Table A3: Relationship between revealed concentration and HHI: Robustness

		One-year Gap			Non-shrinking Firms		
	HHI	Level	Reg. coef. (se)	Adj. R^2	Level	Reg. coef. (se)	Adj. R^2
Baseline (368)	0.11	0.14	1.07 (0.105)	0.22	0.10	0.83 (0.095)	0.17
2-digit industries × region (1838)	0.15	0.14	0.25 (0.05)	0.01	0.10	0.25 (0.055)	0.01
3-digit industries × region (3615)	0.24	0.14	0.18 (0.042)	0.00	0.10	0.25 (0.043)	0.01
4-digit industries × region (5384)	0.30	0.14	0.13 (0.036)	0.00	0.10	0.21 (0.035)	0.01
		Year-by-year (One-year Gap)			Year-by-year (Two-year Gap)		
	HHI	Level	Reg. coef. (se)	Adj. R^2	Level	Reg. coef. (se)	Adj. R^2
Baseline (368)	0.11	0.09	0.59 (0.019)	0.1	0.05	0.62 (0.03)	0.06
2-digit industries × region (1838)	0.15	0.09	0.11 (0.012)	0.00	0.05	0.12 (0.024)	0.00
3-digit industries × region (3615)	0.24	0.09	0.09 (0.013)	0.00	0.05	0.10 (0.023)	0.00
4-digit industries × region (5384)	0.30	0.09	0.07 (0.009)	0.00	0.05	0.09 (0.014)	0.00

Notes: This Table reports robustness results for the re-encounter analysis in Table 2. The first Columns in the upper panel show levels of concentration and regression results for the relationship between the HHI and the average re-encounter rate using a one-year gap (as opposed to a two-year gap in the text). Columns (5) to (7) in the upper panel condition on firms that do not shrink between year t and $t+3$. Columns (2) to (4) in the lower panel report results where we do not pool across years but compute the re-encounter rate year by year (and then average) using a one-year gap. Columns (5) to (7) in the lower panel uses the year-by-year re-encounter rate, but a two-year gap. For all versions, we report baseline results using the data-driven markets and additional market definitions.

Table A4: Persistence of firm-level variables

Dependent variable	Unweighted regression	Weighted regression
p_i	0.924	0.95
	(0.001)	(0.001)
$p_i - w_i$	0.889	0.943
	(0.001)	(0.001)
w_i	0.949	0.975
	(0)	(0)
emp_i	0.99	0.985
	(0.005)	(0.005)
$emp_{i,t} - emp_{i,t-1}$	0.274	0.382
	(0.083)	(0.083)
Observations	483,241	483,241

Notes: This table reports the results of regressing a firm's current productivity, profits, wages, size, and employment growth (shown by row) on its value in the previous year. Reported coefficients are those on the lagged variable. Weighted regressions are weighted by firm employment. Standard errors, clustered by firm, are in parentheses.

Table A5: Model extension with on-the-job search

	Average	Median	5th	25th	75th	95th
Panel A. Parameters						
χ_m	0.0018	0.0017	0.0007	0.0013	0.0022	0.0036
χ_m^*	0.0018	0.0017	0.0007	0.0013	0.0022	0.0036
λ_{e_m}	0.010	0.004	0.002	0.003	0.006	0.016
α	0.3640					
b_m	-98.45	-94.84	-240.20	-154.37	-47.59	53.91
Panel B. Effect of eliminating size-based market power						
%Δ labor share (no OJS)	10.02	2.42	0.53	1.32	4.95	22.16
%Δ labor share	3.83	2.13	0.45	1.24	3.73	10.92
%Δ wage	4.12	2.16	0.55	1.28	4.32	13.15
%Δ productivity	0.10	0.02	-0.00	0.00	0.10	1.54

Notes: This table reports parameters and the effect of removing our mechanism in the extended model with on-the-job search. All measures are calculated for the year 2015. For market- and time-specific parameters χ, λ_e, and b, it reports employment-weighted values. χ_m is the observed monthly job-to-job transition rate of workers who transition from employment in market m to a firm with a higher firm effect. χ_m^* is an adjusted transition rate where we shrink χ_m slightly in a few markets if the observed transition rate is inconsistent with the flow balance within markets. λ_{e_m} is the job offer arrival rate on the job that is implied by χ_m and the flow balance for each firm. α is the re-calibrated bargaining power parameter with on-the-job search. b_m is the re-calibrated flow value of unemployment and measured in the same units as wages. In Panel B, we compute the distribution of the change in the labor share, in wages, and in productivity due to removing our mechanism and then report quantiles of this distribution across markets.

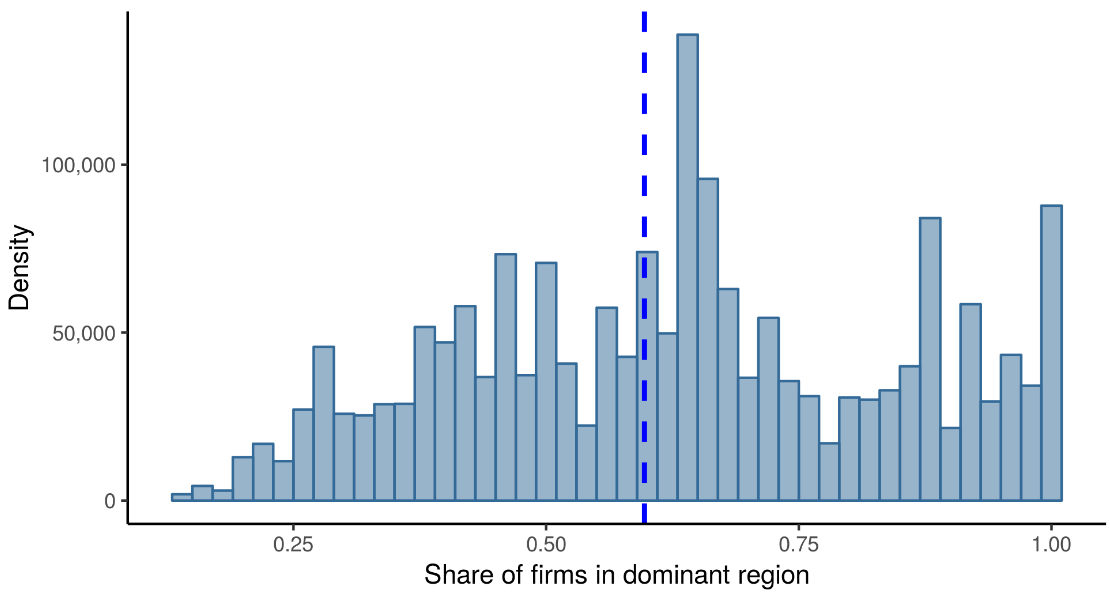
Table A6: Effects of mergers

	Δ HHI		%Δ wages at merging firms		%Δ wages at non-merging firms	
	Average	Median	Average	Median	Average	Median
Baseline (356)	0.046	0.025	-6.8	-3.4	-2.5	-0.7
Alternative market definitions						
2-digit industries × region (1539)	0.078	0.050	-9.2	-4.9	-4.1	-1.5
3-digit industries × region (2450)	0.106	0.077	-12.2	-5.4	-6.4	-1.9
4-digit industries × region (3028)	0.123	0.092	-14.6	-6.2	-8.0	-2.3

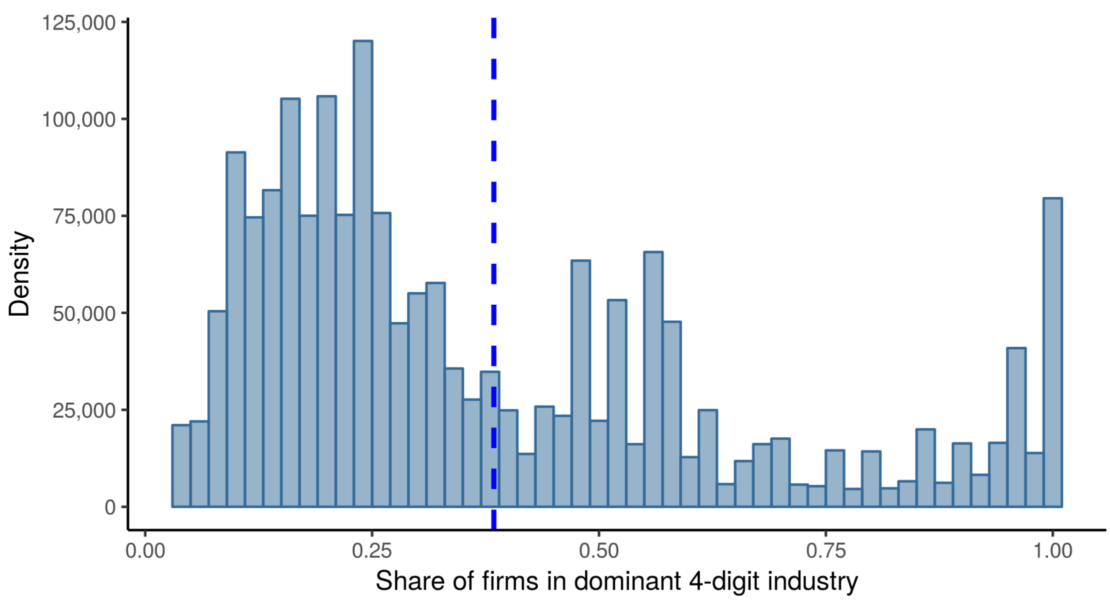
Notes: This table reports sensitivity of the effects of merging the two largest firms in each market to various labor market definitions. We report results for those markets where there are more than two firms and the number of such markets in parentheses. All numbers are employment-weighted statistics across markets.

Figure A1: Data-driven markets are not the same as region or industry

(a) Regions



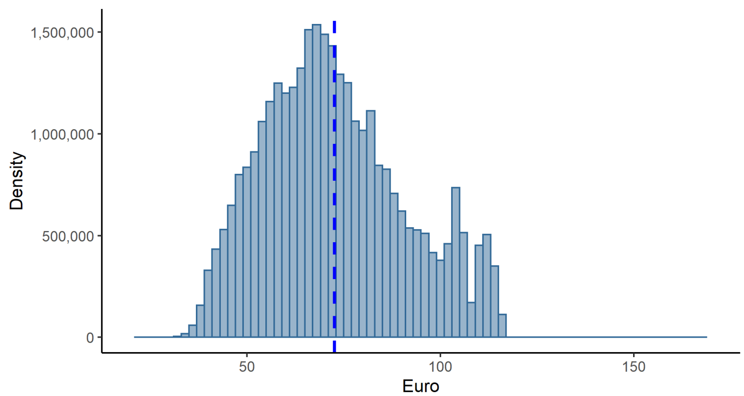
(b) Industries



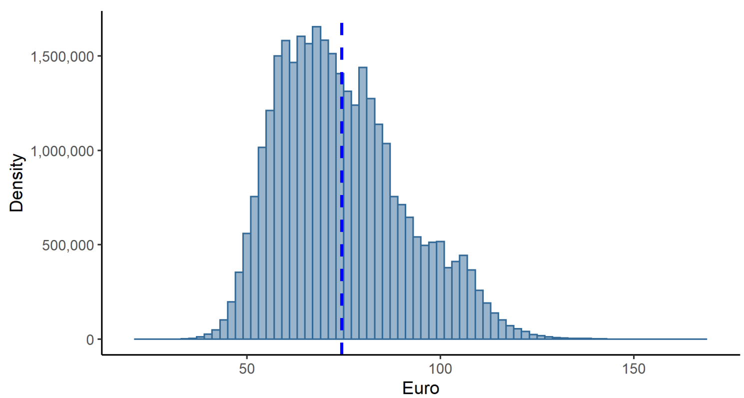
Notes: This Figure shows a sense in which the data-driven labor markets capture industry or geographic boundaries. For each market, we classify its "dominant" region or industry as the region or industry with the largest share of employment. The figures then show the distribution of the share of employment contained in the dominant region or industry. A value of 1 says that all of the employment is in a single region or industry. The figure displays employment-weighted averages over all 368 data-driven labor markets for the year 2015. The dashed line shows the average value.

Figure A2: Distribution of Firm-level Wages

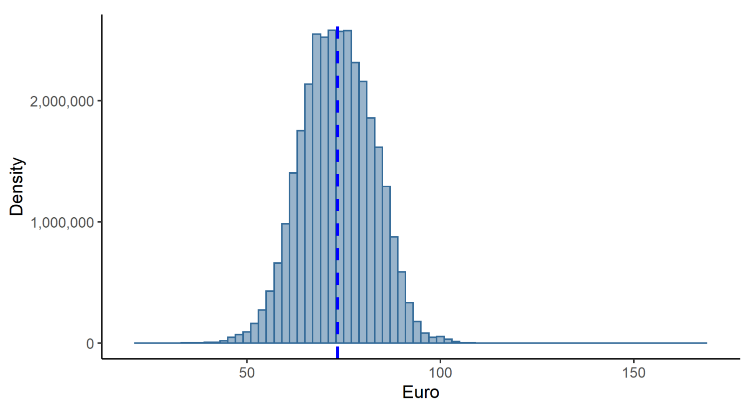
(a) Firm-Level Median



(b) Firm-Level Median of Residualized Real Wages



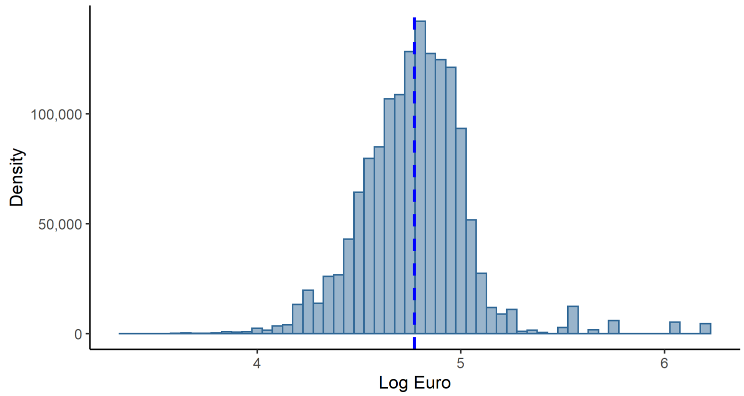
(c) Residualized Real Wages (AKM)



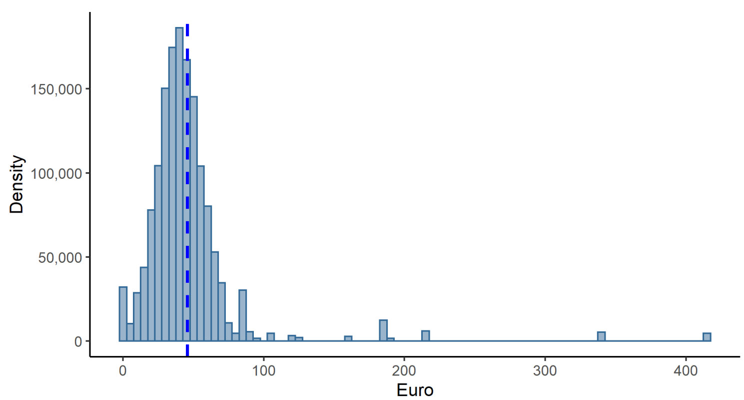
Notes: This figure plots the (employment-weighted) distribution and mean of firm-level median wages in real Euros where the base year for the Austrian CPI is 2000 and where we pool over all years in the sample period. Panel (a) shows actual median wages, Panel (b) shows wages after residualizing, and Panel (c) shows rescaled AKM firm effects.

Figure A3: Distribution of Implied Firm-level Productivity

(a) Log p_i

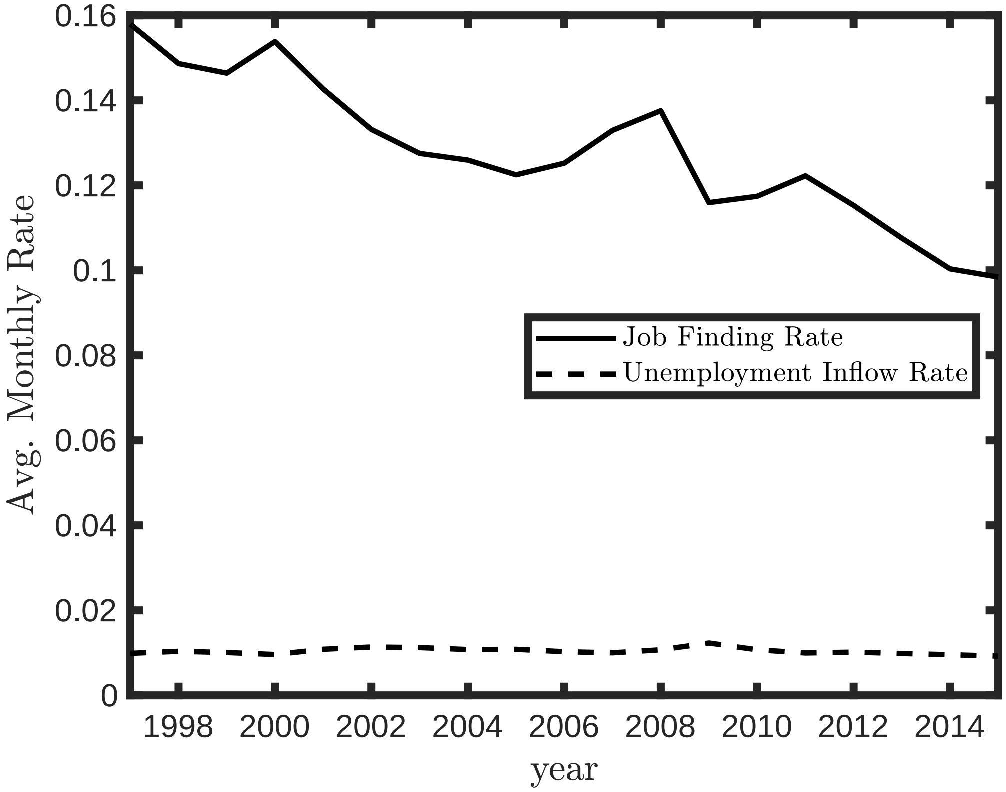


(b) p_i - w_i



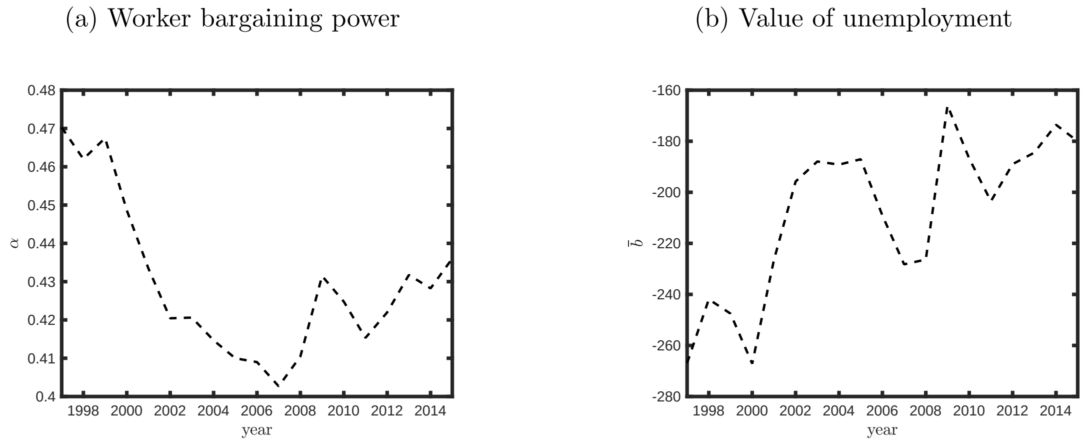
Notes: This figure plots the (employment-weighted) distribution and mean of firm-level productivity in log real Euros where the base year for the Austrian CPI is 2000 for the year 2015. Panel (a) shows log implied productivity while Panel (b) shows profits.

Figure A4: Job finding rate and job destruction rate over time (employment-weighted averages)



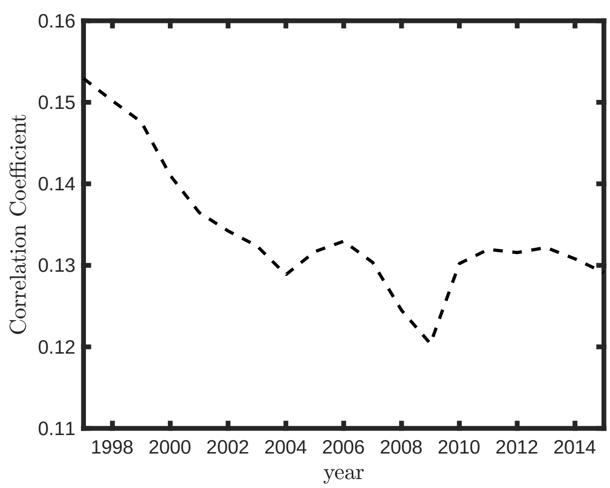
Notes: This figure plots the employment-weighted average of market-specific job finding and job destruction rates over time. For each market m, the yearly rate is an average of twelve monthly rates and the monthly rate is the probability that a worker who is unemployed (employed) on the 1st of a specific month will have a job in market m (be unemployed) on the 1st of the next month. Workers are assigned to the market in which they work. We measure the stock of unemployed based on the market in which they eventually find a job.

Figure A5: Worker bargaining power and value of unemployment and over time



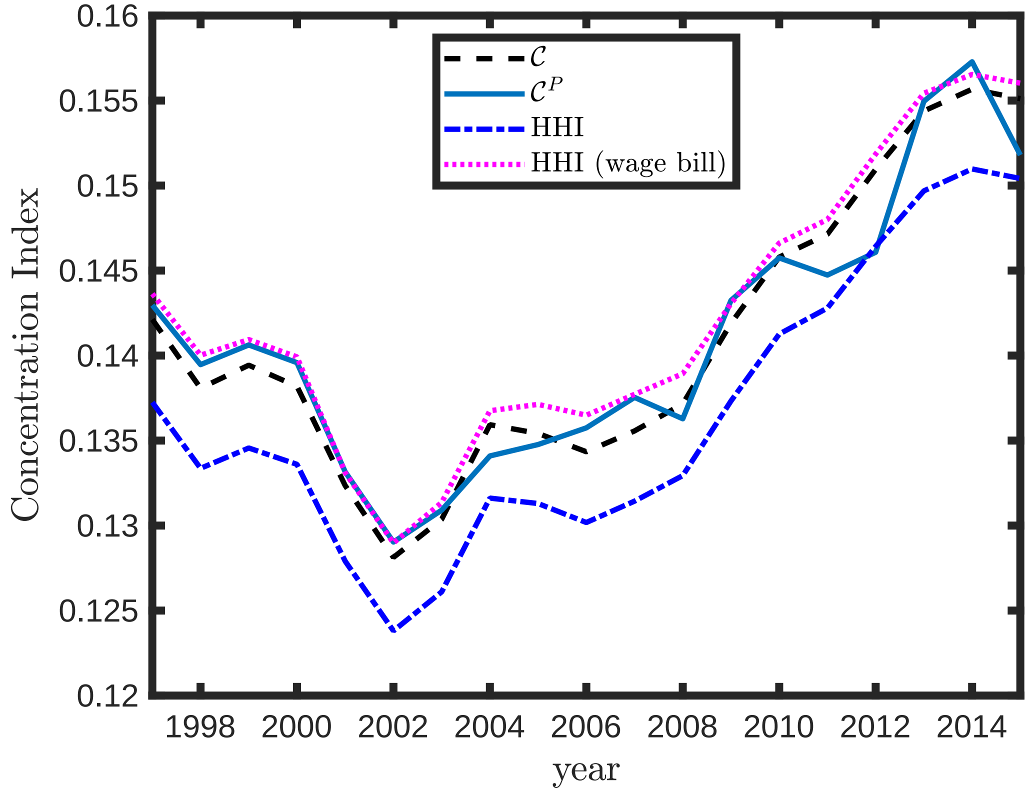
Notes: Panel A of this figure the year-specific values of α that target the labor share from the KLEMS data over time. Panel B plots the employment-weighted average of market specific parameters b over time. For each market m, the parameter b is chosen such that the lowest observed wage in the market equals to the reservation wage.

Figure A6: Size-wage gradient



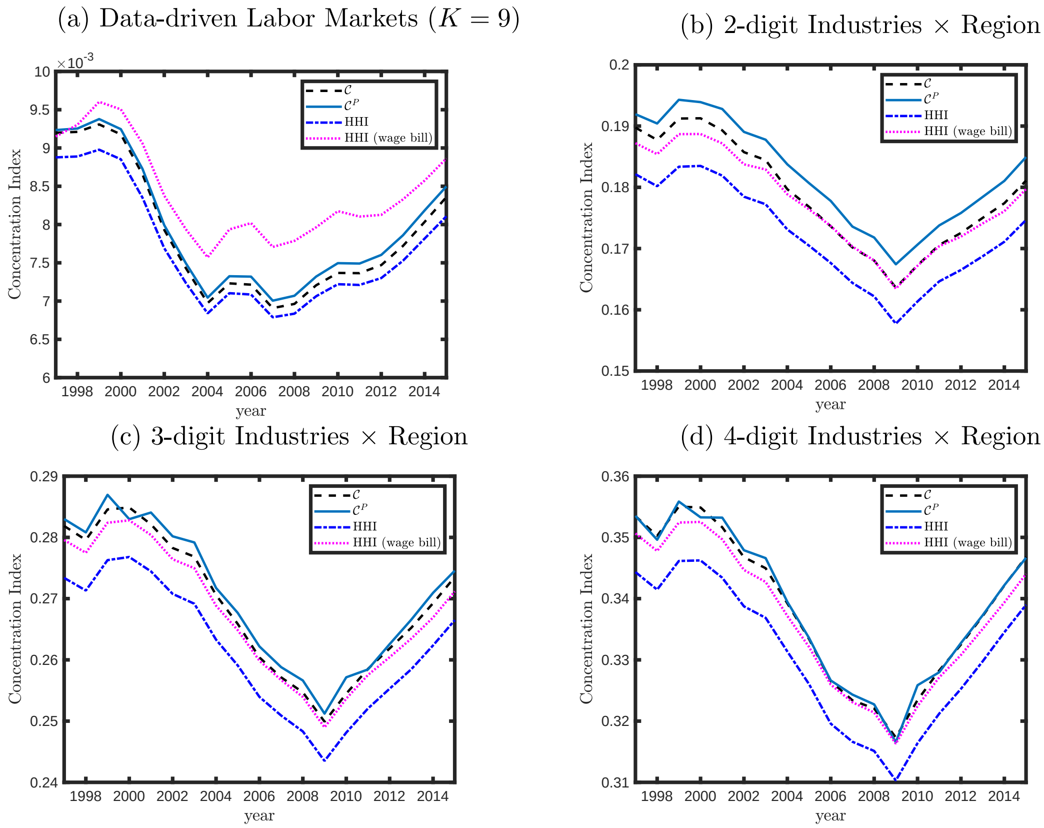
Notes: This figure plots the (employment-weighted average) of the correlation between firm size and firm-level median wages. Firm size is measured at a reference date (August 1st) each year and wages are the median of the firm-level distribution of regular employee wages. The figure displays employment-weighted averages over all 368 data-driven labor markets.

Figure A7: Trends in Labor Market Concentration (unweighted)



Notes: This figure plots concentration indexes $\mathcal{C}$, $\mathcal{C}^P$, HHI and wage-bill HHI from 1997 - 2015 based on micro data from the Austrian labor market database. The figure displays raw averages over all 368 data-driven labor markets.

Figure A8: Trends in Labor Market Concentration – Different Labor Market Definitions



Notes: This figure plots concentration indexes $\mathcal{C}$, $\mathcal{C}^P$, HHI and wage-bill HHI from 1997 - 2015 based on micro data from the Austrian labor market database. The figure displays employment-weighted averages over all markets for various labor market definitions.