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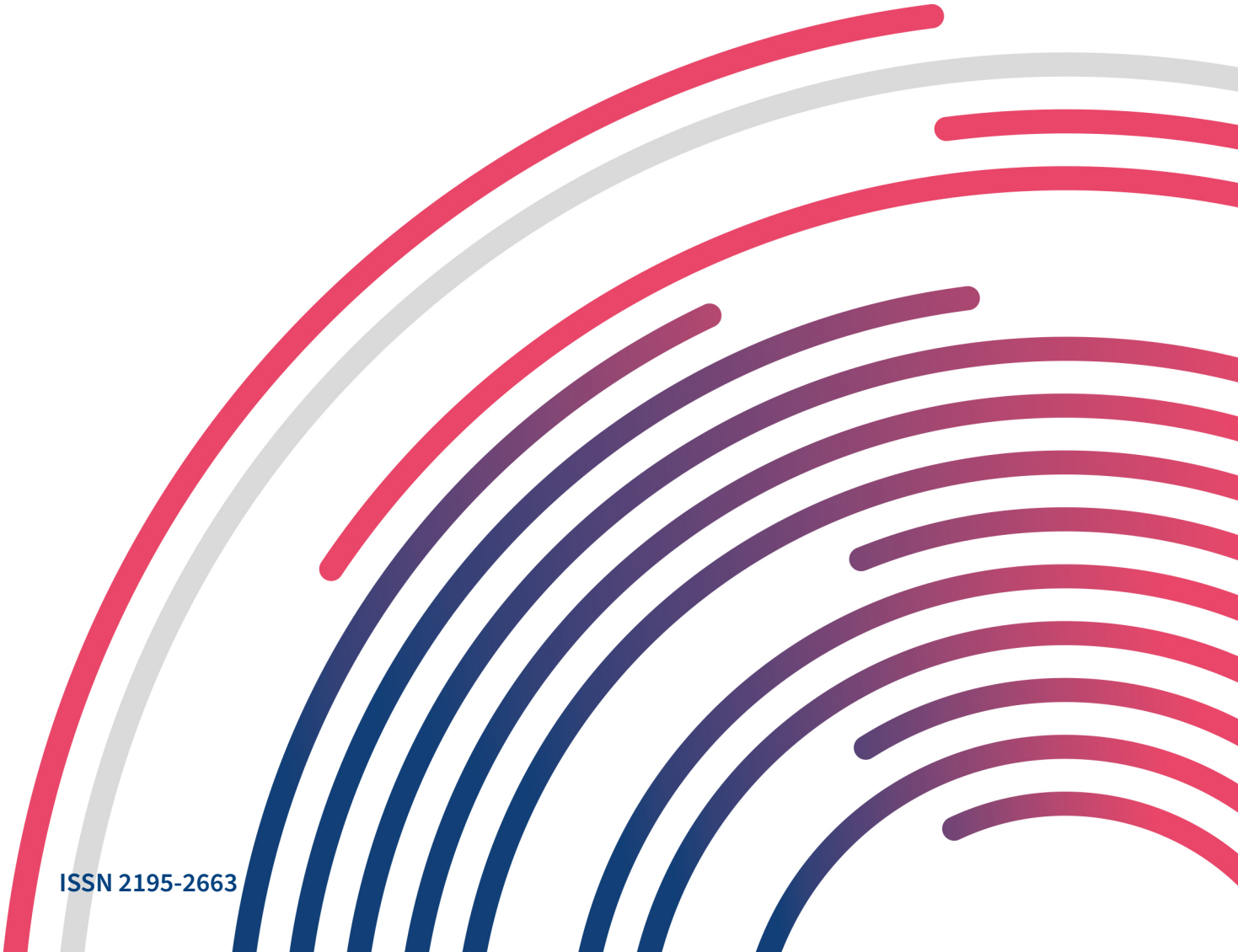
02|2023 Labor Demand on a Tight Leash

Mario Bossler, Martin Popp



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Labor Demand on a Tight Leash

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Mit der Reihe „IAB-Discussion Paper“ will das Forschungsinstitut der Bundesagentur für Arbeit den Dialog mit der externen Wissenschaft intensivieren. Durch die rasche Verbreitung von Forschungsergebnissen über das Internet soll noch vor Drucklegung Kritik angeregt und Qualität gesichert werden.

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Contents

Abstract

We develop a labor demand model that encompasses pre-match hiring cost arising from tight labor markets. Through the lens of the model, we study the effect of labor market tightness on firms' labor demand by applying novel Bartik instruments to the universe of administrative employment data on Germany. In line with theory, the IV results suggest that a 10 percent increase in labor market tightness reduces firms' employment by 0.5 percent. When accounting for search externalities, we find that the individual-firm wage elasticity of labor demand reduces from -0.7 to -0.5 at the aggregate level. For the 2015 minimum wage introduction, the elasticities imply only modest disemployment effects mirroring empirical ex-post evaluations. Moreover, the doubling of tightness between 2012 and 2019 led to a significant slowdown in employment growth by 1.1 million jobs.

Zusammenfassung

In diesem Aufsatz stellen wir ein Arbeitsnachfrage-Modell auf, das Einstellungskosten berücksichtigt, die aufgrund eines angespannten Arbeitsmarktes bei der Besetzung offener Stellen anfallen. Darauf aufbauend schätzen wir den Effekt der Arbeitsmarktanspannung auf die betriebliche Arbeitsnachfrage, indem wir neuartige Bartik-Instrumente sowie administrative Beschäftigungsdaten für Deutschland heranziehen. Im Einklang mit der Theorie deuten die IV-Ergebnisse darauf hin, dass ein zehnprozentiger Anstieg der Arbeitsmarktanspannung die betriebliche Beschäftigung um rund 0,5 Prozent reduziert. Außerdem zeigt sich, dass die betriebliche Lohnelastizität der Arbeitsnachfrage durch Einbeziehung von Suchexternalitäten auf der aggregierten Ebene von -0,7 auf -0,5 sinkt. In Bezug auf die Einführung des gesetzlichen Mindestlohns im Jahr 2015 implizieren die Elastizitäten nur geringfügig negative Beschäftigungseffekte, was die Ergebnisse empirischer Ex-Post-Evaluationen widerspiegelt. Darüber hinaus führte die Verdoppelung der Arbeitsmarktanspannung in Deutschland zwischen 2012 und 2019 zu einer Verringerung des Beschäftigungswachstums um rund 1,1 Millionen Arbeitsplätze.

JEL

J23, J31, J60, D22

Keywords

labor demand, labor market tightness, shift-share instrument, minimum wage

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1 Introduction

Over the past decade, the German economy experienced a remarkable upswing. Between 2012 and 2019, Germany's real gross domestic product grew on average by 1.5 percent each year. At the same time, the German labor market witnessed the biggest expansion since the 1950s: The number of jobs rose by 3.7 million, reaching a record high of 45.2 million in 2019. As a flip side of this so-called "German Labor Market Miracle" (Burda/Seele, 2020), labor market tightness – the ratio of vacancies to job seekers – doubled. Consequently, German businesses lamented the lack of workers (Handelsblatt Global Edition, 2018). For small and medium-sized companies, the shortage of skilled workers was such a severe problem that some managers were secretly hoping for an economic slowdown to ease the situation (Financial Times, 2019). Unfortunately, systematic evidence on the effect of increased labor market tightness on employment is scarce. By and large, a better understanding of tight labor markets would prove insightful as many industrialized economies have been facing labor shortages in recent years. For instance, employers in the U.S. find it increasingly hard to fill their vacancies, with labor market tightness reaching its highest level in the last quarter century (Abraham/Haltiwanger/Rendell, 2020).

In tight labor markets, firms compete for a relatively small number of job seekers to fill a relatively large number of vacancies. Such an imbalance in the labor market gives rise to search frictions that make it difficult for firms to recruit workers (i.e., their job-filling rate is reduced). Thus, to fill their vacancies, firms must spend more cost on recruitment (e.g., by increasing their search intensity). As a consequence, firms' labor demand and, thus, employment falls. Although this channel is highlighted by search theory, standard models of labor demand narrow their analysis to the wage rate but do not consider the role of labor market tightness. The paucity of empirical evidence on the effect of labor market tightness on employment is twofold: On the one hand, detailed information on both vacancies and job seekers per labor market is rarely available. On the other hand, failure to isolate exogenous variation in labor market tightness would lead to spurious estimates.

In this article, we estimate the causal effects of both wages and labor market tightness on labor demand in German firms. For this purpose, we extend the traditional profit-maximization model of firms to include pre-match hiring cost that arise in tight labor markets. The bottom line of our model is that, unlike conventional specifications, higher labor market tightness exerts a negative effect on firms' demand for workers as hiring becomes more costly. In addition, such a negative effect gives rise to search externalities: a separation in one firm lowers labor market tightness and, thus, facilitates recruitment of workers in all other firms. As a consequence, aggregate changes in labor demand feature a self-attenuating feedback mechanism that operates via labor market tightness. These

search externalities render the individual-firm own-wage elasticity of labor demand less negative at the aggregate level. We estimate the model on the universe of social security records from the German labor market between 2012 and 2019. For the purpose of our analysis, we enrich these data with official statistics and survey information on vacancies and job seekers to determine firm-specific exposure to labor market tightness in more than 1,200 occupations.

A naive OLS estimation of our model would provide upward-biased labor demand elasticities. To rule out reverse causality from uncontrolled shifts in labor demand, we instrument wages and labor market tightness with shift-share instruments, building on the popular instrumental variable (IV) strategy from Bartik (1993). In general, Bartik instruments combine national industry shifts with past shares of industries within regions to isolate exogenous variation in variables at the regional level. However, we transfer this shift-share design to the firm level by taking advantage of the fact that a firm employs many occupations, just as a region has many industries. Thus, our novel Bartik-style instruments combine changes by occupation at the national level with predetermined shares of occupations in firms' employment to extract exogenous variation at the firm level. By virtue of this shift-share design, exogeneity is already ensured when either the national trends or the predetermined employment shares are uncorrelated with the error term.

Our data on vacancies and job seekers mirror Germany's favorable macroeconomic performance during the last decade. Between 2012 and 2019, the number of job seekers decreased from four to only two per vacancy. Hence, labor market tightness doubled within only seven years. To ascertain whether higher tightness actually impedes the recruitment of workers, we inspect the cross-sectional relationship between our measure of labor market tightness and various hiring indicators. In line, labor market tightness is positively correlated with pre-match hiring cost, the number of search channels, and the search duration of firms, while it is negatively correlated with the number of applicants per vacancy.

The regression results are in line with our labor demand model that involves positive pre-match hiring cost. As expected, our shift-share instruments yield more negative elasticities than naive OLS regressions. In our baseline IV regression, we arrive at an own-wage elasticity of labor demand to the single firm of -0.7, which reflects negative substitution and scale effects. Moreover, the coefficient for tightness is -0.05, implying that a doubling in labor market tightness lowers firms' employment by 5 percent. Thus, the ratio of vacancies to job seekers constitutes an important determinant for firms' demand for labor. Importantly, empirical checks allow us to corroborate our identification strategy: On the one hand, a decomposition of our Bartik estimates shows that the wage effect is largely determined by the exogenous introduction of the nation-wide minimum wage in 2015. On the other hand, the most important predetermined occupation shares are hardly correlated

with labor demand variables (which would otherwise point towards uncontrolled shifts in labor demand and, thus, reverse causality). The underlying first-stage regressions acknowledge the plausibility of our estimation strategy. Moreover, our results are also robust to a wide range of different specifications, such as more rigorous fixed effects or an alternative construction of the tightness variable. We find that the pattern of negative labor demand elasticities holds for different establishment size classes and both for West and East German firms. Whereas the own-wage elasticity of labor demand for low-productivity firms exceeds the elasticity for high-productivity firms (in absolute terms), the respective effect of tightness turns out to be markedly smaller.

Crucially, the negative tightness effect implies that aggregate changes in labor demand (of whatever reason) trigger a self-dampening feedback cycle: an industry- or economy-wide decline in labor demand lowers labor market tightness which in turn facilitates recruitment. When accounting for these search externalities, we find that the individual-firm own-wage elasticity of labor demand shrinks from -0.7 to -0.5 at the aggregate level.

We use our set of estimates to perform three further analyses of the German labor market. First, Germany introduced a nation-wide minimum wage in 2015. Based on conventional wage elasticities of labor demand, ex-ante simulations suggested that an hourly wage floor of 8.50 Euro would reduce employment by almost 1 million jobs. However, ex-post differences-in-differences estimations have shown only modest disemployment effects. In a simulation exercise, we interact observed wage increases with our aggregate own-wage elasticity of labor demand of -0.5 and find a reduction by 88,000 jobs, which represents a similar order of magnitude to the effects of the available ex-post evaluations. Second, we assess the extent to which the tightening of labor markets in Germany has adversely affected employment. Our simulation implies that the doubling of labor market tightness in Germany between 2012 and 2019 slowed down employment growth by about 1.1 million jobs. Third, we scrutinize additional channels of adjustment and find that firms were willing to make wage and skill concessions only to a limited extent. Hence, the massive increase in tightness did neither result in a substantial wage increase nor a marked downgrading of skill demands.

Our article contributes to several strands of the literature. First, we set up a novel micro-founded model of labor demand that encompasses hiring cost in tight labor markets. By contrast, the textbook model of labor demand is based on a representative profit-maximizing firm that adjusts labor at no cost (Hamermesh, 1993). The textbook model boils down to the fundamental law of labor demand stating that labor demand reacts more elastic to wage changes the easier the substitution of labor, the higher the price responsiveness of product demand, and the higher the labor share in total cost (Marshall, 1890; Hicks, 1932). We extend this standard framework by modeling hiring as costly (Hamermesh/Pfann, 1996) and, in line with survey evidence, assume that higher wages and

labor market tightness amplify pre-match hiring cost (i.e., expenditures for posting vacancies, job advertisement, and interviews). Our framework allows us to derive a hiring-cost adjusted version of the fundamental law. With positive hiring cost, the own-wage elasticity of labor demand is only as large as wages influence unit labor cost (i.e., the sum of wage costs, pre-match hiring costs, and post-match hiring costs). Unlike conventional models, higher labor market tightness also exerts a negative impact on labor demand, namely to the extent that higher tightness raises unit labor cost. As a favorable feature of our model, the ratio of the own-wage to the tightness elasticity of labor demand allows to infer the magnitude of pre-match hiring cost from calibrating only a few model parameters.

Second, we join the proliferation of studies that attempt to estimate the own-wage elasticity of labor demand (Hamermesh, 1986; Nickell, 1986). In their meta-study, Lichter/Peichl/Siegloch (2015) differentiate between two modes of estimation: structural-form and reduced-form models. Structural-form models infer elasticities from estimating parameters of cost or profit functions, which reflect the optimization behavior of firms at given factor prices. In contrast, reduced-form estimations run log-linear models of factor demand using wage rates as an explanatory variable. A major concern with both approaches is the endogeneity of wages, namely that unaccounted shifts of the labor demand curve will yield upward-biased elasticities (Angrist/Krueger, 2001). The use of quasi-experimental variation in wages represents a promising method to address problems of endogeneity. Unfortunately, quasi-experimental studies lack external validity by focusing on narrow policy designs (e.g., low-wage workers when studying variation in minimum wages). In our article, we seek to estimate the causal effect of wages on labor demand while, at the same time, making a generalized statement about this relationship. In particular, our novel Bartik-like instruments are designed to isolate exogenous variation at the firm level without requiring us to restrict the analysis to specific groups of workers or submarkets.

Third, although labor market tightness takes on a central role in search theory, empirical evidence on its implications on the firm level is scarce. To the best of our knowledge, the analysis from Beaudry/Green/Sand (2018), which is also the article that comes closest to our approach, represents the first and only attempt to estimate the causal impact of labor market tightness on labor demand. The authors leverage census data on the U.S. economy between 1970 and 2015 and estimate city-level elasticities using conventional Bartik instruments. The study finds that a 10 percent increase in the employment rate (as a proxy for labor market tightness) reduces employment by about 20 percent. As this negative effect creates search externalities, the aggregate wage elasticity of labor demand shrinks from -1.0 to -0.3 in the aggregate. Our study differs from the aforementioned study in several respects: Importantly, our analysis takes place at the firm level (not only for urban but also for rural areas). Moreover, official statistics in Germany allow us to directly measure labor market tightness on a detailed level without having to resort to proxies. Finally, we estimate our model not in ten-year but in two-year differences. Despite conceptual

differences and an alternative setting, our analysis finds similar wage elasticities of labor demand and buttresses that high labor market tightness is detrimental to employment.

Fourth, our results help to reconcile available evidence on the wage elasticity of labor demand with reported employment effects in minimum wage studies (e.g., Caliendo/Schröder/Wittbrodt, 2019 on Germany). In his seminal contribution, Hamermesh (1993) provides an interval for the conditional (or constant-output) own-wage elasticity of labor demand ranging between -0.75 and -0.15. In line, Lichter/Peichl/Siegloch (2015) find an average elasticity of -0.55 across 151 studies. In contrast, the minimum wage literature frequently arrives at only slightly negative, zero or even positive employment effects (Card/Krueger, 1995; Dolado et al., 1996; Wolfson/Belman, 2019), reflecting wage elasticities which are markedly smaller than those from the labor demand literature. Our results indicate that the scope of the underlying wage variation can contribute to resolving this paradox. As legislation of a minimum wage usually aims at increasing the pay of workers in a wide range of regions or industries, the policy raises the overall wage level and, thus, exerts aggregate effects on labor demand. Hence, it is not the individual-firm but the aggregate own-wage elasticity of labor demand that matters for the assessment of minimum wage policies. When incorporating search externalities between firms, we find that the aggregate own-wage elasticity of labor demand turns out to be markedly smaller (-0.5) than the elasticity of individual firms (-0.7). Hence, a simulation based on the aggregate elasticity delivers only modest disemployment effects for 2015 minimum wage introduction in Germany, mirroring evidence from available ex-post evaluations. In sum, the results highlight the importance of incorporating search externalities when evaluating the impact of minimum wages.

The study is organized as follows. In Section 2, we augment the standard model of labor demand with pre-match hiring cost to highlight the role of labor market tightness. In Section 3, we set up the empirical specification and develop novel Bartik instruments at the firm level. Section 4 describes the data. In Section 5, we present descriptive results on labor market tightness in Germany. Section 6 illustrates the regression results. Section 7 discusses the implications of our results for the 2015 minimum wage introduction in Germany, the doubling of labor market tightness between 2012 and 2019, and the incidence of wage and skill concessions. Finally, we conclude in Section 8.

2 Theoretical Model

We begin with examining the theoretical relationship between wages, labor market tightness, and firms' labor demand to facilitate the later interpretation of our empirical results. Labor demand is a derived demand that originates from firms' ambition to satisfy product demand. The wage rate takes on a key role in the optimization calculus of firms. Under standard assumptions on technology, both negative substitution and negative scale effects imply that the own-wage elasticity of labor demand (i.e., the inverse slope of the labor demand curve) is less than zero (Sakai, 1974; Hamermesh, 1986). In contrast, the theoretical implication of a higher labor market tightness on employment is more subtle. The reason is that traditional models of labor demand assume that employers adjust input factors at no cost (Addison/Portugal/Varejão, 2014). However, given the specific nature of the labor input, the cost of adjusting labor is substantial (Oi, 1962; Muehlemann/Pfeifer, 2016; Yaman, 2019). Importantly, higher labor market tightness amplifies firms' search frictions rendering hiring more costly (Muehlemann/Strupler Leiser, 2018). To shed more light on the relationship between labor market tightness and employment, we propose a tractable model that involves positive hiring cost.

Intertemporal Profit Maximization. Assume that a representative firm with static expectations seeks to maximize profits. The firm's production function, $Y = F(L, K)$, depends on labor L and capital K, each of which exhibits a positive but decreasing marginal product. The firm operates in perfectly competitive product and factor markets. Hence, the firm sells its goods at given price P while employing labor for wage W and purchasing capital at rate R. To simplify the model, we abstract from involuntary layoffs and model an exogenous rate δ at which workers separate from the firm.[1] The firm may decide to hire new workers but, importantly, must spend unit hiring cost C per hire H.[2] Let r denote the firm's subjective discount rate for future profits in continuous time. Over time t, the firm will choose H_t and K_t so as to maximize the sum of contemporary and

[1] We maintain the assumption of homogeneous labor for simplicity. With labor as a homogeneous input factor, it is not rational for the firm to simultaneously hire and dismiss workers.

[2] For ease of presentation, we build on a static framework by assuming that the overall cost of hiring is a linear function of new hires. Under linear adjustment cost, the firm adjusts employment instantaneously to its optimal level L (Hamermesh, 1993). In contrast, quadratic adjustment cost slow down the response to shocks that alter L (Holt et al., 1960). To lower the total cost of adjustment, firms will find it optimal to smoothly adjust labor towards the optimum over several periods (Gould, 1968). With quasi-fixed cost of hiring, firms will only move to the new equilibrium level of employment if foregone profits from being out of equilibrium are larger than the respective cost of adjustment (Hamermesh, 1989). By and large, implementing these dynamics would add little to the understanding of the effect of labor market tightness on employment. For more details on dynamic models of labor demand and the nature of adjustment cost, have a look at Nickell (1986) or Hamermesh/Pfann (1996).

discounted future profits

$$\int_0^{\infty} \left(P_t \cdot Y(L_t, K_t) - W_t \cdot L_t - R_t \cdot K_t - C_t \cdot H_t\right) e^{-rt}\, dt \tag{1}$$

subject to the law of motion for employment: $\dot{L}_t = H_t - \delta \cdot L_t$. To solve the optimization problem, we set up the following Hamiltonian function h where L_t operates as state variable and H_t as control variable:

$$\max_{L,H,K,\lambda} h = \left(P \cdot Y(L_t, K_t) - W \cdot L_t - R_t \cdot K_t - C \cdot H_t\right) e^{-rt} + \lambda_t \cdot \left(H_t - \delta \cdot L_t\right) \tag{2}$$

Using the Euler equation, $\frac{\partial h}{\partial H_t} = 0$, and the maximum principle, $\frac{\partial h}{\partial L_t} = -\dot{\lambda}_t$, we arrive at the optimality condition for labor:

$$P_t \cdot Y_L(L_t, K_t) \stackrel{!}{=} W_t + (\delta + r) \cdot C_t \tag{3}$$

The firm will employ an additional worker as long as the value of the marginal product of labor Y_L exceeds the wage rate plus the amortized cost of hiring (Hamermesh, 1993). The per-period rate of amortization, $\delta + r$, reflects all factors that lower the future value of a contemporaneous hire. On the one hand, the exogenous separation rate δ implies that only a fraction of new hires, $e^{-\delta T}$ is still employed in the firm after T periods. On the other hand, the costs of a new hire arise contemporaneously but, unlike expenses in future periods, they are not discounted by the firm's subjective rate r. By and large, both a higher exogenous separation rate or a higher discount rate of future profits shortens the period during which the worker must amortize the cost of hiring.[3] Due to the linearity assumption on hiring cost, the optimality condition (3) implies that the firm instantaneously adjusts towards a steady state, $\dot{L}_t = 0$, where it hires exactly as many workers as it loses exogenously in each period: $H_t = \delta \cdot L_t$. Thus, for expositional simplicity, we omit time subscripts in the remainder of this section. In the profit-maximizing optimum, unconditional labor demand

$$L = Y_L^{-1}\left(\frac{W + (\delta + r) \cdot C}{P}, K\right) \tag{4}$$

depends on unit labor cost, $W^{\star} \equiv W + (\delta + r) \cdot C$, the optimal level of the capital stock K and the price level P. Under regulatory assumptions on the production function, optimal labor demand is not only decreasing in the wage rate W but also in unit hiring cost C.

Hiring Cost. We decompose unit hiring cost into a pre-match and a post-match component (Yashiv, 2006). Pre-match hiring cost Φ comprises all search cost of filling a

[3] In the special case that both the exogenous separation rate and the subjective discount rate is zero, optimal labor demand is no longer a function of hiring cost. By contrast, if the exogenous separation rate is 1, the overall hiring cost must be recovered already in the period of hiring.

vacancy with a suitable candidate. This cost includes expenditures for posting vacancies, job advertisement, screening candidates, and interviews. Post-match hiring cost Ψ involves adaption and disruption costs after the contract was signed. Adaption costs arise because new hires have an initially lower productivity and require formal training. In addition, informal instruction of new hires by incumbent workers disrupts the production process.

In the following, we take into account that filling a vacancy becomes more difficult in tighter labor markets where the number of open vacancies V is relatively high compared to the number of unemployed persons U (Mortensen/Pissarides, 1999; Pissarides, 2000). To attract workers in tight labor markets, the firm must search longer or increase its search effort (e.g., by using more costly search channels or interviewing more candidates). Accordingly, we assume that labor market tightness, $\theta = \frac{V}{U}$, is positively associated with pre-match hiring cost (Pissarides, 2009). Furthermore, we assume that pre-match hiring costs increase with the wage rate (Beaudry/Green/Sand, 2018). For ease of presentation, we assume fixed post-match hiring costs which are plausibly unrelated to labor market tightness.[4] Overall, the functional form for unit hiring cost is

$$C = \Phi + \Psi = c \cdot W^{\phi_1} \cdot \theta^{\phi_2} + \Psi \tag{5}$$

where $c \geq 0$, $\phi_1 \geq 0$, $\phi_2 \geq 0$, and $\Psi \geq 0$. To support our formulation of hiring cost, we provide validation for the positive relationship between wages, labor market tightness, and pre-match hiring cost using cross-sectional information on successful hiring processes (see Section 5).

Wages, Labor Market Tightness, and Labor Demand. The fundamental law of labor demand describes the key determinants of firms' profit-maximizing labor demand. According to the law, the own-wage elasticity of labor demand can be decomposed into substitution and scale effects (Hamermesh, 1993):

$$\eta_W^L \equiv \frac{\partial \ln L}{\partial \ln W} = -(1 - s_L) \cdot \sigma - s_L \cdot \eta_P^Y \tag{6}$$

Absent hiring cost, the law states that labor demand is more elastic (i.e., the unconditional own-wage elasticity of labor demand becomes more negative), the ...

1. ... the higher the elasticity of substitution between labor and capital, σ, and
2. ... the higher the price elasticity of product demand, $\eta_P^Y = -\frac{Y_P \cdot P}{Y}$, and

[4] We are aware of only one study that examines the impact of labor market tightness on hiring cost. Using survey data on Switzerland, Muehlemann/Strupler Leiser (2018) find a positive relationship between labor market tightness and pre-match hiring cost, but no such association for post-match hiring cost.

3. ... the higher the share of labor in total cost, s_L.[5]

In Appendix 8, we combine the optimality condition for labor (3), the optimality condition for the capital stock, a product market equilibrium condition, and our formulation of unit hiring cost (5) to derive a hiring-cost adjusted version of the fundamental law of labor demand:

$$\eta_W^L \equiv \frac{\partial ln\, L}{\partial ln\, W} = \left(\frac{W}{W^\star} + \phi_1 \cdot \frac{(\delta + r) \cdot c \cdot W^{\phi_1} \cdot \theta^{\phi_2}}{W^\star} \right) \cdot \left(-(1 - s_L) \cdot \sigma - s_L \cdot \eta_P^Y \right) \quad (7)$$

In this formulation, the prevalence of positive unit hiring cost drives a wedge between unit labor cost and the wage rate. Thus, the first term in (7) describes the elasticity of unit labor cost with respect to the wage rate, whereas the second term refers to the elasticity of labor demand to unit labor cost. Specifically, the elasticity of unit labor cost with respect to the wage rate is the weighted sum of the relative wage effects on the three components of unit labor cost: namely the wage rate (entering with factor 1), pre-match hiring costs (entering with factor ϕ_1), and post-match hiring costs (entering with factor 0). The weights refer to the share of the wage rate, the share of pre-match hiring costs, and the share of post-match hiring costs in unit labor cost. Thus, in addition to (6), labor demand becomes more elastic, the

4. ... the higher the share of the wage rate in unit labor cost, $\frac{W}{W^\star}$, and
5. ... the higher the elasticity of pre-match hiring cost to the wage rate, ϕ_1, and
6. ... the higher the share of pre-match hiring costs in unit labor cost, $\frac{(\delta+r)\, c\, W^{\phi_1}\, \theta^{\phi_2}}{W^\star}$.

As we model labor market tightness as a determinant of hiring cost, we further derive the elasticity of labor demand with respect to labor market tightness (see Appendix 8):

$$\eta_\theta^L \equiv \frac{\partial ln\, L}{\partial ln\, \theta} = \phi_2 \cdot \frac{(\delta + r) \cdot c \cdot W^{\phi_1} \cdot \theta^{\phi_2}}{W^\star} \cdot \left(-(1 - s_L) \cdot \sigma - s_L \cdot \eta_P^Y \right) \quad (8)$$

Analogously to (7), the elasticity equals the elasticity of labor demand with respect to unit labor cost multiplied by the elasticity of unit labor cost to to labor market tightness. The latter elasticity is the relative effect of labor market tightness on pre-match hiring cost, ϕ_2, weighted by the share of pre-match hiring costs in unit labor cost. Overall, unconditional labor demand reacts more elastically to changes in labor market tightness, ...

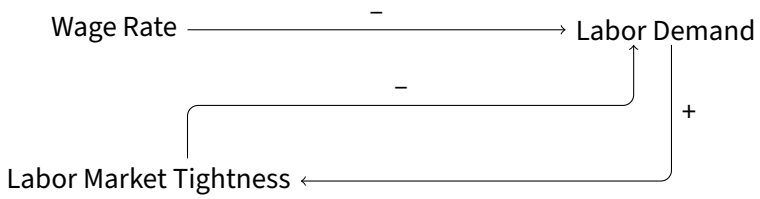
1. ... the higher the elasticity of pre-match hiring cost with respect to tightness, and
2. ... the higher the share of pre-match hiring costs in unit labor cost, and
3. ... the higher the elasticity of labor demand with respect to unit labor cost.

[5] These relationships describe three of Marshall's (1890) "Four Laws of Derived Demand". Regarding the third law, Hicks (1932) notes that a higher labor share renders labor demand more elastic only when, in absolute terms, the price elasticity of product demand exceeds the elasticity of substitution.

So far, our theoretical model postulates that labor market tightness purely raises hiring cost. However, when labor markets tighten, firms may also raise wages to attract workers and, thus ease congestion in the hiring process. In search-and-matching, bargaining, or efficiency-wage models, higher labor market tightness will also exert a positive effect on wages. In Appendix 8, we derive a version of Equation (8) that also incorporates a direct effect of tightness on the wage rate. Since, in our baseline empirical model, we will jointly estimate the effect of wages and tightness on realized labor demand, we are conditioning on wages when estimating the elasticity of labor demand with respect to tightness. Thereby, we do not capture effects of wage changes that stem from a changing tightness. To substantiate this regression approach, we will later show that a tightness-induced rise in wages plays only a minor role in our setting: First, we point out in Section 6 that the omission of the wage variable leaves the effect of higher labor market tightness on labor demand essentially unchanged. Second, in Section 7, we directly estimate the effect of labor market tightness on wages which turns out to be rather small.

Search Externalities and Feedback Cycle. Our model highlights that not only higher wages but also higher labor market tightness reduce firms' labor demand. Unlike traditional models of labor demand, this framework implicitly incorporates search (or congestion) externalities from firms' employment decisions at the aggregated level, namely that an increased employment in one firm complicates recruitment in other firms by intensifying search frictions. Due to these externalities, aggregate changes in labor demand feature a self-attenuating feedback mechanism via labor market tightness, as illustrated in Figure 1.

Figure 1: Feedback Cycle via Labor Market Tightness



NOTE. — The figure visualizes how a labor demand response to a changing wage rate triggers a self-attenuating feedback cycle, as implied by our theoretical model. Source: Own illustration.

As a matter of fact, the impact of a single firm's change in employment on labor market tightness is certainly negligible when firms are small in relation to the overall size of the labor market. However, even when the labor market is atomistic, the feedback mechanism becomes relevant when many firms alter their labor demand simultaneously (e.g., from responding to an increase in a nation-wide minimum wage). When firms act in concert, an aggregate decline in labor demand will reduce labor market tightness which in turn will stimulate labor demand of individual firms. Ultimately, this self-dampening feedback cycle

implies that the aggregate reduction in labor demand becomes less negative than the sum of firms' individual first-round responses.

To derive the feedback mechanism formally, we assume that the economy is in the steady state: $\dot{L} = H - \delta \cdot L = 0$. Suppose that there is a constant-returns-to-scale Cobb-Douglas matching function: $M(U,V) = \kappa \cdot U^{\mu} \cdot V^{1-\mu}$ with $\kappa > 0$ and $0 < \mu < 1$.[6] When substituting hires H by the number of successful matches $M(U,V)$, we can reformulate the steady-state condition as:

$$\theta \equiv \frac{V}{U} = \left(\frac{\delta \cdot L}{\kappa \cdot U} \right)^{\frac{1}{1-\mu}} \tag{9}$$

Thus, labor market tightness θ is an increasing function of aggregate employment. Specifically, a first-round reduction in aggregate labor demand by 1 percent lowers labor market tightness by

$$\nu \equiv \frac{\partial ln\, \theta}{\partial ln\, L} = \frac{1}{1-\mu} \cdot \left(1 - \frac{\partial ln\, U}{\partial ln\, L}\right) \tag{10}$$

percent. This reduction in labor market tightness relieves some congestion in the hiring process and, by virtue of Equation (8), stimulates the demand for labor in all other firms by $\omega = \nu \cdot \eta_{\theta}^{L}$ percent.[7] This second-round increase in labor demand will in turn raise labor market tightness by ω^2 percent, which again translates into a third-round reduction in labor demand by ω^3 (and so forth). Overall, aggregate changes in labor demand (of whatever reason) trigger a self-dampening feedback cycle to the extent that aggregate labor demand creates congestion in the hiring process via increased tightness. If $|\omega| < 1$, search externalities reduce the first-round response in aggregate labor demand by factor $(1 - \frac{1}{1-\omega})$.[8]

In terms of the wage effect, knowledge about the relative strength of the feedback mechanism (i.e., ω), allows us to derive the aggregate own-wage elasticity of labor demand

$$\tilde{\eta}_{W}^{L} = \frac{\eta_{W}^{L}}{1 - \omega} = \frac{\eta_{W}^{L}}{1 - (\nu \cdot \eta_{\theta}^{L})} \tag{11}$$

which, by accounting for search externalities, captures the ultimate response of aggregate labor demand to aggregate wage changes (Beaudry/Green/Sand, 2018). When, according to theory, ω is below zero, the aggregate own-wage elasticity of labor demand $\tilde{\eta}_{W}^{L}$ becomes less negative than the own-wage elasticity of labor demand η_{W}^{L} of an individual firm.

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[6] Petrongolo/Pissarides (2001) provide a review on studies that seek to estimate matching functions. The authors conclude that the majority of studies find support for the constant-returns-to-scale assumption.

[7] Conventional models of labor demand rule out such a built-in feedback cycle by assuming *a priori* that labor market tightness has no effect on labor demand, i.e., $\eta_{\theta}^{L} = 0$.

[8] Using a geometric series, we can derive that only a fraction of the first-round response in labor demand survives the self-attenuating feedback cycle:
$1 + \omega + \omega^2 + \cdots = \sum_{t=0}^{\infty} \omega^t = \lim_{T \to \infty} \sum_{t=0}^{T} \omega^t = \lim_{T \to \infty} \frac{1-\omega^{T+1}}{1-\omega} = \frac{1}{1-\omega}$. Note that the geometric series converges only when $|\omega| = |\nu \cdot \eta_{\theta}^{L}| < 1$.

3 Empirical Design

Empirical Model. According to theory, employers reduce their labor demand not only when wages rise but also when labor markets tighten. To test these propositions, we set up the following empirical model in first differences

$$\Delta \, ln \, L_{it} \; = \; \eta_0 \; + \; \eta_W^L \cdot \Delta \, ln \, W_{it} \; + \; \eta_\theta^L \cdot \Delta \, ln \, \theta_{it} \; + \; \zeta_t \; + \; \Delta \, \varepsilon_{it} \tag{12}$$

to estimate the causal effect of both wages and labor market tightness on firms' labor demand. Specifically, we regress the log difference in firm i's labor demand in year t, $\Delta \, ln \, L_{it}$, on the respective log differences in wages, $\Delta \, ln \, W_{it}$, and labor market tightness, $\Delta \, ln \, \theta_{it}$. Moreover, the model includes an intercept η_0, a set of year fixed effects ζ_t, and an idiosyncratic error term $\Delta \, \varepsilon_{it}$. We are interested in the coefficients η_W^L and η_θ^L which capture the labor demand elasticities with respect to wages and labor market tightness.

Labor market tightness is typically measured at the level of regional labor markets. However, regional labor market tightness may not be a precise measure for firms' shortages if a firm only recruits from specific occupational labor markets within a region.[9] To take into account the occupational demands of individual firms, we develop a measure of firm-specific labor market tightness

$$\theta_{it} = \sum_{o=1}^{O} \frac{L_{oit}}{L_{it}} \cdot \frac{V_{ort}}{U_{ort}} \tag{13}$$

where $\frac{V_{ort}}{U_{ort}}$ is the ratio between vacancies in an occupation o, in region r, at year t and the number of unemployed in the same occupation-by-region-by-year cell. We weight these occupation-specific measures of labor market tightness in a firm's region by the respective shares of occupations in each firm's overall employment, $\frac{L_{oit}}{L_{it}}$. For instance, if a restaurant i employs cooks and waiters at fifty percent each, half of its firm-specific labor market tightness is defined by the number of vacancies of cooks relative to the number of unemployed cooks in that region and the other half by the respective labor market tightness for waiters. Thus, we obtain an occupation-weighted regional labor market tightness that is tailored towards an individual firm's labor demand. Favorably, our firm-specific measure of labor market tightness puts only a weight on occupations that are currently employed while disregarding irrelevant occupations. The measure simply postulates that firms expand in scale without restructuring towards new occupations. In Section 5, we substantiate empirically that firms' occupational composition of vacancy

[9] Occupations play a particularly important role in German labor markets. Under the dual vocational system in Germany, apprenticeship training determines the occupation of workers when they enter the labor market with only little re-training and occupational mobility later on in a career (Rhein/Trübswetter/Nisic, 2013).

shares resembles their composition of employment shares by showing that our employment-based measure of labor market tightness is highly correlated with an analogous vacancy-based measure from survey information (see Figure C5).

In the baseline specification, we estimate our empirical model (12) in two-year differences of dependent and independent variables. Biennial changes allow adjustments to take two years to materialize, thus identifying firms' responses to changes in wages and labor market tightness in the longer run. By contrast, in the short run (e.g., for one-year differences), open vacancies are not necessarily filled yet and the stock of capital remains fixed. Hence, the overall labor demand response may not be observed after one year, implying that adjustments would be underestimated. In line, Jung (2014) reports that German firms need about 1.8 years to complete half of the desired adjustment towards their optimal labor demand. In the results section, we present a major robustness check related to the choice of the lag difference, where the magnitude of labor demand elasticities can vary due to the speed of adjustment.

Threats to the Identification. Our empirical model delivers reduced-form effects in the sense that it captures effects of wages without conditioning on product prices, levels of production or capital input. Hence, we are estimating an unconditional own-wage elasticity of labor demand that operates through all potential adjustment channels, namely substitution effects as well as scale effects. In general, this framework yields a comprehensive effect of wages on labor demand, which is desirable provided that the variation in wages and labor market tightness is exogenously identified. While differencing eliminates unobserved time-invariant heterogeneity capturing all permanent differences between firms (including the industry, the location, or firms' permanent growth potential), we still require exogeneity of the differenced independent variables.[10]

In our differenced model (12), the threats of identification are twofold. First, a major source of endogeneity arises from the interplay between labor demand and labor supply. When estimating own-wage elasticities of labor demand, we seek to determine the inverse slope of the labor demand curve. Hence, variation in wages should represent movements along the labor demand curve rather than shifts of the curve itself. Given the positive relationship between wages and labor supply, shifts of the labor demand curve will result in an upward bias (Wright, 1928; Angrist/Krueger, 2001). For instance, a positive firm-specific productivity shock will stimulate labor demand of the firm, leading to a simultaneous increase in the market wage. Traditional models of labor demand attempt to mitigate this problem by relying on micro-level data (Hamermesh, 1993; Lichter/Peichl/Siegloch, 2015). Under the

[10] From Equation (4), we know that changes in total factor productivity, capital and the product price enters the differenced error term. Hence, we must ensure that our variation in wages or tightness does not stem from changes in the omitted variables at the respective firm.

assumption of perfect competition, labor demand of an individual firm has a negligible effect on market wages (i.e., the price-taking firm faces an exogenously given wage rate). In reality, however, firms are not necessarily small in relation to the market, and, hence, the assumption of competitive labor markets may not hold.

The second threat of identification stems from reverse causality between labor demand and labor market tightness (see Figure 1). Specifically, we are interested in the effects of labor market tightness on firms' employment. At the same time, however, Equation (10) implies that any change in employment directly impacts labor market tightness. As an increase in labor demand will raise tightness, the feedback mechanism leads to an upward bias. If the true effect of labor market tightness on labor demand is negative, as suggested by the theory, the estimate could be biased towards zero or it may even turn positive. Although labor demand responses of entire regions or industries certainly entail stronger feedback mechanisms, the assumption that single firms always have a negligible effect on labor market tightness is not readily justified.

Identification Strategy. Since a naive OLS estimation of Equation (12) is likely to provide biased results, we estimate our model based on variation from instrumental variables (see Appendix 8 for details on the 2SLS specification). We propose three new shift-share instruments in the tradition of Bartik (1993). Bartik instruments exploit the inner product structure of endogenous variables to deliver plausibly exogenous variation at the regional level (Goldsmith-Pinkham/Sorkin/Swift, 2020). These instruments became popular through a wide range of applications, such as identifying the labor market effects of regional demand shocks (Blanchard/Katz, 1992), the effects of local migration shocks (Card, 2001), the effects of region-specific import competition (Autor/Dorn/Hanson, 2013; Dauth/Findeisen/Suedekum, 2014), or the analysis of regional labor demand (Beaudry/Green/Sand, 2012, 2018). However, we do not seek to identify employment effects at the level of regions but for individual firms. For this purpose, we develop novel Bartik instruments that provide variation at the firm level. In particular, we take advantage of the fact that firms differ in the occupational composition of their workforce and, thus, are differently exposed to common shocks.

We begin with developing a Bartik instrument for exogenous wage changes at the firm level. A firm's change in wages can be described by the following accounting identity:

$$\Delta \, ln \, W_{it} \; = \; \sum_{o=1}^{O} \, s_{iot} \cdot g_{W_{iot}} \tag{14}$$

A firm's growth in average wages $\Delta \, ln \, W_{it}$ equals the growth in average wages in each occupational group of the firm $g_{W_{iot}}$ weighted by the respective occupational employment shares in that firm s_{iot}. The firm-specific growth rate of wages in an occupation can be

decomposed in a nation-wide occupation-level growth rate and an additive idiosyncratic firm- and occupation-specific growth rate

$$g_{W_{iot}} = g_{W_{ot}} + \tilde{g}_{W_{iot}} \tag{15}$$

where $\tilde{g}_{W_{iot}}$ is designed to capture firm i's divergence from the national growth rate of occupation-specific wages $g_{W_{ot}}$. This divergence in wage growth may, for instance, capture firm-specific trends in variables that co-determine firms' labor demand - namely factor productivity, capital stock, or product prices. Thus, the idiosyncratic component of firms' wage growth may correlate with uncontrolled factors that shift firms' labor demand curve and, thus, may result in a spurious estimate. To avoid endogeneity from firm-specific labor demand shocks, we rely only on nation-wide occupation-specific wage growth, which is - under certain conditions stated below - immune against reverse causality (i.e., the national wage growth cannot be reasonably altered by a single firm's labor demand). Hence, our firm-level Bartik instrument which is meant to exogenously predict wage changes looks as follows:

$$Z_{W_{it}} = \sum_{o=1}^{O} s_{io\tau} \cdot g_{W_{ot}} = \sum_{o=1}^{O} \frac{L_{io\tau}}{L_{i\tau}} \cdot \Delta \, ln \, W_{ot} \tag{16}$$

Specifically, our shift-share instrument is the inner product of initial employment shares of occupations within firms, $\frac{L_{io\tau}}{L_{i\tau}}$, and occupation-specific growth rates at the national level, $\Delta \, ln \, W_{ot}$. To ensure exogeneity, the instrument (16) departs from (14) in two dimensions: On the one hand, we fix firm-specific occupation shares at an early period τ, implying that the shares are predetermined. On the other hand, the growth rate includes only occupational shocks at the national level.

To isolate Bartik-style variation for firm-specific labor market tightness θ_{it}, we rewrite Equation (13) as follows:

$$\Delta \, ln \, \theta_{it} = \sum_{o=1}^{O} s_{iot} \cdot g_{\theta_{ort}} \tag{17}$$

Our firm-specific measure of labor market tightness relies on tightness at the market level and becomes firm-specific by weighting with occupational shares in firm's employment. Hence, the growth rate $g_{\theta_{ort}}$ features subscripts for both occupations and regions, which define the labor market. Rewriting the growth rate of labor market tightness as the difference between the growth rate of vacancies and the growth rate of unemployed yields a difference of two shift-share expressions:

$$\theta_{it} = \sum_{o=1}^{O} s_{iot} \cdot (g_{V_{ort}} - g_{U_{ort}}) = \sum_{o=1}^{O} s_{iot} \cdot g_{V_{ort}} - \sum_{o=1}^{O} s_{iot} \cdot g_{U_{ort}} \tag{18}$$

Building on this identity, we analogously define two separate Bartik instruments for vacancies and unemployed, Z_V and Z_U, which are meant to generate exogenous variation

in firm-specific tightness:

$$Z_{V_{it}} = \sum_{o=1}^{O} s_{io\tau} \cdot g_{V_{ot}} = \sum_{o=1}^{O} \frac{L_{io\tau}}{L_{i\tau}} \cdot \Delta \ln V_{ot} \tag{19}$$

$$Z_{U_{it}} = \sum_{o=1}^{O} s_{io\tau} \cdot g_{U_{ot}} = \sum_{o=1}^{O} \frac{L_{io\tau}}{L_{i\tau}} \cdot \Delta \ln U_{ot} \tag{20}$$

Note that we replace the occupational growth rate of vacancies and unemployment in the regional labor market by the national growth rates and, again, we harness predetermined occupation shares $\frac{L_{io\tau}}{L_{i\tau}}$ from the base year τ.

Bartik instruments can be straightforwardly constructed from accounting identities but do not necessarily provide a valid identification strategy. The exclusion restriction of our three Bartik-style instruments Z_W, Z_V, and Z_U is fulfilled when either the predetermined firm-specific occupation shares or the national growth rates are uncorrelated with the error term (Goldsmith-Pinkham/Sorkin/Swift, 2020; Borusyak/Hull/Jaravel, 2022).

Given the design of our firm-level Bartik instruments, it is plausible to assume that at least one of the two conditions holds. On the one hand, national growth patterns might stem from exogenous sources (e.g., wage growth due to a higher minimum wage or an increase in job seekers from a sudden influx of migrants) or labor supply shocks (e.g., higher female labor force participation). In both cases, the explanatory variable would not be correlated with the error term. Moreover, when exposition to labor demand shocks is not correlated between firms, a single firm's labor demand decision cannot reasonably shape national growth patterns (i.e., the use of the Bartik instrument protects against reverse causality). On the other hand, even if labor demand shocks correlate across firms (e.g., a common technology shock), exogeneity is maintained when the predetermined occupation shares (i.e., differential exposure to common shocks) are uncorrelated with the error term. By the choice of a base year τ that lies far in the past, we ensure that the shares do not exert an effect on firms' contemporary changes in labor demand other than through the channel of the explanatory variables (i.e., the level of past shares is uncorrelated with changes in uncontrolled determinants of firms' contemporary labor demand). By and large, the identifying idea behind our Bartik instrument is that firms face different exogenous exposure to national growth in the variable of interest based on their assigned occupational composition from the past.

Goldsmith-Pinkham/Sorkin/Swift (2020) show that the Bartik estimator can be decomposed into a weighted sum of just-identified IV estimators that use each share as an instrument. The so-called Rotemberg weights for the separately identified IV estimates (i.e., for each occupation-by-year combination in our setting) depend on the product of the national growth rate and the covariance between share and endogenous regressor. The Rotemberg

weights sum up to 1 while, in certain circumstances, some weights can take negative values which complicate a LATE interpretation of the Bartik estimates. In the empirical part of the article, we will decompose our Bartik estimators for wages and labor market tightness into weights and just-identified IV estimates. In particular, the Rotemberg weights will highlight the subset of occupations to which the final Bartik estimator is most sensitive. For these occupations, we will i) inspect the sources of identifying variation and ii) assess whether past shares correlate with contemporaneous shifts in labor demand.

Finally, we must clarify that, besides exogeneity, the identification also requires that the three instruments need to be relevant. In other words, the instrumental variables need to be strong predictors for the endogenous explanatory variables. We illustrate and test this final but crucial assumption empirically.

4 Data

Integrated Employment Biographies. To bring our empirical model to the data, we assemble information from three independent data sources on the German labor market: the Integrated Employment Biographies, the Official Statistics from the German Federal Employment Agency, and the IAB Job Vacancy Survey. The Integrated Employment Biographies (IEB) compiles manifold sources of administrative labor market records on Germany (Müller/Wolter, 2020). From the IEB, we use the universe of employment notifications of all workers subject to social security contributions, which are collected from employers in Germany as part of the mandatory reporting requirement. In particular, the data cover the entirety of regular full-time, regular part-time, and marginal part-time workers.[11] The IEB provides day-to-day information on workers' employment histories, such as workers' establishment, daily gross wages, type of contract, place of work as well as an indicator whether workers have a full- or part-time contract.[12] For the years 2010-2014, the IEB additionally includes information on the number of individual hours worked. Importantly, the IEB data also offer exceptionally rich information on workers' 5-digit

[11] The data exclude only self-employed, civil servants, and family workers as these groups are not obliged to pay social security contributions.

[12] We apply a two-step imputation technique to impute right-censored wages above the upper earnings limit on social security contributions (Card/Heining/Kline, 2013). In a first step, we calculate fitted wages from a Tobit regression to generate average wages per establishment (excluding the observation at hand). In a second step, we re-estimate the Tobit regression with this variable as an additional covariate, thus arriving at final imputations. Specifically, we regress log daily wages of full-time workers on age, (square of) log establishment size, share of low-skilled and high-skilled workers within the establishment, share of censored observations excluding the observation at hand as well as dummies for one-person establishments, establishments with more than ten full-time employees, German nationality, 5-digit KldB occupation, and 3-digit NUTS region. Separate Tobit models are estimated for each combination of year (2012-2019), gender (2 groups), and education (3 groups).

occupation, distinguishing between a total of $O = 1,286$ occupational categories.[13] For our analysis, we select all employment spells covering June 30 of the years 1999-2019.[14]

For the years 2012-2019, we construct a panel dataset by calculating the number of workers and average daily wages for each establishment. The term "establishment" comprises all plants of a company that share the same economic activity within a municipality.[15] For lack of permanent information on individual working hours, we follow standard practice and restrict our baseline analysis to full-time workers in regular employment (who are supposed to work a similar number of hours). In a further check, we also include regular part-time and marginal part-time workers by imputing average hourly wages from the available information on hours (between 2012 and 2014).[16] Throughout the study, we exclude apprentices and people in partial retirement schemes.

Labor Market Tightness. We define occupational labor markets as combinations of 5-digit KldB occupation and commuting zone.[17] We employ the 5-digit classification for two reasons: First, it differentiates between occupations in the highest available level of detail. Second, it further delivers valuable information on the level of skill requirement, namely whether workers are helpers, professionals, specialists, or experts. It is highly important to distinguish between requirement levels since tasks with different levels of complexity plausibly define segregated labor markets even if the underlying 4-digit occupation is identical. In this respect, Deming/Kahn (2018) show that that skill requirements are key predictors of wage patterns. In addition, Ziegler (2021) finds that job postings with higher skill requirements offer higher remuneration but involve a longer vacancy duration.

[13] In particular, we utilize information on the German Classification of Occupations (KldB) from the year 2010. The four leading digits describe the type of occupation whereas the fifth digit designates the level of skill requirement (helper, professional, specialist, or expert). The variable is available in the IEB data from 2012 onward. For earlier years, we transcode information on the KldB classification from the year 1988 into time-consistent information on the KldB occupation from the year 2010 using available crosswalks.

[14] In principle, IEB information is available from 1975 (West Germany) and 1993 (East Germany) onward. However, we refrain from analyzing information up to and including 1998 because no information on marginal employment was available for this period.

[15] Throughout this study, we use the terms "establishment" and "firm" interchangeably.

[16] For the available hours information during 2012-2014, an indicator whether firms report actual hours (hours worked) or contractual hours (hours paid) is not available. We therefore apply the heuristic from Dustmann et al. (2022) and harmonize the hours information to depict contractual hours plus overtime. In a next step, we pool the available information for 2012-2014 to impute the hours information for the years 2015-2019. Specifically, for each combination of contract type (5 groups), gender (2 groups), and education (3 groups), we regress daily contractual hours (plus overtime) on a set of individual- and establishment-level covariates and use the fitted models to impute missing information on hours for the years 2015-2019. Finally, we divide daily wages by (imputed) daily contractual hours (incl. overtime) to arrive at hourly wages.

[17] We employ the graph-theoretical method from Kropp/Schwengler (2016) to merge 401 administrative districts (3-digit NUTS regions) to more appropriate commuting zones. Given commuting patterns from the Federal Employment Agency for the years 1999-2019, our optimization yields $R = 51$ commuting zones with strong interactions within but few connections between zones.

We gather process data on posted vacancies and job seekers from the Federal Employment Agency (FEA) to construct our measure of firm-specific labor market tightness. For each June 30 between 2012 and 2019, we draw official statistics on the stock of registered vacancies (Federal Employment Agency, 2019), including the targeted 5-digit KldB occupation and commuting zone (in terms of workplace). In Germany, there is no obligation for firms to register vacancies with the Federal Employment Agency. To quantify the overall stock of registered plus unregistered vacancies for each labor market and year, we divide the number of registered vacancies by the yearly share of registered vacancies from the IAB Job Vacancy Survey (Bossler et al., 2020). The IAB Job Vacancy Survey (IAB-JVS) is a representative establishment survey with a focus on recruitment behavior and, in particular, asks firms about their number of registered and unregistered vacancies. When constructing yearly shares of registered vacancies, we differentiate between three levels of skill requirement: occupations for helpers, for professionals, and for specialists along with experts.[18]

In contrast to vacancies, it is mandatory to register as unemployed with the Federal Employment Agency to be eligible for benefits from unemployment insurance or social assistance. For the same labor market and years, we extract official information on the number of job seekers (Federal Employment Agency, 2018), namely registered unemployed plus employed workers searching for a job via the Federal Employment Agency.[19] For each labor market (i.e., each combination of 5-digit occupation and commuting zone) and year, we divide the overall stock of registered plus unregistered vacancies by the stock of job seekers. Next, we apply (13) and weight these ratios with contemporaneous shares of 5-digit occupations in firms' overall employment from the IEB to arrive at a measure of firm-specific labor market tightness.

Shift-Share Instruments. In a final step, we build our firm-level shift-share instruments from Equations (16), (19) and (20). To this end, we interact biennial national changes in average wages, stock of vacancies, and stock of job seekers per occupation with IEB information on firms' shares of occupations in their employment from the past. Specifically, we choose the base year of employment shares so as to maximize the time lag with the estimation period (i.e., 2012-2019). Hence, in most cases, the base year refers to 1999 (35.6 percent) or, alternatively, the year of birth for firms that entered the labor market at a later stage (0.9-5.0 percent per year from 2000 onward).

[18] From the IAB Job Vacancy survey, we calculate the following shares of registered vacancies in all vacancies, averaged over 2012-2019: helpers (46.1 percent), professionals (45.6 percent), specialists and experts (31.1 percent).

[19] Abraham/Haltiwanger/Rendell (2020) find that the number of effective job searchers features a higher explanatory power in the matching function than the mere stock of unemployed persons.

Descriptive Statistics. Our final dataset (including employment, average wages, labor market tightness, and instrumental variables) refers to the near-universe of establishments in Germany and contains a total 21,689,291 establishment-year observations. The panel covers 4,205,183 establishments, which we monitor, on average, 5.2 times between 2012 and 2019. Tracked establishments employ a total of 278,633,024 workers, which equals 32.9-36.7 million workers per year or 78-82 percent of overall employment in Germany.

Table 1 displays descriptive statistics for our model variables (at the establishment level). An average establishment employs 7.4 regular full-time and 5.4 regular or marginal part-time workers. On average, mean earnings of regular full-time workers per calendar day and establishment amount to 84.7 Euro. In terms of average hourly wages, this mean is 15.6 Euro for regular full-time and 12.6 Euro for part-time workers. Our average firm-specific labor market tightness is 0.64, implying that the occupational labor markets of the firm feature two unfilled jobs for every three job seekers. During the period of study, our Bartik instruments deliver an average two-year growth rate in mean earnings by 5.6-5.7 percent for regular full-time workers and 8.8 percent for (regular and marginal) part-time workers. Our Bartik instruments for the stock of vacancies and job seekers reflect that labor market tightness increased substantially during 2012-2019: the instrument for vacancies features an average two-year growth rate of 17.7 percent whereas the instrument for job seekers implies a rate of shrinkage by 8.8 percent every two years.

5 Results: Labor Market Tightness

After having risen steadily for several decades, Germany's unemployment rate reached a peak of 13 percent in the mid-2000s. During that time, the muted economic environment also deterred firms from posting vacancies. Thus, labor market tightness in Germany reached an all-time low in 2005. Since then, the German labor market has undergone a remarkable transformation, accompanied by significant employment growth. Dustmann et al. (2014) attribute this reversal to the flexibility and decentralization of the wage-setting process resulting in lower real wages. Notwithstanding, a comprehensive reform of German labor market institutions in the years 2003-2005 (the so-called Hartz laws) contributed to the labor market upswing (Krause/Uhlig, 2012; Hochmuth et al., 2021). Among others, these laws re-structured the Federal Employment Agency and reduced the generosity of unemployment benefits to increase worker's incentive to accept jobs. A number of studies demonstrate that the Hartz reforms came along with an increased matching efficiency (Fahr/Sunde, 2009; Klinger/Rothe, 2012; Launov/Wälde, 2016). As a side effect of the economic recovery, labor market tightness started to increase again (Burda/Seele, 2020).

Table 1: Descriptive Statistics

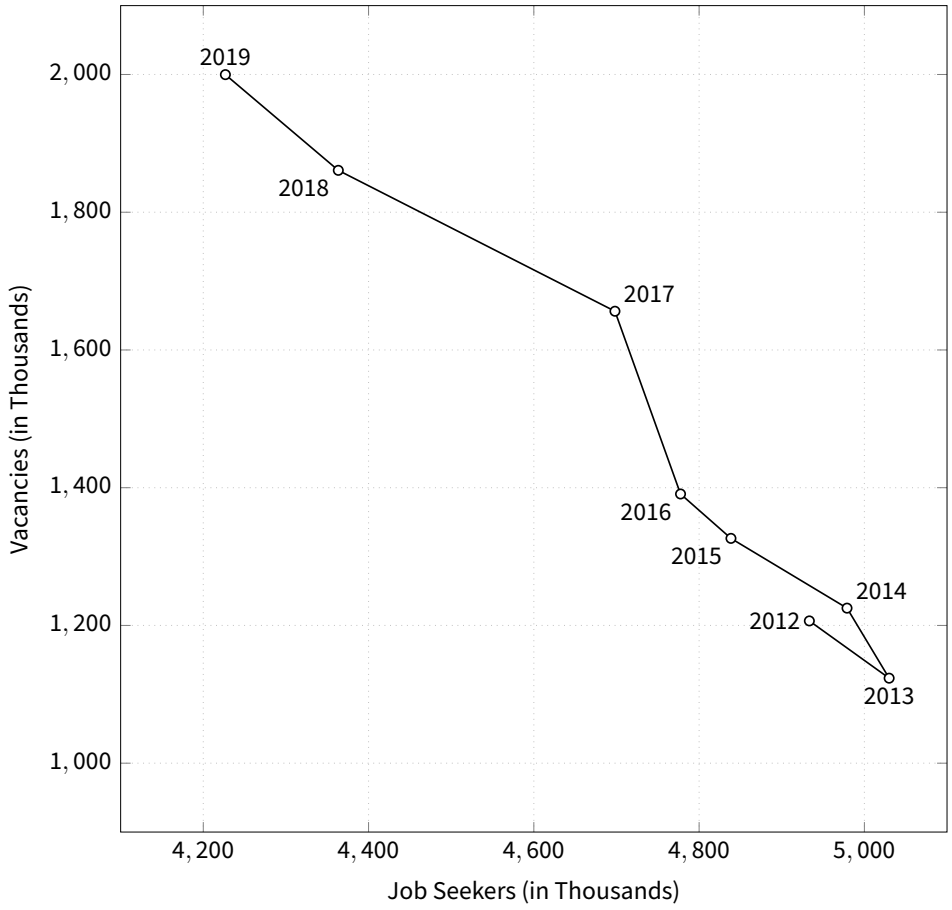
	Mean	P25	P50	P75	Stand. Dev.	Obser-vations
L^{FT}	7.417	0	1	3	79.60	21,689,291
L^{PT}	5.429	1	2	4	32.86	21,689,291
W^{FT} (Daily)	84.69	57.53	77.07	102.1	43.62	12,848,860
W^{FT} (Hourly)	15.56	10.46	14.11	18.85	8.100	12,848,860
W^{PT} (Hourly)	12.58	7.488	10.75	15.42	9.749	18,907,646
V/U	0.636	0.127	0.329	0.740	1.201	21,689,291
Log L^{FT}	1.246	0.000	1.099	1.946	1.260	12,848,860
Log L^{PT}	0.965	0.000	0.693	1.609	1.023	18,907,646
Log W^{FT} (Daily)	4.320	4.052	4.345	4.626	0.507	12,848,860
Log W^{FT} (Hourly)	2.623	2.347	2.647	2.937	0.513	12,848,860
Log W^{PT} (Hourly)	2.345	2.013	2.375	2.736	0.629	18,907,646
Log V/U	-1.154	-2.002	-1.078	-0.285	1.251	21,262,679
$Z_{W^{FT}}$ (Daily)	0.056	0.047	0.055	0.064	0.017	16,300,305
$Z_{W^{FT}}$ (Hourly)	0.057	0.047	0.056	0.064	0.017	16,300,305
$Z_{W^{PT}}$ (Hourly)	0.088	0.060	0.074	0.115	0.039	16,300,305
Z_V	0.177	0.061	0.194	0.302	0.228	16,300,305
Z_U	-0.088	-0.169	-0.103	-0.014	0.137	16,300,305

NOTE. — The table shows descriptive statistics for the model variables between 2012 and 2019. All statistics reflect establishment-year observations. The establishment-specific measure of labor market tightness is constructed by weighting the ratio of vacancies to job seekers per labor market by occupational employment in the corresponding establishment. Labor markets refer to combinations of KldB-5 occupations and commuting zones. The instrumental variables refer to shift-share instruments of biennial national changes in employment weighted by past occupational employment in the respective establishment. L = Employment (in Heads). KldB = German Classification of Occupations. PX = Xth Percentile. Stand. Dev. = Standard Deviation. U = Job Seekers. V = Vacancies. W = Average Wages (in Euro). Z = Shift-Share Instrument. Sources: Integrated Employment Biographies + Official Statistics of German Federal Employment Agency + IAB Job Vacancy Survey, 1999-2019.

The economic prosperity continued in the following decade. Simultaneously, demographic change led to a decline in the number of unemployed, especially in East Germany (Schneider/Rinne, 2019). As a result, the increase in labor market tightness accelerated during the 2010s.

Beveridge Curve. Next, we show the development of labor market tightness in the German labor market between 2012 and 2019. The Beveridge curve relates the number of job seekers to the number of vacancies. A diagonal movement along the Beveridge curve describes the cyclicality of labor markets. In a recession (boom), the number of job seekers increases (decreases) while the number of vacancies decreases (increases). Thus, the labor market becomes slacker (tighter). In contrast, shifts in the Beveridge curve imply changes in the matching efficiency.

Figure 2: Beveridge Curve



NOTE. — The figure shows the Beveridge curve for Germany between 2012 and 2019. The numbers of registered vacancies and job seekers stem from notifications to the German Federal Employment Agency. We divide the stock of registered vacancies by the yearly share of registered vacancies per requirement level from the IAB Job Vacancy Survey to account for unregistered vacancies. Sources: Official Statistics of the German Federal Employment Agency + IAB Job Vacancy Survey, 2012-2019.

Figure 2 displays the Beveridge curve for Germany for our period of analysis. Between 2012 and 2013, labor market tightness decreased slightly during the sovereign debt crisis in the Euro area. From 2013 to 2019, we observe a sharp increase in the number of vacancies by 800,000 while the number of job seekers declined in a similar order of magnitude. In this period, the ratio of vacancies to job seekers rose steadily from 0.23 to 0.47: while we report four job seekers per vacancy in 2013, there were only two job seekers per vacancy in 2019, implying a doubling in labor market tightness. Importantly, the increase in labor market tightness is not just driven by a certain subset of occupations. In Appendix 8, Figure C1 displays less aggregated Beveridge curves for eight occupational areas. Despite some idiosyncrasies, all occupational areas moved towards a higher tightness during the period of analysis. The increase in labor market tightness coincides with a significant and long-lasting phase of prosperity of the German economy, which came along with a

significant employment expansion, rising from 42.0 million employees in 2012 to 45.2 million employees in 2019. Moreover, Figure C2 demonstrates that the rise in labor market tightness was accompanied by a markedly higher share of firms that face labor shortages.

Labor Market Tightness, Wages, and Recruitment Indicators. As outlined in Section 2, labor market tightness is hypothesized to exert an effect on the demand for labor through increased hiring cost. When labor market tightness increases, it becomes more costly to hire additional workers. Consequently, firms' labor demand declines.

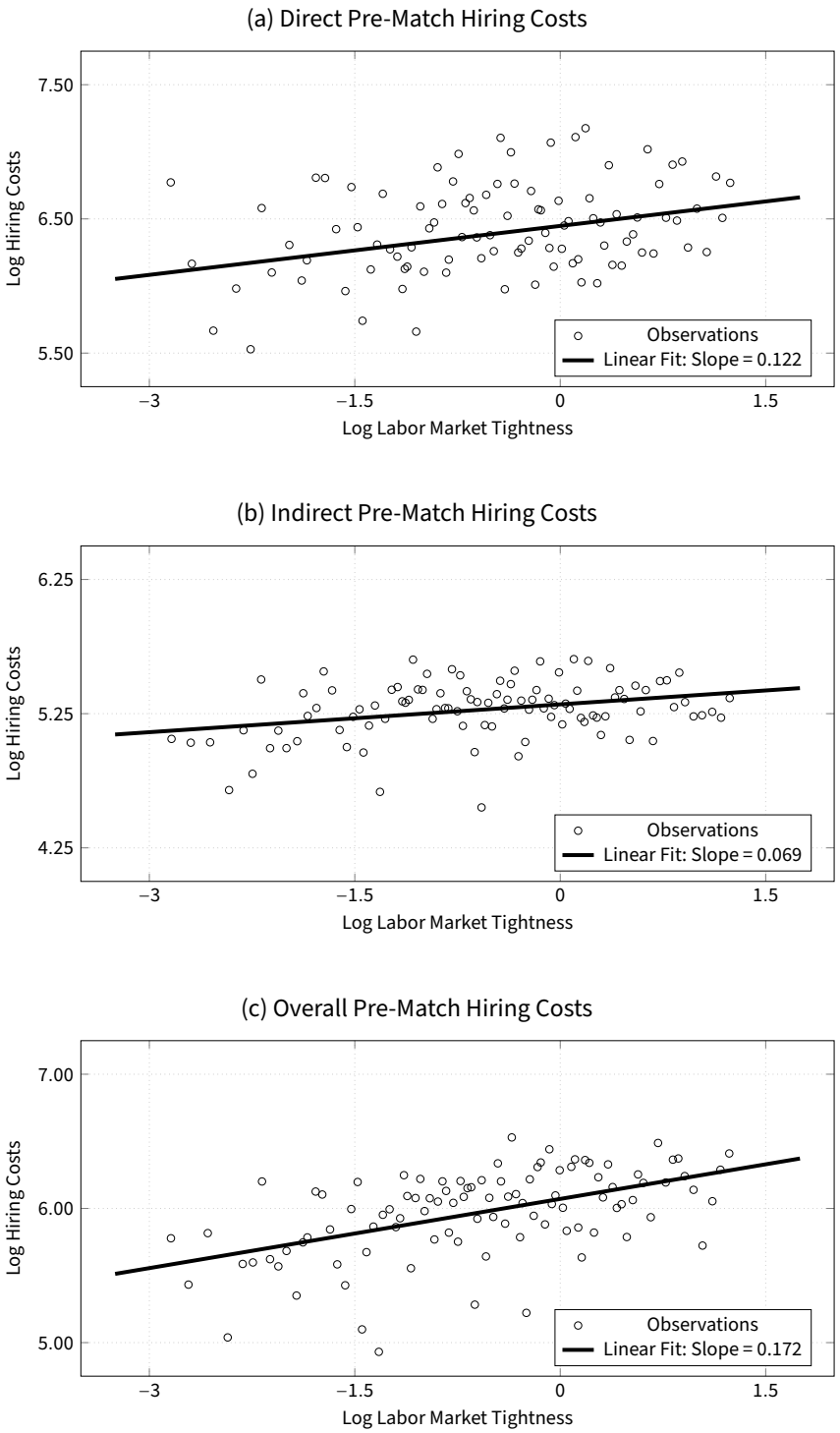
The IAB Job Vacancy Survey allows us to shed some light on the mediating channels underlying the relationship between labor market tightness and labor demand. In repeated cross-sections, the survey includes questions on the respective firm's most recent successful process of hiring.[20] The survey includes information on the following recruitment indicators: direct pre-match hiring cost (in Euro), search effort (in working hours), the number of search channels, the number of applicants, and search duration (in days).[21] In addition, we combine the survey information on search effort (in working hours) with IEB information on the respective firm's average wage rate to arrive at a measure of indirect pre-match hiring cost (in Euro). We find that, on average, a successful hiring process involves 869 Euro of direct and 427 Euro indirect pre-match hiring cost (deflated to the year 2015).

Based on the firm's location and its targeted 5-digit KldB occupation, we enrich our survey-based recruitment indicators with the respective labor market tightness. Figure 3 illustrates the cross-sectional correlations between labor market tightness and pre-match hiring cost. Specifically, we display scatter plots of percentile bins of the tightness variable along with an OLS-based linear fit. Panel a) shows that higher labor market tightness is associated with higher direct pre-match hiring cost, such as expenditures for posting vacancies, job advertisement, or headhunters. In addition, Panel b) implies that increased tightness also involves higher indirect pre-match hiring cost, namely for screening candidates, job interviews, and signing contracts. Taken together, the cross-sectional information suggest that a doubling in labor market tightness raises overall pre-match hiring cost of successful hiring processes by 17.2 percent (Panel c). In a similar fashion, Figure C3 illustrates that higher wages also come along with higher direct and indirect pre-match hiring costs. Overall, the cross-sectional relationships of pre-match hiring cost with labor market tightness and wages provide an empirical foundation for our formulation of hiring cost in Equation (5).

[20] Crucially, this survey information is highly selective in the sense that it does not include information on the recruitment process when a vacancy remains unfilled or is not posted at all due to prohibitively high hiring cost. We suspect that correlates of tightness and hiring indicators would be even larger if unfilled positions were included, simply because the available information on successful hires is a positive selection of all hiring processes.

[21] Unfortunately, the IAB Job Vacancy Survey does not inquire information on post-match hiring cost.

Figure 3: Labor Market Tightness and Pre-Match Hiring Costs



NOTE. — The figures show binned scatterplots with 100 hundred markers to depict cross-sectional correlations between log labor market tightness and the log of direct, indirect, and overall pre-match hiring costs. Whereas direct pre-match hiring costs (in Euro) are asked separately in the IAB Job Vacancy Survey, we calculate indirect pre-match hiring costs (in Euro) by multiplying the search effort (in working hours) by the firm's average hourly wage rate of i) workers in human resource management (KldB-2010 Code: 715) or, if not available, ii) managers or, if not available, iii) all workers. Pre-match hiring costs were deflated with base year 2015. Labor markets are combinations of 5-digit KldB occupations and commuting zones. We trim labor market tightness at the 5th and 95th percentile. The numbers of observed successful hires are: 12,348 for direct, 29,641 for indirect, and 24,884 for overall pre-match hiring costs. Sources: Integrated Employment Biographies + Official Statistics of Federal Employment Agency + IAB Job Vacancy Survey, 2014-2015, 2017-2019.

Figure C4 illustrates correlations between labor market tightness and the three remaining recruitment indicators that drive pre-match hiring cost: the number of applicants, the number of search channels, and the search duration. Labor market tightness and the number of applicants are negatively correlated, mirroring the definition of labor market tightness, which includes the number of job seekers in the denominator. Higher labor market tightness also makes firms use more search channels (such as using private placement services), which further raises pre-match hiring cost.[22] Higher labor market tightness also entails a longer search duration for hires, which is the time dimension of pre-match hiring cost.

Building on Equation (13), we weight our measures of labor market tightness by firms' occupational employment shares to construct a firm-specific measure of labor market tightness. In order for this measure to capture firms' difficulty to fill their vacancies, firms' occupational composition of vacancies must resemble their composition of employment. To address this concern, we gather information on the occupational structure of firms' open vacancies from the IAB Job Vacancy Survey and construct an analogous measure of firm-specific labor market tightness that is based on the vacancy shares of occupations. Using record linkage, we contrast this vacancy-based measure with our employment-based measure of labor market tightness (Figure C5). Favourably, we find a strongly positive and linear relationship between both measures. We view this pattern as supporting evidence in favor of our employment-based firm-specific labor market tightness that we are able to leverage for the universe of firms in the IEB (see Section 6).

By and large, the correlation patterns from the IAB Job Vacancy Survey substantiate the theoretical mechanism that higher (firm-specific) labor market tightness raises hiring cost of firms. Hence, it is plausible that labor market tightness also has a causal effect on firms' demand for labor.

[22] Between 2012 and 2019, the IAB Job Vacancy includes time-consistent information on the following ten search channels for successful hiring processes: advertisement in newspapers or magazines, advertisement on own website, advertisement on online job boards, contact to the federal employment agency (FEA), internet services of FEA, pool of applicants to other positions, private placement services, internal job advertisement, personal contacts of employees, and selection among apprentices, leased workers, or interns.

6 Results: Labor Demand Effects

Baseline Results. In this section, we present our empirical results of the labor demand analysis. We estimate labor demand elasticities with respect to changes in wages and labor market tightness. Table 2 displays the baseline estimates, including potentially endogenous OLS estimates and instrumental variable estimates from 2SLS. The first column presents results from a naive OLS estimation of Equation (12). While the own-wage elasticity of labor demand is negative, albeit small, the elasticity with respect to tightness turns out to be positive, unlike suggested by theory. However, as pointed out in Section 3, the OLS estimates may feature an upward bias due to reverse causality.

To address the bias in either case, we use our Bartik-style instruments (16), (19), and (20) to insulate exogenous variation in wages and labor market tightness in a second, third and fourth specification. To begin with, we solely estimate the effect of wages on employment, using the wage instrument (16). As expected in comparison to OLS, the wage elasticity of labor demand turns out to be more negative, implying that firms lower employment by 0.73 percent when wages increase by 1 percent. Based on the instruments for vacancies (19) and unemployed (20), Column (3) displays the 2SLS effect of tightness on employment without accounting for wages. In contrast to OLS, the estimated elasticity turns negative, indicating that an increase in labor market tightness by 1 percent reduces employment by 0.05 percent on average.

Finally, Column (4) displays effects of wages and tightness from a joint IV model, in which both variables exert an additive impact on firms' labor demand. We refer to this model as our baseline specification, which is described by Equation (12). In our baseline estimation, the own-wage elasticity of labor demand is -0.73, and the elasticity of labor demand with respect to tightness is -0.05. The effects are statistically significant at 1 percent levels. Interestingly, both elasticities remain largely unchanged compared to the separate estimations in Columns (2) and (3). On the one hand, this finding shows that the instruments for wages and tightness do not interact with each other. On the other hand, by comparing Column (4) with Column (3), we can rule out that labor market tightness substantially affects labor demand through changes in wages because controlling for the wage channel does not alter the tightness effect.[23].

[23] The similarity of the tightness effect between Column (3) and Column (4) implies that, in Equation (A.34) in Appendix 8, the relative effect of labor market tightness on wages, γ, is close to zero. In this case, Equation (A.34) collapses to our baseline version of the elasticity of labor demand with respect to tightness (8).

Table 2: Effects of Wages and Labor Market Tightness on Employment

	(1) Δ Log L^{FT}	(2) Δ Log L^{FT}	(3) Δ Log L^{FT}	(4) Δ Log L^{FT}
Δ Log W^{FT}	-0.136***	-0.733***		-0.730***
	(0.002)	(0.022)		(0.022)
Δ Log V/U	0.047***		-0.054***	-0.051***
	(0.000)		(0.002)	(0.002)
Fixed Effects	Year	Year	Year	Year
Instruments	None	$Z_{W^{FT}}$	Z_V, Z_U	$Z_{W^{FT}}$, Z_V, Z_U
Observations	7,993,993	7,993,993	7,993,993	7,993,993
Clusters	1,801,671	1,801,671	1,801,671	1,801,671
F: Δ Log W^{FT}		9,952		3,322
F: Δ Log V/U			45,522	30,380

NOTE. — The table displays OLS and IV regressions of differences in log employment (of regular full-time workers) per establishment on differences in the log of average daily wages and the log of labor market tightness. The instrumental variables refer to shift-share instruments of biennial national changes in occupations weighted by past occupational employment in the respective establishment. The lag difference is two years. Labor markets are combinations of 5-digit KldB occupations and commuting zones. Standard errors (in parentheses) are clustered at the establishment level. F = F Statistics of Excluded Instruments. FT = Full-Time. KldB = German Classification of Occupations. L = Employment. U = Job Seekers. V = Vacancies. W = Average Daily Wages. Z = Shift-Share Instrument. * = p<0.10. ** = p<0.05. *** = p<0.01. Sources: Integrated Employment Biographies + Official Statistics of the German Federal Employment Agency + IAB Job Vacancy Survey, 1999-2019.

Favourably, our underlying theoretical model in Section 2 allows us to validate the plausibility of our baseline results by examining the magnitude of pre-match unit hiring cost. Given Equation (6) and (7), it is easy to show that the ratio of the tightness elasticity of labor demand to the own-wage elasticity of labor demand simply reflects the ratio of the tightness elasticity of unit labor cost to the own-wage elasticity of unit labor cost (i.e., the elasticity of labor demand to unit labor cost cancels out):

$$\frac{\eta_{\theta}^{L}}{\eta_{W}^{L}} = \frac{\phi_2 \cdot (\delta + r) \cdot C}{W + \phi_1 \cdot (\delta + r) \cdot C} \tag{21}$$

Thus, the ratio of baseline estimates in Column (4) of Table 2 implies that the relative effect of tightness on unit labor cost is about 1/14 of the relative wage effect on unit labor cost.[24] Given this proportion, it is possible to approximate the magnitude of pre-match hiring cost (as a fraction of annual wage payments) by collecting additional information on only few model parameters:

$$\frac{C}{W} = \frac{1}{(\delta + r) \cdot \left(\phi_2 \cdot \frac{\eta_{W}^{L}}{\eta_{\theta}^{L}} - \phi_1\right)} \tag{22}$$

[24] We calculate this fraction as: $\frac{\eta_{\theta}^{L}}{\eta_{W}^{L}} = \frac{-0.051}{-0.730} \approx \frac{1}{14}$.

Using IEB data for our period of study, we arrive at a yearly separation rate of 23.0 percent for full-time workers (i.e., $\delta = 0.23$). Absent causal evidence on both successful and failed hiring processes, we simply postulate that pre-match hiring cost are a linearly homogeneous function of wages and tightness, with each having an equally large influence (i.e., in Equation (5), we set $\phi_1 = \phi_2 = 0.5$). Moreover, we assume that firms' subjective discount rate r equals 10 percent per year (i.e., $r = 0.1$). Given this calibration, our baseline estimates imply that pre-match unit hiring cost amount to 45.5 percent of annual wage payments for the average full-time worker. This result is consistent with the empirical literature, although it falls at the upper end of the wide range of available estimates. Nevertheless, estimating a structural model of gross adjustment on the German IEB data, Yaman (2019) finds that the sum of pre- and post-match hiring cost add up to 1.7 annual salaries of full-time workers. Moreover, Hamermesh/Pfann (1996) synthesize the literature and highlight that pre-match hiring (together with training costs) are potentially large, with some studies arriving at 1 year of annual wage payments.

Overall, the results suggest that higher labor market tightness renders job filling more difficult and, thus, more expensive for firms. Vice versa, higher tightness facilitates job finding from the perspective of workers. Thus, our results mirror macroeconomic evidence on Germany showing that higher labor market tightness raises the job finding rate of unemployed workers (Kohlbrecher/Merkl/Nordmeier, 2016).

Empirical Checks on Identification Strategy. In a next step, we decompose our Bartik estimator to shed more light on the identifying variation underlying our estimates, as proposed by Goldsmith-Pinkham/Sorkin/Swift (2020). We fully present these shift-share diagnostics in Appendix 8. Specifically, we deconstruct our Bartik estimates into Rotemberg weights (see Table D1) and just-identified IV estimates (see Figure D1), separately for the wage instrument, the vacancy instrument, and the job seeker instrument.[25] The key messages from these diagnostics are as follows: First, the quantitative magnitude of negative Rotemberg weights is small in all cases, thus allowing for a LATE interpretation of our Bartik estimates.[26] Second, the largest positive weights for the wage effects relate to the intervals 2013-2015 and 2014-2016, which both cover the first-time introduction of national minimum wage in 2015. By contrast, the identifying variation is more evenly distributed across years for the vacancy and job seeker instrument, which is in line with a steadily

[25] For ease of computation, we carry out the decomposition using a random 50 percent sample of firms for the second and third specification (of Table 2), thus focusing on either the wage or the labor market tightness effect.

[26] As the vacancy and the job seeker instrument exert an opposite impact on labor market tightness (i.e., the vacancy-to-job-seekers ratio), the joint normalization of their Rotemberg weights to 1 implies that the weights for the job seeker instrument feature opposite signs (i.e., negative weights for the job seeker instrument must be interpreted as positive ones and vice versa).

tightening labor market during our period of analysis. Third, the distribution of Rotemberg weights across occupations is highly skewed. The top five occupations with the largest weight account for 44.5 (wage instrument), 33.6 (vacancy instrument), and 27.1 percent (job seeker instrument) of the sum of absolute Rotemberg weights. For the wage effect, the top five occupations comprise gastronomy workers, medical assistants, hairdressers, cooks, and farmers. In line with the distribution of weights across years, earnings in these low-wage occupations were highly affected by the 2015 minimum wage, corroborating that this policy intervention drives a significant fraction of our identifying variation. For the tightness effect, sales workers receive by far the largest weight, seemingly because employment of these workers strongly follows the business cycle. Fourth, the vacancy instrument determines about three quarters of the labor market tightness effect whereas the remaining quarter stems from the job seeker instrument. Thus, the tightness effect is predominantly identified by demand rather than supply forces. Fifth, the just-identified IV estimates show substantial heterogeneity across occupations.

Given the logic of the Bartik estimator, exogeneity of either the national growth rates or the predetermined employment shares would suffice to establish unbiasedness. Favorably, our decomposition highlighted that a large part of the variation underlying our estimated wage effect stems from an exogenous event which is the first-time introduction of a statutory nation-wide minimum wage in Germany. On top, we follow Goldsmith-Pinkham/Sorkin/Swift (2020) and perform a further empirical check to examine whether predetermined occupational shares are uncorrelated with the error term (i.e., with uncontrolled determinants of changes in labor demand). Using survey information from the IAB Establishment Panel, we regress firms' predetermined occupational employment shares on a set of labor demand and labor supply variables in the very same year. If the cross-sectional variation between shares and the level of labor demand variables turns out to be low, then the correlation with changes in labor demand variables (in the far-off future) should be even smaller. We narrow our analysis to the top five occupations with the largest Rotemberg weights.

The supply-determining variables such as the female employment share and the share of foreign citizens are strongly correlated with shares in the top five occupations from the wage effect (see Panel a) of Table D1). By contrast, demand shifters like capital investment or business expectations are hardly correlated with the occupational shares. An exception is firms' labor productivity which is negatively correlated with most relevant occupations. However, this negative cross-sectional correlation simply reflects that firms with high shares in these low-wage occupations are less productive and, accordingly, are more strongly affected by the exogenous wage increase from the minimum wage introduction in 2015. Finally, for the vacancy and job seeker instrument (see Panel b) and c) of Table D1), the predetermined shares of top five occupations are more strongly correlated with supply

rather than demand variables, supporting that we observe an effect that is identified from exogenous changes in tightness rather than demand-driven reverse causality.

Table 3: First-Stage Regressions

	(1) Δ Log W^{FT}	(2) Δ Log V/U	(3) Δ Log W^{FT}	(4) Δ Log V/U
$Z_{W^{FT}}$	0.636***		0.635***	-0.260***
	(0.006)		(0.006)	(0.019)
Z_V		0.452***	0.001***	0.452***
		(0.002)	(0.000)	(0.002)
Z_U		-0.447***	0.001	-0.447***
		(0.003)	(0.001)	(0.003)
Fixed Effects	Year	Year	Year	Year
Observations	7,993,993	7,993,993	7,993,993	7,993,993
Clusters	1,801,671	1,801,671	1,801,671	1,801,671
F Statistics of Excluded Instruments	9,952	45,522	3,322	30,380

NOTE. — The table displays the underlying first-stage regressions of the IV estimations in Column (2), (3), and (4) from Table 2. The instrumental variables refer to shift-share instruments of biennial national changes in occupations weighted by past occupational employment in the respective establishment. The lag difference is two years. Labor markets are combinations of 5-digit KldB occupations and commuting zones. Standard errors (in parentheses) are clustered at the establishment level. FT = Full-Time. KldB = German Classification of Occupations. L = Employment. U = Job Seekers. V = Vacancies. W = Average Daily Wages. Z = Shift-Share Instrument. * = p<0.10. ** = p<0.05. *** = p<0.01. Sources: Integrated Employment Biographies + Official Statistics of the German Federal Employment Agency + IAB Job Vacancy Survey, 1999-2019.

Table 3 presents the underlying first-stage regressions for the second specification in Column (1), the third specification in Column (2), and the fourth and baseline specification in Columns (3) and (4). The first-stage estimates show that our wage instrument is a good predictor for wage changes. A national wage increase by 10 percent (weighted by firms' past occupational employment shares) raises firms' wages by 6.4 percent, which is large and positive. Similarly, the instruments for vacancies and unemployed predict well shifts in labor market tightness, with signs of the coefficients featuring the expected directions: a national increase in vacancies (job seekers) by 10 percent raises (lowers) firm-specific labor market tightness by 4.52 (4.47) percent. The F statistics for the joint exclusion of the instruments are sufficiently large in all cases. Hence, the irrelevance of the instruments is clearly rejected, demonstrating that our shift-share design delivers strong instruments. [27]

[27] In Appendix 8, we provide a visual inspection of the first stages in Figure E1, which illustrates favorable correlation patterns between the instruments and their respective endogenous variable. In addition, in Table E1, we further display reduced-form regressions of the outcome variable on the instruments. Each instrument shows the expected signs implied by the baseline 2SLS estimates. The reduced-form effects turn out lower than second-stage elasticities, which is in line with the intuition that national shifts should exert an effect on firms' employment smaller than effects of direct changes at the firm level.

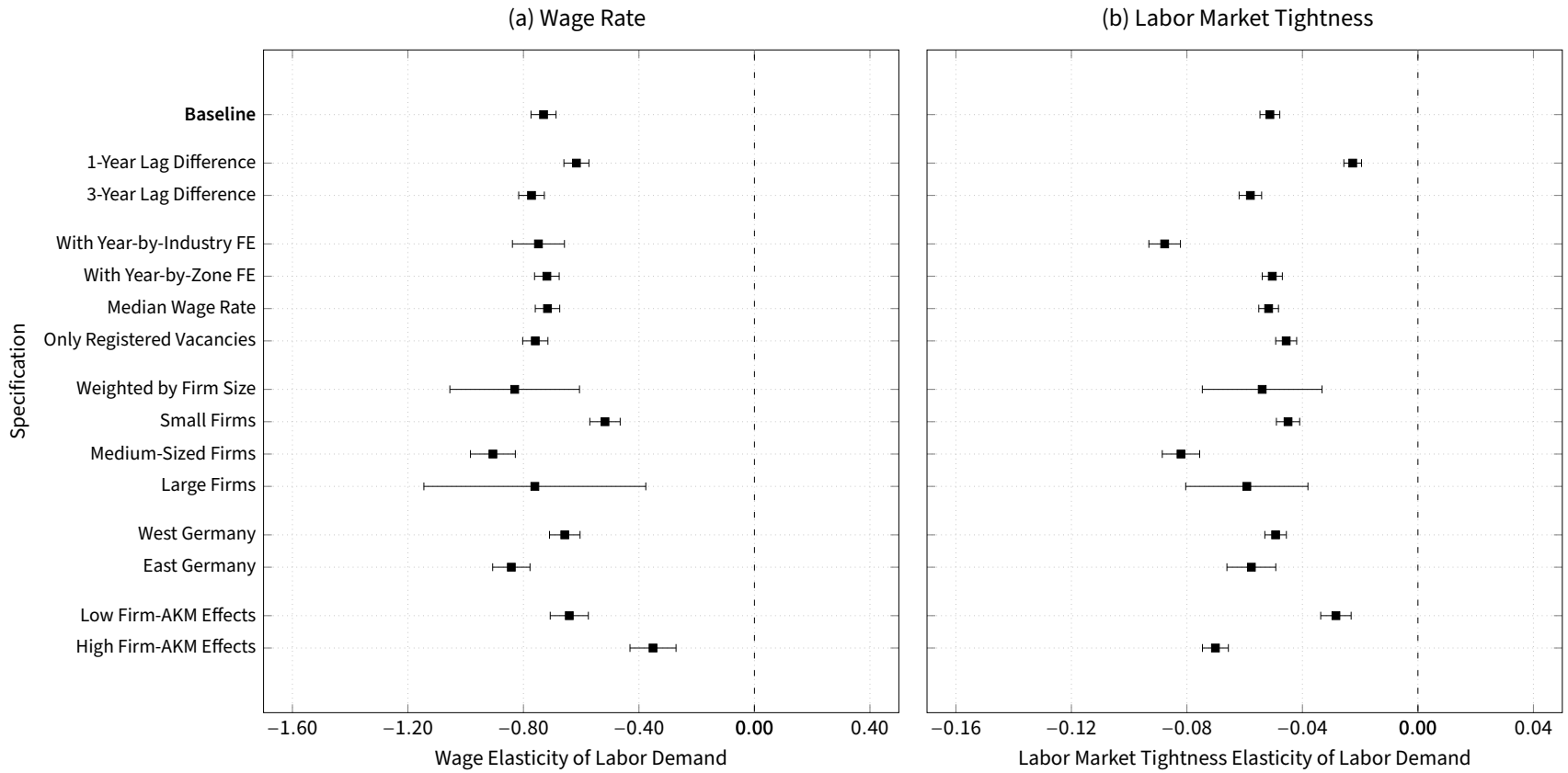
Sensitivity and Heterogeneity. We examine the sensitivity and underlying heterogeneity of our baseline estimates in various respects. The corresponding results are visualized in Figure 4 whereas the detailed regression results are assembled in Appendix 8. First, we address the choice of the lag difference. As elaborated in Section 3, we specify the empirical model in two-year lags to estimate long-run elasticities. The results show that the wage effect in the specification with one-year differences is slightly lower, indicating that overall labor demand responses do not fully materialize in the short run due to adjustment cost (Nickell, 1986). However, the elasticity barely increases for three-year differences. We observe a similar pattern when looking at the tightness effect, which turns out to be smaller for one-year differences as well. Again, the smaller coefficient for one-year differences likely reflects sluggish responses in labor demand.

Next, we carry out robustness checks relating to the regression specification and the measurement of the model variables. Specifically, we additionally differentiate the year fixed effects by 2-digit industries or commuting zones to more rigorously control for common labor demand shocks (which, if the predetermined shares were correlated with growth rates, the Bartik instrument may not protect against). The results do not change substantially when including the more disaggregated fixed effects.[28] This robustness is well in line with our correlation analysis that attributed only a minor role to labor demand shocks across firms (see Table D1), lending further credence to a causal interpretation of our elasticity estimates. Regarding the measurement of the model variables, we replace the log average wage by the log median wage which is robust against outliers and the top-coding of wages at the social security limit. Furthermore, we use registered vacancies instead of total vacancies for the measurement of labor market tightness. In both cases, the elasticities retain a negative sign and feature a similar order of magnitude, corroborating that our results are not driven by a certain operationalization of the model variables.

Next, we scrutinize whether wage and tightness effects differ by firm size. Up to now, the coefficients have expressed average effects across firms. First, we weight observations by employment to assign larger firms more importance. The results remain fairly robust. Second, we differentiate between three establishment size categories: small (1-9 workers), medium-sized (10-99), and large establishments (more than 100 workers). Small establishments feature a less negative wage elasticity (-0.5) than the average, but the tightness effect is only slightly smaller than the effect in the baseline estimation. Medium-sized establishments exhibit above-average effects (-0.9 and -0.08). The elasticities of large establishments resemble those from the overall sample. In all three size classes, the ratio of the tightness to the wage effect is close to 1/14, as implied by our baseline estimates.

[28] Including industry-by-year fixed effects is idiosyncratic in the sense that the underlying variation stems from firms whose occupational structure is different from the 2-digit industry average. Nevertheless, the elasticities remain in the ballpark of our baseline estimates.

Figure 4: Sensitivity and Heterogeneity of Labor Demand Effects



NOTE. — The figure illustrates estimated labor demand elasticities for a variety of specifications. The baseline IV estimation regresses differences in log employment (of regular full-time workers) per establishment on differences in the log of average daily wages and the log of labor market tightness. The instrumental variables for average wages, vacancies, and job seekers refer to shift-share instruments of biennial national changes in occupations weighted by past occupational employment in the respective establishment. In the baseline regression, the lag difference is two years. Baseline labor markets are combinations of 5-digit KldB occupations and commuting zones. Each point estimate features a 95 percent confidence interval. Sources: Integrated Employment Biographies + Official Statistics of the German Federal Employment Agency + IAB Job Vacancy Survey, 1999-2019.

We additionally differentiate between establishments from West and East Germany as well as those with low and high productivity. Labor demand in East Germany reacts more sensitively to wage shifts, mirroring that East Germany lags behind West Germany in terms of productivity (Müller, 2013). But, in line with the literature (Schnabel, 2016), the difference between these elasticities is not substantial. The tightness effects in West and East Germany are not significantly different. We approximate productivity by firm fixed effects from log-linear wage regressions in the spirit of Abowd, Kramarz, and Margolis (1999, hereafter 'AKM') for the years 2012-2019. These AKM-firm effects reflect a relative wage premium paid to all regular full-time workers within the firm, conditional on individual and year fixed effects. In line with rent-sharing, the own-wage elasticity of labor demand for firms with low productivity (i.e., below the median AKM effect) turns out to be more negative than for highly productive firms. At the same time, the negative effect of labor market tightness on firms' labor demand is nearly three times smaller for low-productivity firms, reflecting that labor shortage poses a more severe problem to highly productive firms. We observe descriptively that these highly productive firms expand in terms of employment during 2012-2019 whereas the group of low-productive firms tends to remain stable on average. Hence, the presented AKM heterogeneity suggests that the rise in tightness restricts additional employment growth rather than forcing firms to shrink.

For lack of adequate data, conventional labor demand studies on administrative data from Germany usually report own-wage elasticities of labor demand only for full-time workers. However, the recently available IEB information on individual hours worked allows us to analyze also the labor demand for (regular or marginal) part-time workers. Table 4 shows own-wage elasticities and tightness effects by labor outcome. In Column (1), we first present results for our baseline of full-time workers but based on our constructed measure of hourly (instead of daily) wage rates (see Section 4). Reassuringly, we arrive at quantitatively similar elasticities which lends credence to our hourly wage measure. Interestingly, in Column (2), the estimated own-wage elasticity for part-time workers turns out to be only slightly negative and insignificant, which is in line with Freier/Steiner (2010) who find that the demand for part-time employees is less responsive to wage changes for male workers in West Germany. In contrast, we observe a significantly negative tightness effect on part-time workers which is similar in size to that of full-time workers.

Search Externalities. Hamermesh (1993) emphasizes that firm-level responses overstate aggregate changes in employment to the extent that workers transition between firms within the aggregate. In line, meta-regressions indicate that own-wage elasticities of labor demand at the industry level are smaller than estimates based on wage variation within single firms (Lichter/Peichl/Siegloch, 2015). In the presence of search frictions (i.e., $\eta_{\theta}^{L} < 0$), an employer's labor demand decision affects the hiring decision in other firms through search externalities (see Section 2). In such a setting, the feedback effect on labor market

Table 4: Labor Demand Effects by Labor Outcome

	(1) Δ Log L^{FT}	(2) Δ Log L^{PT}
Δ Log W^{FT}	-0.713***	
	(0.021)	
Δ Log W^{PT}		-0.067
		(0.060)
Δ Log V/U	-0.048***	-0.043***
	(0.002)	(0.002)
Fixed Effects	Year	Year
Instruments	$Z_{W^{FT}}$, Z_V, Z_U	$Z_{W^{PT}}$, Z_V, Z_U
Observations	7,993,993	11,448,610
Clusters	1,801,671	2,693,588
F: Δ Log W^{FT}	2,952	
F: Δ Log W^{PT}		69
F: Δ Log V/U	30,360	31,085

NOTE. — The table displays IV regressions of differences in log employment per establishment on differences in the log of average hourly wages and the log of labor market tightness. The instrumental variables refer to shift-share instruments of biennial national changes in occupations weighted by past occupational employment in the respective establishment. The lag difference is two years. Labor markets are combinations of 5-digit KldB occupations and commuting zones. Full-time employment includes regular full-time workers whereas part-time employment encompasses regular part-time and marginal part-time workers. Standard errors (in parentheses) are clustered at the establishment level. F = F Statistics of Excluded Instruments. FT = Full-Time. KldB = German Classification of Occupations. L = Employment. PT = Part-Time. U = Job Seekers. V = Vacancies. W = Average Hourly Wages. Z = Shift-Share Instrument. * = p<0.10. ** = p<0.05. *** = p<0.01. Sources: Integrated Employment Biographies + Official Statistics of the German Federal Employment Agency + IAB Job Vacancy Survey, 1999-2019.

tightness will partly offset any first-round response in labor demand. As a consequence, the aggregate own-wage elasticity of labor demand (i.e., including these so-called search or congestion externalities) will be less negative than the own-wage elasticity of labor demand of the single firm to the extent that higher aggregate employment amplifies search frictions.

To gauge the magnitude of the feedback effect, $\omega = \nu \cdot \eta_{\theta}^{L}$, we estimate the following auxiliary regression, which is a log-linearized version of Equation (9):

$$\Delta ln\, \theta_{rt} = \zeta + \nu \cdot \Delta ln\, L_{rt} + \Delta \varepsilon_{rt} \tag{23}$$

Specifically, we estimate the impact of changes in aggregate employment, L_{rt}, on regional labor market tightness, defined as $\theta_{rt} = \frac{V_{rt}}{U_{rt}}$. To rule out bias from reverse causality, we construct a traditional Bartik instrument employment at the regional level: $Z_{L_{rt}} = \sum_{o=1}^{O} \frac{L_{ro\tau}}{L_{r\tau}} \cdot \Delta ln\, L_{ot}$. The regressions refer to the years 2012-2019 and we set the base

period τ at year 1999 to ensure predetermined occupation shares. We specify regions in terms of our 51 commuting zones and estimate Equation (23) in one-year differences.

Columns (1) and (2) in Table 5 display the IV results of the auxiliary regression. In line with theory, the feedback effect of aggregate employment on labor market tightness, ν, turns out to be significantly positive both for regular full-time and for part-time workers. Specifically, we find that a 1 percent increase in regional employment of regular full-time workers raises labor market tightness by 9.3 percent. With a value of 10.4, we arrive at a similar order of magnitude for part-time workers. Such a positive impact of aggregate employment on labor market tightness gives rise to a self-dampening feedback cycle when aggregate employment shifts. Both effects are in line with the descriptive observation that employment increased by roughly 10 percent during our period of analysis while labor market tightness increased by about 100 percent.

Table 5: Auxiliary Regression of LM Tightness on Aggregate (Un-)Employment

	(1) Δ Log V/U	(2) Δ Log V/U	(3) Δ Log U	(4) Δ Log U
Δ Log L^{FT}	9.285*** (0.969)		-4.039*** (0.386)	
Δ Log L^{PT}		10.36*** (1.697)		-4.264*** (0.667)
Instruments	$Z_{L^{FT}}$	$Z_{L^{PT}}$	$Z_{L^{FT}}$	$Z_{L^{PT}}$
Observations	357	357	357	357
Clusters	51	51	51	51
F: Δ Log L^{FT}	155		155	
F: Δ Log L^{PT}		65		65

NOTE. — The table displays IV regressions of differences in log labor market tightness per commuting zone on differences in the log of aggregate full-time/part-time (un-)employment in the respective commuting zone. The instrumental variables refer to shift-share instruments of yearly national changes in occupations weighted by occupational employment in the respective commuting zone as of 1999. The lag difference is one year. Labor markets are combinations of 5-digit KldB occupations and commuting zones. Full-time employment includes regular full-time workers whereas part-time employment encompasses regular part-time and marginal part-time workers. Standard errors (in parentheses) are clustered at the commuting-zone level. F = F Statistics of Excluded Instruments. FT = Full-Time. KldB = German Classification of Occupations. L = Employment. LM = Labor Market. PT = Part-Time. U = Job Seekers. V = Vacancies. Z = Shift-Share Instrument. * = p<0.10. ** = p<0.05. *** = p<0.01. Sources: Integrated Employment Biographies + Official Statistics of the German Federal Employment Agency + IAB Job Vacancy Survey, 1999-2019.

To check the plausibility of these values, we make use of Equation (10) and decompose ν into the elasticity of matching with respect to the stock of vacancies, $1-\mu$, and the elasticity of regional unemployment with respect to regional employment, $\frac{\partial ln U}{\partial ln L}$. We quantify the latter effect by estimating the impact of regional employment on the number of job seekers per region in an analogous specification to (23). As before, we make use of the traditional Bartik instrument for regional employment. Columns (3) and (4) in Table 5 show that higher

employment significantly reduces the number of job seekers in a region. Quantitatively, an increase in full-time (part-time) employment by 1 percent is associated with a reduction in job seekers by 4.0 (4.3) percent. Given the estimates from Table 5, we solve Equation (10) for $1-\mu$. We arrive at a matching elasticity with respect to the stock of vacancies of 0.54 for full-time and 0.51 for part-time workers.[29] Favorably, these implied matching elasticities are well in line with the empirical literature on the matching function. Specifically, Fahr and Sunde (2006a; 2006b) estimate matching functions from regional panel data of Germany and find matching elasticities in the range between 0.4 and 0.5 for the stock of vacancies.

Finally, we insert our estimates $\hat{\eta}_W^L$ and $\hat{\eta}_\theta^L$ from Table 4 as well as $\hat{\nu}$ from Table 5 into Equation (11) to calculate the aggregate own-wage elasticity of labor demand. Thus, by virtue of the self-correcting feedback mechanism, the individual-firm own-wage elasticity of labor demand for full-time workers shrinks from -0.71 to -0.49 when accounting for search externalities at the aggregate level.[30] In a similar fashion, the aggregate own-wage elasticity of labor demand for part-time workers shrinks from -0.07 to -0.05. In both cases, by factoring in the feedback cycle, the wage elasticities shrink by around thirty percent. Overall, the feedback cycle follows an infinite geometric series, but it effectively dies off after two cycles (i.e., the converging value is only about 10 percent off the limit value after two periods).

Our results mirror related evidence on the U.S. from Beaudry/Green/Sand (2018) who report an own-wage elasticity of labor demand of -1.0 which reduces to -0.3 when taking into account the feedback cycle. However, this comparison is hampered by the fact that the authors use employment rates as a proxy for labor market tightness and do not directly estimate the feedback effect of employment on labor market tightness.

7 Discussion

In this section, we discuss the implications of our findings in three further analyses. First, we examine Germany's 2015 minimum wage introduction in the light of our results. Second, we quantify the effect of the substantial increase in labor market tightness on employment during the years 2012-2019. Third, we investigate whether firms made wage or skill concessions in order to mitigate search frictions associated with higher labor market tightness. In the following, we will briefly summarize the results. For more detailed information on the analyses, we refer the reader to Appendix 8.

[29] $1-\mu = \frac{1-\frac{\partial lnU}{\partial lnL}}{\nu} = \frac{1-(-4.039)}{9.285} = 0.54$ for full-time and $\frac{1-(-4.264)}{10.36} = 0.51$ for part-time workers.

[30] $\tilde{\eta}_W^L = \frac{\eta_W^L}{1-(\nu \cdot \eta_\theta^L)} = \frac{-0.713}{1-(-0.048 \cdot 9.285)} = -0.49$ for full-time and $\frac{-0.067}{1-(-0.043 \cdot 10.36)} = -0.05$ for part-time workers.

Minimum Wage Introduction in 2015. In Germany, a national minimum wage was introduced for the first time on January 1, 2015. We use our estimated own-wage elasticities of labor demand for full- and part-time workers to simulate the employment effects of this policy intervention. Using a worker-level difference-in-difference-in-difference specification, we estimate that the minimum wage introduction of 8.50 Euro per hour raised the aggregate wage level by 0.7 percent for full-time and 3.3 percent for part-time workers, respectively (see Table F1). We multiply these effects with our estimated own-wage elasticities of labor demand to arrive at the aggregate minimum wage effect on employment. Our baseline simulation absent search externalities (i.e., when using the individual-firm own-wage elasticities for full- and part-time workers from Table 4) yields a negative effect on employment of -126,299 workers (see Table F1). Crucially, however, this effect disregards that an aggregate reduction in labor demand also reduces labor market tightness via search externalities. When incorporating this feedback cycle (i.e., by instead using the aggregate own-wage elasticities of labor demand), the disemployment effect reduces to -87,844 workers. Overall, this effect mirrors evidence from ex-post evaluations of the 2015 minimum wage which unanimously find that employment effects were small (Bossler/Gerner, 2020; Caliendo/Schröder/Wittbrodt, 2019).

The literature offers several explanations to rationalize the absence of large disemployment effects of minimum wages (Schmitt, 2015), namely adjustments along the hours margin, product price adjustments, productivity increases, non-compliance, and monopsony power. Our analysis provides an additional explanation for this puzzle: after an aggregate reduction in employment, search externalities lower labor market tightness which, in turn, facilitates recruitment for firms that are willing to hire. This mechanism closely mirrors findings from Dustmann et al. (2022), who show that most of the firm-level employment reduction is offset by reallocation of workers to competing employers. Our estimates suggest that reallocation of workers reduces the disemployment effect of minimum wages by around thirty percent.

Employment Trends and Labor Market Tightness. In Section 5, we have shown that the German labor market has considerably tightened between 2012 and 2019. Specifically, labor market tightness doubled within only seven years. Our baseline results in Table 3 imply that a 100 percent increase in tightness lowers firm-level employment of full- and part-time workers by around 5 percent. Using these elasticities, we quantify the impact of the doubling in labor market tightness on aggregate employment in Germany for the period of our analysis. Specifically, in a counterfactual analysis, we compare the observed aggregate employment growth with a hypothetical scenario in which labor market tightness had not changed (i.e., we fix the ratio of vacancies to job seekers at its 2012 level). In this hypothetical scenario, for each year, we multiply the observed relative change in tightness by our estimated elasticities of labor demand with respect to tightness (separately

for full- and part-time workers), and subtract the respective sum from the factual stock of employment.

While observed total employment rose from 32.9 million employees in 2012 to 36.7 million jobs in 2019, our simulation implies that it could have risen to 37.8 million jobs if labor market tightness had not changed. Thus, in the absence of increasing labor market tightness, employment could have grown by an additional 1.1 million jobs until 2019. Overall, our results imply that the increase in labor market tightness considerably dampened the positive employment trend, underlining the importance of search frictions in tight labor markets.

Wage and Skill Concessions. Finally, firms facing higher labor market tightness do not necessarily have to settle for lower employment levels. Instead, these firms could still manage to expand or retain their workforce by making concessions, e.g., by raising wages or by recruiting workers with lower skills. We empirically address the conjecture that firms need to make concessions to maintain their employment (growth) in tight labor markets. Building on the same instrumental variable approach as in our analysis of labor demand, we regress the average wage level of firms and the fraction of unskilled workers in a firm on our measure of labor market tightness (see Table F3).

On average, the doubling in tightness raises mean wages of full-time workers in a firm by almost 1 percent. While the wage response is significantly positive, the magnitude of this effect is fairly small (i.e., just about a fifth of the negative employment response).[31] However,firms' positive but small wage response is in line with the empirical literature on the wage curve for Germany, which relates wages to the unemployment rate (Baltagi/Blien/Wolf, 2009; Bellmann/Blien, 2001). Regarding skill demand, we also observe only a limited extent of concessions. Starting from an average share of 6.4 percent, our results imply that the doubling in tightness raised the share of low-skill workers in firms' employment by only 0.3 percentage points. Overall, the estimates suggest that the extent of firms' wage and skill concessions was fairly small in practice, providing an explanation for the markedly negative effect of labor market tightness on employment.

[31] Note that our baseline estimates in Column (4) of Table 2 do not capture wage adjustments in the course of an increased tightness because we are conditioning on wages while estimating the effect of tightness on labor demand. However, even when discarding the wage level in Column (3) of Table 2, the tightness effect on employment shows a similar order of magnitude, reflecting the relatively small extent of wage concessions.

8 Conclusion

Conventional models of labor demand emphasize that employment is negatively related to wage changes. In this article, we derive a theoretical labor demand model which, unlike standard practice, incorporates search frictions from increased labor market tightness. In tight labor markets, firms compete for relatively few workers to fill a large number of vacancies. As higher labor market tightness raises the pre-match cost of recruiting workers, it becomes more costly and, thus, less attractive for firms to hire. Hence, not only higher wages but also higher labor market tightness reduces firms' demand for labor. Importantly, the impact of labor market tightness on firms' labor demand gives rise to search externalities: A reduction in labor demand by one firm improves the recruitment opportunities for all other firms in the same market. As a consequence, aggregate changes in labor demand (of whatever reason) alter labor market tightness which, in turn, gives rise to a self-weakening feedback cycle, as pointed out by Beaudry/Green/Sand (2018). Hence, search externalities partly offset any first-round response in labor demand.

We determine the effect of wages and labor market tightness on firms' demand for labor by leveraging the universe of administrative employment records in Germany along with official statistics and survey data on vacancies and job seeker. To address issues of endogeneity, we develop novel Bartik instruments at the firm level. We take advantage of the fact that, due to their occupational composition, firms are differently exposed to shocks at the national level. Thus, our instrumental variables rely on predetermined employment shares in firms and national shifts at the level of occupations. The IV results are in line with the predictions from our model (i.e., they exhibit a negative sign), and, as expected, they turn out to be more negative than the respective OLS estimates. We find that a 10 percent increase in labor market tightness reduces firms' employment by 0.5 percent. Further, we report an own-wage elasticity of demand for full-time workers of about -0.7. When incorporating the negative feedback cycle via search externalities, the aggregate own-wage elasticity of labor demand reduces to -0.5. In addition, our analysis reveals that the demand for part-time workers is considerably less elastic than for full-time workers.

We use our elasticities to analyze the 2015 national minimum wage introduction in Germany. Regarding this reform, ex-ante simulations from the literature suggest massive disemployment effects. By contrast, empirical ex-post evaluations tend to find only modest disemployment effects. By incorporating search externalities, the disemployment effects of the national minimum wage decreases by 30 percent, which brings elasticity-based simulation results closer to the findings of empirical ex-post evaluations. By and large, the simulation highlights the importance of search externalities when predicting employment effects of minimum wage policies. Hence, in their simulations, researchers should

incorporate aggregate own-wage elasticities of labor demand which, unlike elasticities to the single firm, account for search externalities.

Finally, we address the doubling of labor market tightness in the German labor market between 2012 and 2019 and predict the consequences for aggregate employment from a counterfactual exercise. While employment rose by 3.8 million jobs in this period, we find that an additional 1.1 million jobs could have been created in the absence of a rise in labor market tightness. This result is of high political interest as it implies that the employers' complaints about labor shortages, which came along with the rise in labor market tightness, has had massive consequences on aggregate employment in Germany. While employment growth was significantly hampered by the massive increase in tightness, we do not observe substantial concessions by employers. Wages barely increased in the course of rising labor market tightness, and we observe only small skill concessions.

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Appendix

A. Hiring-Cost Adjusted Version of Fundamental Law of Labor Demand

In a first step, we derive a hiring-cost adjusted version of the fundamental law of derived demand, that is, we identify the determinants of the own-wage elasticity of labor demand in a model with positive hiring cost. In a second step, we derive the elasticity of labor demand with respect to labor market tightness, which we model as a determinant of hiring cost.

The Wage Effect on Labor Demand. We begin with combining the optimality condition for labor (3) with our proposed formulation for unit hiring cost (5):

$$\underbrace{P \cdot Y_L(L,K)}_{\substack{\text{marginal value}\\ \text{product of labor}}} = \underbrace{W}_{\substack{\text{wage}\\ \text{rate}}} + \underbrace{(\delta + r) \cdot c \cdot W^{\phi_1} \cdot \theta^{\phi_2}}_{\substack{\text{amortized}\\ \text{pre-match}\\ \text{hiring costs}}} + \underbrace{(\delta + r) \cdot \Psi}_{\substack{\text{amortized}\\ \text{post-match}\\ \text{hiring costs}}} \equiv \underbrace{W^*}_{\substack{\text{unit}\\ \text{labor cost}}} \tag{A.1}$$

Thus, the marginal value product of labor must equal the unit cost of labor W^* which is the sum of the wage rate, the amortized pre-match hiring costs, and amortized post-match hiring costs. In the long run, the firm can also optimize the level of the capital stock. Thus, the marginal value product of capital must equal the capital rate:

$$P \cdot Y_K(L,K) = R \tag{A.2}$$

Moreover, we assume that the product market is cleared:

$$\underbrace{Y(L,K)}_{\substack{\text{product}\\ \text{supply}}} = \underbrace{Y^d(P)}_{\substack{\text{product}\\ \text{demand}}} \tag{A.3}$$

We totally differentiate Equations (A.1), (A.2), and (A.3) with respect to the wage rate W:

$$Y_L \cdot P_W + P \cdot (Y_{LL} \cdot L_W + Y_{LK} \cdot K_W) = 1 + \phi_1 \cdot (\delta + r) \cdot c \cdot W^{\phi_1 - 1} \cdot \theta^{\phi_2} \tag{A.4}$$

$$Y_K \cdot P_W + P \cdot (Y_{KL} \cdot L_W + Y_{KK} \cdot K_W) = 0 \tag{A.5}$$

$$Y_L \cdot L_W + Y_K \cdot K_W + \eta_P^Y \cdot P_W \cdot \frac{Y}{P} = 0 \tag{A.6}$$

Given the definition of the price elasticity of product demand, $\eta_P^Y = -Y_P \cdot \frac{P}{Y}$, the derivative of the right-hand side of Equation (A.3), $Y_P \cdot P_W$, can be rearranged to $-\eta_P^Y \cdot \frac{Y}{P} \cdot P_W$, culminating in Equation (A.6).

In the following, we assume that the production technology is characterized by constant returns to scale. As a consequence, the following two properties apply:

$$Y_{LL} = -\frac{K}{L} \cdot Y_{LK} \tag{A.7}$$

$$Y_{KK} = -\frac{L}{K} \cdot Y_{LK} \tag{A.8}$$

Under the additional assumption of perfect competition, Euler's product exhaustion theorem holds:

$$Y = L \cdot Y_L + K \cdot Y_K \tag{A.9}$$

The elasticity of substitution describes the percentage change in the relative use of labor and capital, when the marginal productivity ratio between both factors increases by 1 percent. Intuitively, the elasticity describes the ease of substituting labor by capital without changing output. Given Equations (A.7), (A.8), and (A.9), the elasticity of substitution becomes:

$$\sigma \equiv \frac{ln\,\frac{K}{L}}{ln\,\frac{Y_L}{Y_K}} = \frac{Y_L \cdot Y_K}{Y \cdot Y_{LK}} \geq 0 \tag{A.10}$$

Inserting Equations (A.1), (A.2), (A.7), (A.8), and (A.10) into the system of total derivatives (A.4), (A.5), and (A.6) yields after rearrangement:

$$Y \cdot \sigma \cdot P_W - \frac{K}{L} \cdot R \cdot L_W + R \cdot K_W = Y \cdot P \cdot \sigma \cdot \frac{1 + \phi_1 \cdot (\delta + r) \cdot c \cdot W^{\phi_1 - 1} \cdot \theta^{\phi_2}}{W^\star} \tag{A.11}$$

$$Y \cdot \sigma \cdot P_W + W^\star \cdot L_W - \frac{L}{K} \cdot W^\star \cdot K_W = 0 \tag{A.12}$$

$$Y \cdot \eta_P^Y \cdot P_W + W^\star \cdot L_W + R \cdot K_W = 0 \tag{A.13}$$

In matrix notation, the system looks as follows:

$$\underbrace{\begin{pmatrix} Y \cdot \sigma & -\frac{K}{L} \cdot R & R \\ Y \cdot \sigma & W^\star & -\frac{L}{K} \cdot W^\star \\ Y \cdot \eta_P^Y & W^\star & R \end{pmatrix}}_{\mathbf{A}} \cdot \underbrace{\begin{pmatrix} P_W \\ L_W \\ K_W \end{pmatrix}}_{\mathbf{x}} = \underbrace{\begin{pmatrix} Y \cdot P \cdot \sigma \cdot \frac{1 + \phi_1 (\delta + r) c W^{\phi_1 - 1} \theta^{\phi_2}}{W^\star} \\ 0 \\ 0 \end{pmatrix}}_{\mathbf{a}} \tag{A.14}$$

Given this equation system, we calculate the derivative of unconditional labor demand with respect to the wage rate using Cramer's rule: $L_W = \frac{|\mathbf{A}_2|}{|\mathbf{A}|}$. To arrive at the numerator matrix $\mathbf{A}_2$, we replace the second column in the denominator matrix **A** by **a**:

$$L_W = \frac{|\mathbf{A}_2|}{|\mathbf{A}|} = \frac{\begin{vmatrix} Y \cdot \sigma & Y \cdot P \cdot \sigma \cdot \frac{1+\phi_1 (\delta+r) c W^{\phi_1 - 1} \theta^{\phi_2}}{W^\star} & R \\ Y \cdot \sigma & 0 & -\frac{L}{K} \cdot W^\star \\ Y \cdot \eta_P^Y & 0 & R \end{vmatrix}}{\begin{vmatrix} Y \cdot \sigma & -\frac{K}{L} \cdot R & R \\ Y \cdot \sigma & W^\star & -\frac{L}{K} \cdot W^\star \\ Y \cdot \eta_P^Y & W^\star & R \end{vmatrix}} \tag{A.15}$$

Given the rule of Sarrus, the ratio of determinants becomes:

$$L_W = \frac{-Y^2 \cdot P \cdot \sigma \cdot \frac{1+\phi_1 (\delta+r) c W^{\phi_1 - 1} \theta^{\phi_2}}{W^\star} \cdot W^\star \cdot \frac{L}{K} \cdot \eta_P^Y - Y^2 \cdot \sigma^2 \cdot P \cdot R \cdot \frac{1+\phi_1 (\delta+r) c W^{\phi_1 - 1} \theta^{\phi_2}}{W^\star}}{2 \cdot R \cdot Y \cdot \sigma \cdot W^\star + Y \cdot \eta_P^Y \cdot R \cdot W^\star - W^\star \cdot R \cdot Y \cdot \eta_P^Y + \frac{L}{K} \cdot Y \cdot \sigma \cdot (W^\star)^2 + Y \cdot \sigma \cdot \frac{K}{L} \cdot R^2} \tag{A.16}$$

Building on Equations (A.1), (A.2), and (A.9), the derivative simplifies to:

$$L_W = \frac{\frac{-Y^2 \cdot P \cdot \sigma \cdot (R \cdot K \cdot \sigma + W^\star \cdot L \cdot \eta_P^Y)}{K \cdot \frac{W^\star}{1+\phi_1 (\delta+r) c W^{\phi_1 - 1} \theta^{\phi_2}}}}{\frac{P^2 \cdot \sigma \cdot Y^3}{L \cdot K}} \tag{A.17}$$

$$= -L \cdot \frac{1 + \phi_1 \cdot (\delta + r) \cdot c \cdot W^{\phi_1 - 1} \cdot \theta^{\phi_2}}{W^\star} \cdot \left(\underbrace{\frac{R \cdot K}{P \cdot Y}}_{1 - s_L} \cdot \sigma + \underbrace{\frac{W^\star \cdot L}{P \cdot Y}}_{s_L} \cdot \eta_P^Y \right) \tag{A.18}$$

$$= L \cdot \frac{1 + \phi_1 \cdot (\delta + r) \cdot c \cdot W^{\phi_1 - 1} \cdot \theta^{\phi_2}}{W^\star} \cdot \Big(-(1 - s_L) \cdot \sigma - s_L \cdot \eta_P^Y \Big) \tag{A.19}$$

Finally, multiplying Equation (A.19) by $\frac{W}{L}$ yields the unconditional own-wage elasticity of labor demand. In doing so, we arrive at a hiring-cost adjusted version of the fundamental law of labor demand:

$$\eta_W^L = \underbrace{\left(\frac{W}{W^\star} + \phi_1 \cdot \frac{(\delta + r) \cdot c \cdot W^{\phi_1} \cdot \theta^{\phi_2}}{W^\star} \right)}_{\substack{\text{elasticity of unit labor cost} \\ \text{with respect to} \\ \text{wage rate}}} \cdot \underbrace{\Big(-(1 - s_L) \cdot \sigma - s_L \cdot \eta_P^Y \Big)}_{\substack{\text{elasticity of labor demand} \\ \text{with respect} \\ \text{to unit labor cost}}} \tag{A.20}$$

The standard version (6) of the fundamental law of labor demand (Hamermesh, 1993) represents the elasticity of labor demand with respect to unit labor cost. In our model, however, the prevalence of positive hiring cost drives a wedge between unit labor cost $W^\star$ (i.e., the cost of an additional unit labor) and the wage rate W. Thus, in the hiring-cost adjusted formulation (A.20), the standard version of the fundamental law of labor demand is scaled by the elasticity of unit labor cost with respect to the wage rate. This elasticity is a weighted sum of the relative wage effects on the three components of unit labor cost,

namely the wage rate (entering with factor 1), pre-match hiring costs (entering with factor ϕ_1), and post-match hiring costs (entering with factor 0). The weights refer to the share of the wage rate, the share of pre-match hiring costs, and the share of post-match hiring costs in unit labor cost. By and large, the hiring-cost adjusted version of the fundamental law of labor demand implies that labor demand reacts more elastically to wage changes, ...

1. ... the higher the share of the wage rate in unit labor cost, and
2. ... the higher the elasticity of pre-match hiring cost with respect to the wage rate,
3. ... the higher the share of pre-match hiring costs in unit labor cost, and
4. ... the higher the elasticity of labor demand with respect to unit labor cost.

In the absence of both pre-match hiring costs, $c = 0$, and post-match hiring costs, $\Omega = 0$, unit labor cost equal the wage rate, $W^{\star} = W$, and equation (A.20) would collapse to (6).

The Tightness Effect on Labor Demand. In addition to the wage rate, our model also allows us to derive the elasticity of labor demand with respect to labor market tightness. For this purpose, we totally differentiate Equations (A.1), (A.2), and (A.3) with respect to θ:

$$Y_L \cdot P_\theta + P \cdot (Y_{LL} \cdot L_\theta + Y_{LK} \cdot K_\theta) = \phi_2 \cdot (\delta + r) \cdot c \cdot W^{\phi_1} \cdot \theta^{\phi_2 - 1} \tag{A.21}$$

$$Y_K \cdot P_\theta + P \cdot (Y_{KL} \cdot L_\theta + Y_{KK} \cdot K_\theta) = 0 \tag{A.22}$$

$$Y_L \cdot L_\theta + Y_K \cdot K_\theta + \eta_P^Y \cdot P_\theta \cdot \frac{Y}{P} = 0 \tag{A.23}$$

Using (A.1), (A.2), (A.7), (A.8), and (A.10), we rearrange the equation system as follows:

$$Y \cdot \sigma \cdot P_\theta - \frac{K}{L} \cdot R \cdot L_\theta + R \cdot K_\theta = Y \cdot P \cdot \sigma \cdot \frac{\phi_2 \cdot (\delta + r) \cdot c \cdot W^{\phi_1} \cdot \theta^{\phi_2 - 1}}{W^{\star}} \tag{A.24}$$

$$Y \cdot \sigma \cdot P_\theta + W^{\star} \cdot L_\theta - \frac{L}{K} \cdot W^{\star} \cdot K_\theta = 0 \tag{A.25}$$

$$Y \cdot \eta_P^Y \cdot P_\theta + W^{\star} \cdot L_\theta + R \cdot K_\theta = 0 \tag{A.26}$$

In matrix notation, the system of derivatives is:

$$\underbrace{\begin{pmatrix} Y \cdot \sigma & -\frac{K}{L} \cdot R & R \\ Y \cdot \sigma & W^{\star} & -\frac{L}{K} \cdot W^{\star} \\ Y \cdot \eta_P^Y & W^{\star} & R \end{pmatrix}}_{\mathbf{B}} \cdot \underbrace{\begin{pmatrix} P_\theta \\ L_\theta \\ K_\theta \end{pmatrix}}_{\mathbf{x}} = \underbrace{\begin{pmatrix} Y \cdot P \cdot \sigma \cdot \frac{\phi_2 \, (\delta + r) \, c \, W^{\phi_2} \, \theta^{\phi_2 - 1}}{W^{\star}} \\ 0 \\ 0 \end{pmatrix}}_{\mathbf{b}} \tag{A.27}$$

As before, we calculate the derivative of unconditional labor demand using Cramer's rule, the rule of Sarrus, and Equations (A.1), (A.2), and (A.9):

$$L_\theta = \frac{|\mathbf{B}_2|}{|\mathbf{B}|} = \frac{\begin{vmatrix} Y \cdot \sigma & Y \cdot P \cdot \sigma \cdot \frac{\phi_2 \, (\delta + r) \, c \, W^{\phi_1} \, \theta^{\phi_2 - 1}}{W^\star} & R \\ Y \cdot \sigma & 0 & -\frac{L}{K} \cdot W^\star \\ Y \cdot \eta_P^Y & 0 & R \end{vmatrix}}{\begin{vmatrix} Y \cdot \sigma & -\frac{K}{L} \cdot R & R \\ Y \cdot \sigma & W^\star & -\frac{L}{K} \cdot W^\star \\ Y \cdot \eta_P^Y & W^\star & R \end{vmatrix}} \tag{A.28}$$

$$= \frac{\frac{-Y^2 \cdot P \cdot \sigma \cdot \left(R \cdot K \cdot \sigma + W^\star \cdot L \cdot \eta_P^Y\right)}{K \cdot \frac{W^\star}{\phi_2 \, (\delta + r) \, c \, W^{\phi_1} \, \theta^{\phi_2 - 1}}}}{\frac{P^2 \cdot \sigma \cdot Y^3}{L \cdot K}} \tag{A.29}$$

$$= L \cdot \frac{\phi_2 \cdot (\delta + r) \cdot c \cdot W^{\phi_1} \cdot \theta^{\phi_2 - 1}}{W^\star} \cdot \Big(-(1 - s_L) \cdot \sigma - s_L \cdot \eta_P^Y \Big) \tag{A.30}$$

In a last step, we multiply Equation (A.30) by $\frac{\theta}{L}$ to arrive at the elasticity of labor demand with respect to labor market tightness:

$$\eta_\theta^L = \underbrace{\phi_2 \cdot \frac{(\delta + r) \cdot c \cdot W^{\phi_1} \cdot \theta^{\phi_2}}{W^\star}}_{\substack{\text{elasticity of unit labor cost} \\ \text{with respect to} \\ \text{labor market tightness}}} \cdot \underbrace{\Big(-(1 - s_L) \cdot \sigma - s_L \cdot \eta_P^Y \Big)}_{\substack{\text{elasticity of labor demand} \\ \text{with respect to} \\ \text{unit labor cost}}} \tag{A.31}$$

Analogously to (A.20), the elasticity equals the elasticity of labor demand with respect to unit labor cost multiplied by the elasticity of unit labor cost to labor market tightness. The latter elasticity is the relative effect of labor market tightness on pre-match hiring cost, ϕ_2, weighted by the share of pre-match hiring costs in unit labor cost. Overall, unconditional labor demand reacts more elastically to changes in labor market tightness, ...

1. ... the higher the elasticity of pre-match hiring cost with respect to tightness, and
2. ... the higher the share of pre-match hiring costs in unit labor cost, and
3. ... the higher the elasticity of labor demand with respect to unit labor cost.

In the absence of pre-match hiring cost, $c = 0$, or if labor market tightness had no effect on pre-match hiring cost, $\phi_2 = 0$, the elasticity would equal zero, as in standard models of labor demand.

So far, we have postulated that higher labor market tightness purely raises hiring cost. To counteract congestion in the hiring process, the so-called wage curve propagates that

increased labor market tightness also makes firms pay higher wages. In the following, we suppose that the wage rate is a function of labor market tightness. Specifically,

$$W \;=\; w \cdot \theta^{\gamma} \tag{A.32}$$

where $w > 0$ and $\gamma \geq 0$. Given this relationship, we differentiate Equations (A.1), (A.2), and (A.3) with respect to θ and reformulate the equation system as follows:

$$\underbrace{\begin{pmatrix} Y \cdot \sigma & -\frac{K}{L} \cdot R & R \\ Y \cdot \sigma & W^{\star} & -\frac{L}{K} \cdot W^{\star} \\ Y \cdot \eta_P^Y & W^{\star} & R \end{pmatrix}}_{\mathbf{C}} \cdot \underbrace{\begin{pmatrix} P_\theta \\ L_\theta \\ K_\theta \end{pmatrix}}_{\mathbf{x}} = \underbrace{\begin{pmatrix} Y \cdot P \cdot \sigma \cdot \frac{\gamma\, w\, \theta^{\gamma-1} + (\gamma\,\phi_1 + \phi_2)\,(\delta+r)\, c\, w^{\phi_1}\, \theta^{\gamma\,\phi_1+\phi_2-1}}{W^{\star}} \\ 0 \\ 0 \end{pmatrix}}_{\mathbf{c}} \tag{A.33}$$

We solve the equation system using Cramer's rule and derive the elasticity of labor demand with respect to tightness, taking into account the wage-curve relationship:

$$\eta_\theta^L \;=\; \underbrace{\left(\gamma \cdot \frac{W}{W^{\star}} \;+\; \left(\gamma \cdot \phi_1 \;+\; \phi_2\right) \cdot \frac{(\delta + r) \cdot c \cdot W^{\phi_1} \cdot \theta^{\phi_2}}{W^{\star}} \right)}_{\substack{\text{elasticity of unit labor cost} \\ \text{with respect to} \\ \text{labor market tightness}}} \cdot \underbrace{\left(\;-\,(1 - s_L) \cdot \sigma \;-\; s_L \cdot \eta_P^Y \right)}_{\substack{\text{elasticity of labor demand} \\ \text{with respect to} \\ \text{unit labor cost}}} \tag{A.34}$$

The difference between (A.31) and (A.34) is twofold. On the one hand, a 1 percent increase in labor market tightness raises the wage rate by γ percent. On the other hand, this wage increase further amplifies pre-match hiring cost by $\gamma \cdot \phi_1$ percent, because pre-match hiring costs depend on the wage rate which is now a function of tightness. Thus, labor demand also reacts more elastically to changes in tightness, ...

4. ... the higher the elasticity of the wage rate with respect to tightness, and
5. ... the higher the share of the wage rate in unit labor cost, and
6. ... the higher elasticity of pre-match hiring cost with respect to the wage rate.

Finally, note that, if labor market tightness exerted no effect on wage (i.e., $\gamma = 0$), Equation (A.34) collapses to (A.31).

B. Empirical 2SLS Specification

Exploiting the exogenous variation of the Bartik-instruments, we estimate the empirical model (10) using two-stage least squares (2SLS). Provided that the exclusion restrictions are fulfilled, 2SLS estimation yields consistent estimates for the parameters of interest. As we estimate effects of two endogenous variables, we run a system of the following two first-stage regressions

$$\Delta ln W_{it} = \pi_{10} + \pi_{11} \cdot Z_{W_{it}} + \pi_{12} \cdot Z_{V_{it}} + \pi_{13} \cdot Z_{U_{it}} + \zeta_{1t} + \Delta \varepsilon_{1it} \tag{B.1}$$

$$\Delta ln \theta_{it} = \pi_{20} + \pi_{21} \cdot Z_{W_{it}} + \pi_{22} \cdot Z_{V_{it}} + \pi_{23} \cdot Z_{U_{it}} + \zeta_{2t} + \Delta \varepsilon_{2it} \tag{B.2}$$

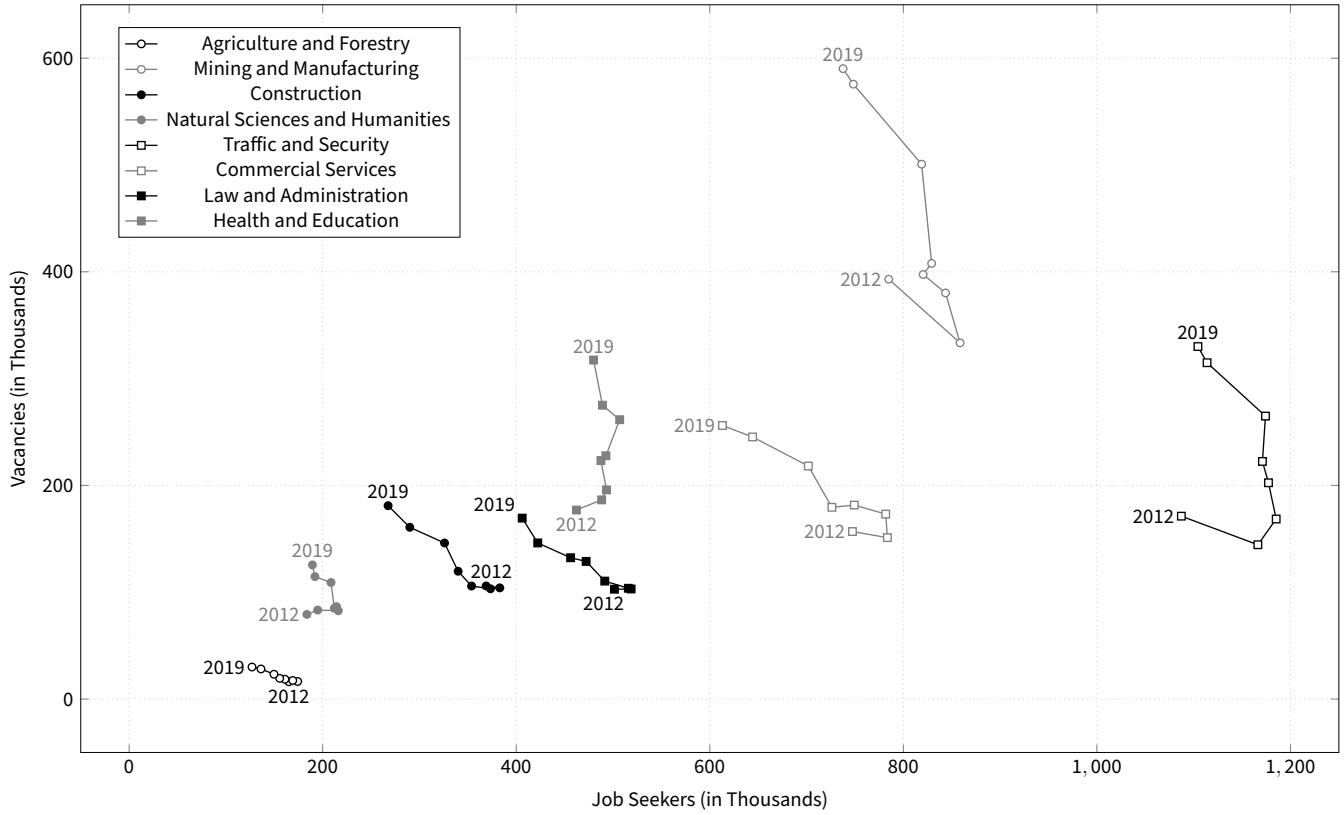
where both first-stage equations include our three instruments as well as year effects for each year t. The first-stage regressions are designed to extract exogenous variation in the regressors of interest. In the second stage,

$$\Delta ln L_{it} = \eta_0 + \eta_W^L \cdot \widehat{\Delta ln W_{it}} + \eta_\theta^L \cdot \widehat{\Delta ln \theta_{it}} + \zeta_t + \Delta \varepsilon_{it} \tag{B.3}$$

we run our empirical model (12) on the predictions from the first-stage regressions. When the exogeneity assumptions hold, the residual term $\Delta \varepsilon_{it}$ is uncorrelated with the remaining variation in the variables of interest. Note that all instrumental variable estimates are obtained from Stata's ivreg2 command. Thereby, the inference is automatically adjusted for the two step procedure of 2SLS.

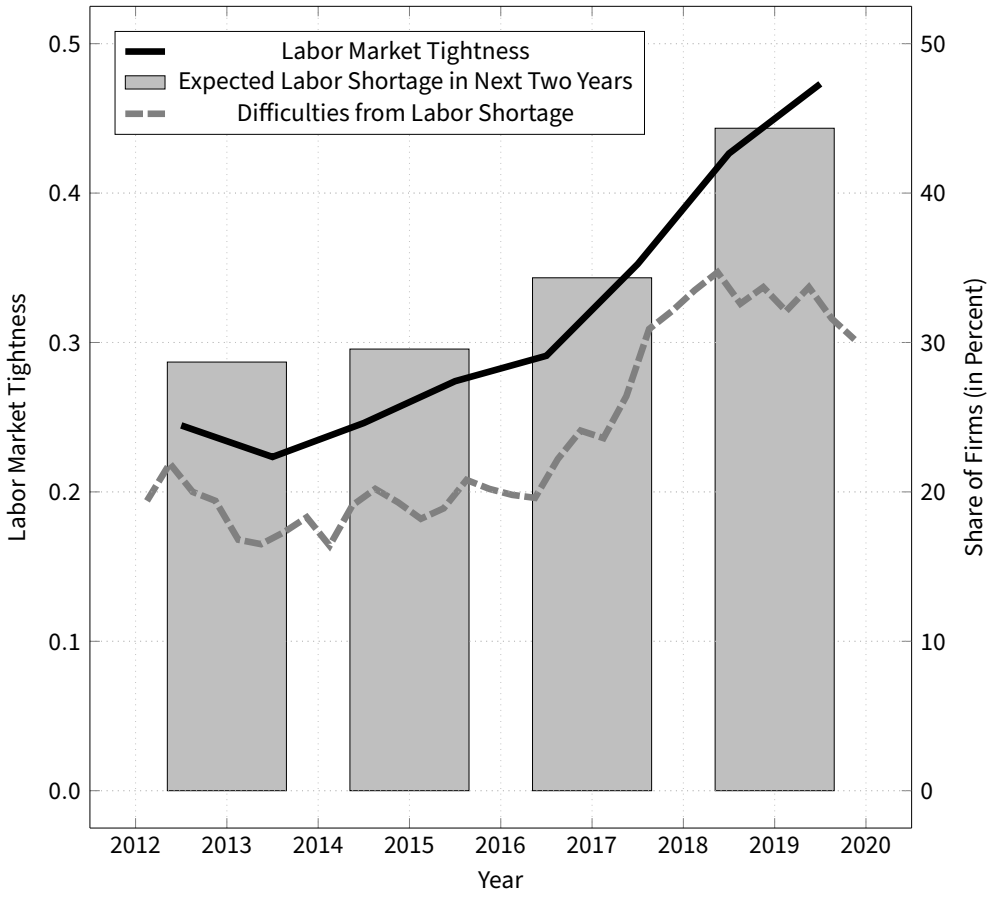
C. Labor Market Tightness and Hiring Cost: Further Evidence

Figure C1: Beveridge Curve by Occupational Areas



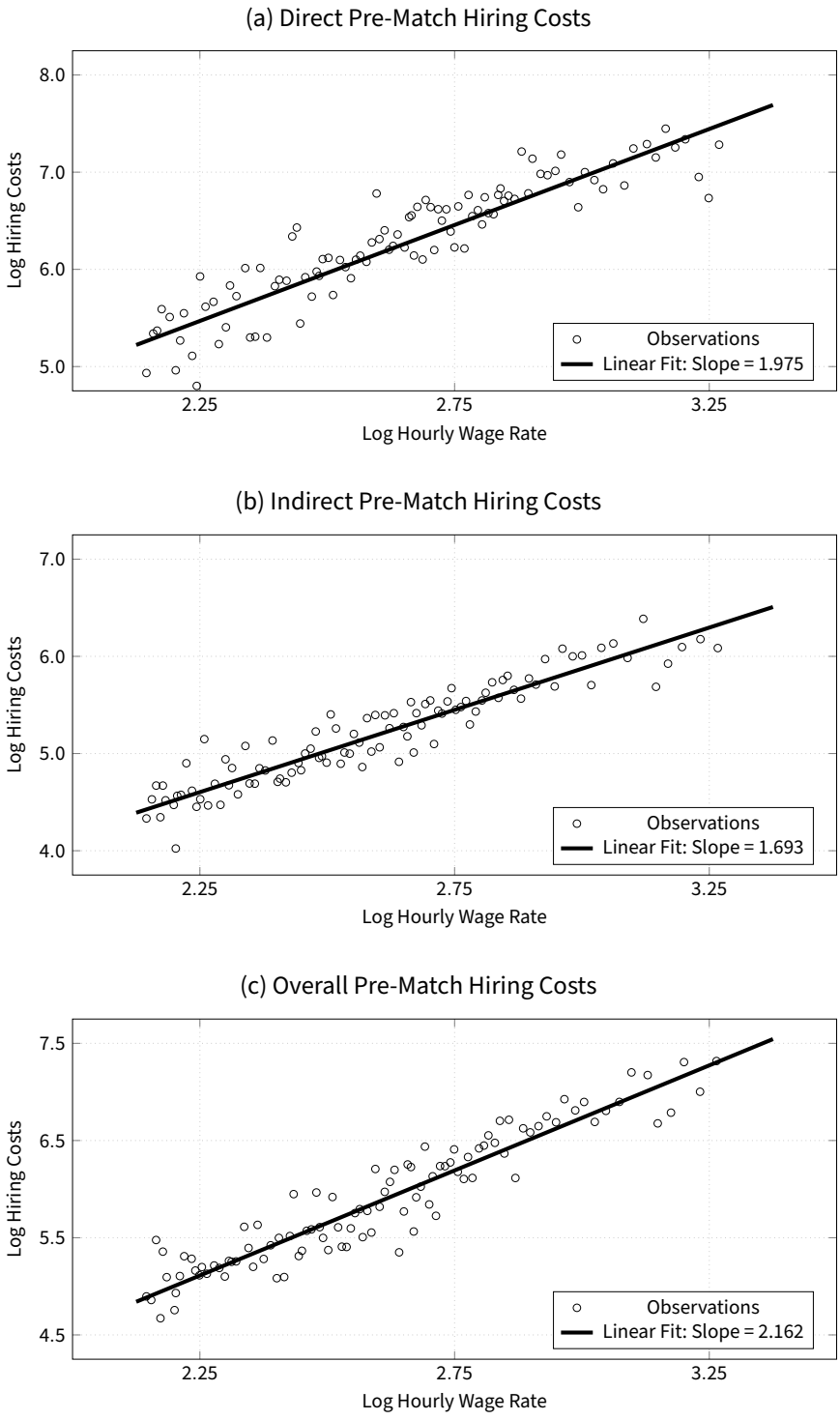
NOTE. — The figure shows Beveridge curves by occupational area for Germany between 2012 and 2019. The occupational areas refer to 1-digit KldB occupations. For ease of presentation, we group together natural sciences and humanities. KldB = German Classification of Occupations. Sources: Official Statistics of the German Federal Employment Agency + IAB Job Vacancy Survey, 2012-2019.

Figure C2: Labor Market Tightness vs. Survey Information on Labor Shortage



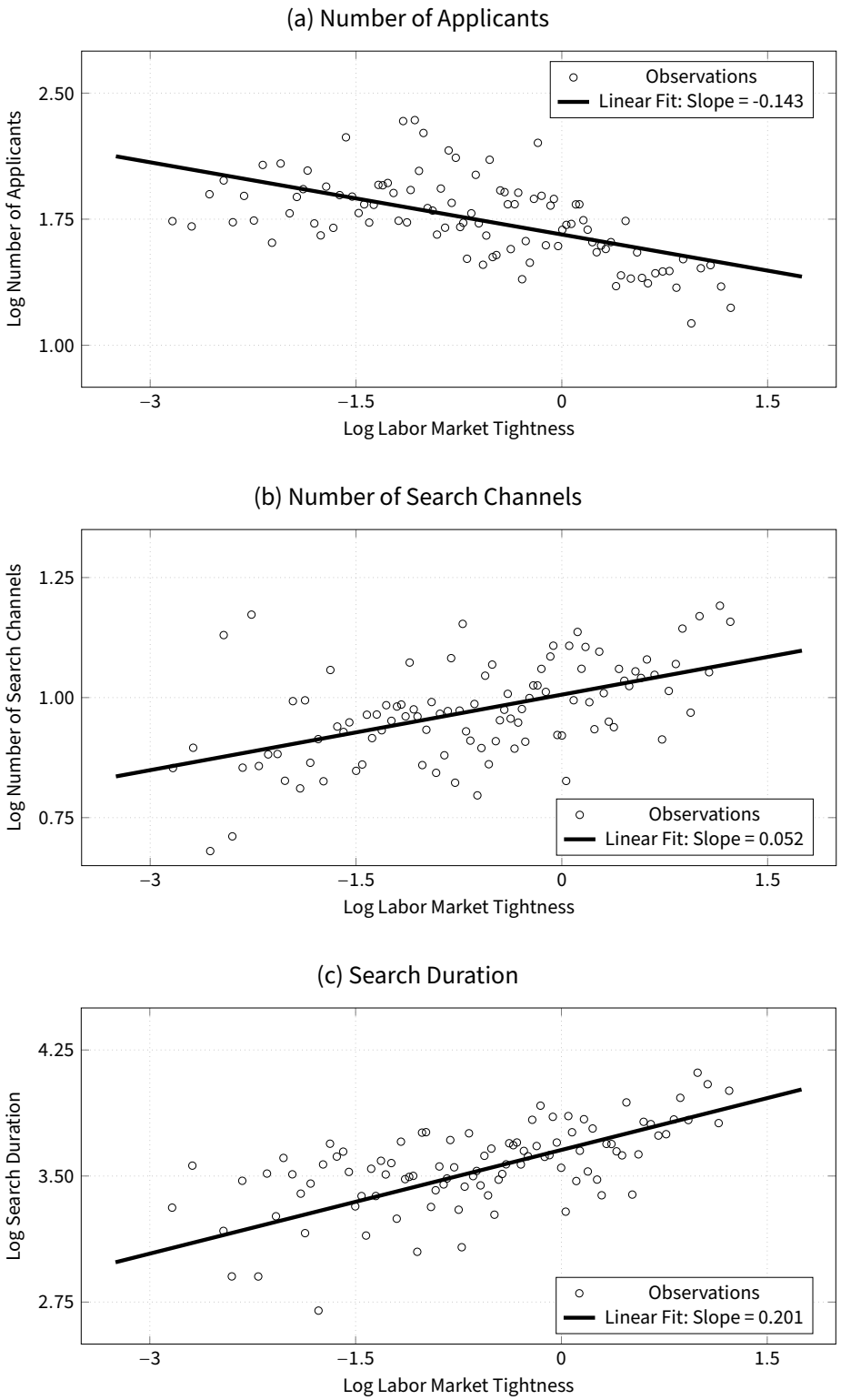
NOTE. — The figure contrasts our measure of labor market tightness (left axis) with survey information on the percentage share of firms that face (difficulties from) a shortage of skilled labor (right axis). The IAB Establishment Panel asks establishments whether they expect labor shortage in the upcoming years. The KfW-ifo Skilled Labor Barometer surveys companies on whether they experience adverse impacts on business operations from a shortage of skilled workers. Source: Official Statistics of the German Federal Employment Agency + IAB Establishment Panel + KfW-ifo Skilled Labor Barometer, 2012-2019.

Figure C3: Hourly Wage Rate and Pre-Match Hiring Costs



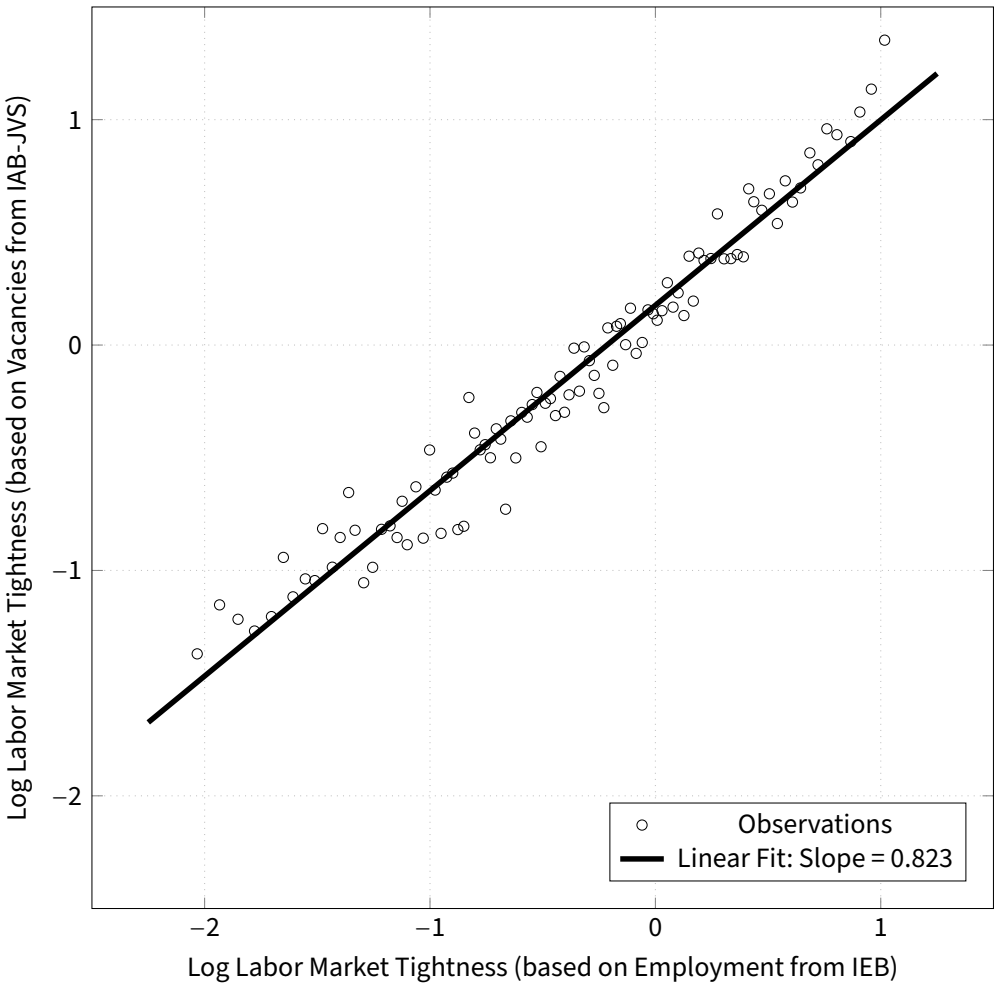
NOTE. — The figures show binned scatterplots with 100 hundred markers to depict cross-sectional correlations between the log hourly wage rate upon hiring and the log of direct, indirect, and overall pre-match hiring costs. Whereas direct pre-match hiring costs (in Euro) are asked separately in the IAB Job Vacancy Survey, we calculate indirect pre-match hiring costs (in Euro) by multiplying the search effort (in working hours) by the firm's average hourly wage rate of i) workers in human resource management (KldB-2010 Code: 715) or, if not available, ii) managers or, if not available, iii) all workers. Pre-match hiring costs and the hourly wage rate (upon hiring) were deflated with base year 2015. We trim hourly wages (in Euro) at the 5th and 95th percentile. The numbers of observed successful hires are: 13,085 for direct, 31,933 for indirect, and 26,886 for overall pre-match hiring costs. Sources: Integrated Employment Biographies + Official Statistics of Federal Employment Agency + IAB Job Vacancy Survey, 2014-2015, 2017-2019.

Figure C4: Labor Market Tightness and Hiring Indicators



NOTE. — The figures show binned scatterplots with 100 hundred markers to depict cross-sectional correlations between log labor market tightness and the log of the number of applicants, the number of search channels, and search duration (in days). Labor markets are combinations of 5-digit KldB occupations and commuting zones. We trim labor market tightness at the 5th and 95th percentile. On average, a successful hire features 15.3 applicants, 3.2 search channels, and a search duration of 59.4 days. The numbers of observed successful hires are: 44,020 for the number of applicants, 52,063 for the number of search channels, and 42,747 for search duration. Sources: Official Statistics of Federal Employment Agency + IAB Job Vacancy Survey, 2012-2019.

Figure C5: Vacancy- vs. Employment-Based Firm-Specific Labor Market Tightness



NOTE. — The figure shows a binned scatterplot with 100 hundred markers to contrast our employment-based measure of log firm-specific labor market tightness with an analogous vacancy-based measure for the very same firm. While our employment-based measure builds on administrative employment shares in the IEB, the vacancy-based measure is constructed from cross-sectional information in the IAB Job Vacancy Survey on a subset of firms' top five occupations with the highest number of unfilled vacancies. The number of observations is 24,323. Sources: Integrated Employment Biographies + Official Statistics of the German Federal Employment Agency + IAB Job Vacancy Survey, 2012-2019.

D. Bartik-Instrument Diagnostics

Table D1: Summary of Rotemberg Weights
(a) Effect of Wage Rate

Panel A: Negative and Positive Rotemberg Weights					
	Sum	Mean	Share		
Positive	1.0908	0.0015	0.9232		
Negative	-0.0908	-0.0002	0.0768		
Overall	1.0000	0.0008	1.0000		
Panel B: Correlations					
	$\hat{\alpha}_o$	g_o	$\hat{\eta}_o$	$\hat{F}_o$	$\sqrt{var(z_o)}$
Rotemberg Weight ($\hat{\alpha}_o$)	1				
National Growth Rate (g_o)	0.1850	1			
Just-Identified Coefficient ($\hat{\eta}_o$)	-0.0845	-0.0340	1		
First-Stage F Statistic ($\hat{F}_o$)	0.9118	0.0969	-0.0439	1	
Variance of Shares ($\sqrt{var(z_o)}$)	0.4282	-0.0146	-0.1582	0.4411	1
Panel C: Rotemberg Weights by Years					
	Sum	Mean			
2012 - 2014	0.1155	0.0001			
2013 - 2015	0.2691	0.0002			
2014 - 2016	0.2716	0.0002			
2015 - 2017	0.0952	0.0001			
2016 - 2018	0.1072	0.0001			
2017 - 2019	0.1414	0.0001			
Panel D: Top Five Occupations by Rotemberg Weights					
	$\hat{\alpha}_o$	g_o	$\hat{\eta}_o$	$\hat{F}_o$	Occ. Share
Gastronomy Workers (II)	0.1396	0.0501	-0.3495	903.94	2.1095
Medical Assistants (II)	0.1139	0.0264	-1.3368	941.03	1.5520
Hairdressers (II)	0.0966	0.0496	-2.0212	506.85	0.5531
Cooks (II)	0.0965	0.0377	-0.7576	889.64	1.9774
Farmers (I)	0.0789	0.0455	0.0250	339.04	0.2859
Panel E: Just-Identified Coefficients by Negative and Positive Rotemberg Weights					
	$\hat{\alpha}$-Weight. Sum	Share	Mean		
Positive	-0.4564	0.6268	-4.4440		
Negative	-0.2717	0.3732	1.3175		
Overall	-0.7280	1.0000	-2.1205		

NOTE. — The table displays statistics about the Rotemberg weights underlying our estimated wage effect on labor demand. For ease of computation, we derive the statistics by running specification (2) in Table 2 on a random 50 percent sample of firms. In all cases, we report statistics about the aggregated weights with normalized growth rates (i.e., we subtract the per-period average across occupations). Panel A reports the share, mean, and sum by negative and positive Rotemberg weights. For the occupations with the 100 highest absolute Rotemberg weights, Panel B delivers correlations between the Rotemberg weights, the normalized national two-year growth rates, the just-identified coefficient estimates, the first-stage F statistics of the occupational employment share in the base year, and the standard deviations in the occupational employment shares across firms. Panel C displays the sum of Rotemberg weights across years (in terms of two-year intervals). Panel D describes the top five occupations with the largest Rotemberg weights, including the occupational employment share in the overall labor market (multiplied by 100 for legibility). The Roman number (in parentheses) denotes the level of skill requirements: helpers (I), professionals (II), specialists (III), or experts (IV). Panel E shows how the values of the just-identified coefficients vary by positive and negative Rotemberg weights. CI = Confidence Interval. Occ. = Occupation. Weight. = Weighted. Sources: Integrated Employment Biographies + Official Statistics of the German Federal Employment Agency + IAB Job Vacancy Survey, 1999-2019.

Summary of Rotemberg Weights (Cont.)
(b) Effect of Labor Market Tightness: Vacancy Instrument

Panel A: Negative and Positive Rotemberg Weights			
	Sum	Mean	Share
Positive	1.6418	0.0021	0.6078
Negative	-0.0979	-0.0003	0.0362
Overall	1.5439	0.0015	0.6440

Panel B: Correlations					
	$\hat{\alpha}_o$	g_o	$\hat{\eta}_o$	$\hat{F}_o$	$\sqrt{var(z_o)}$
Rotemberg Weight ($\hat{\alpha}_o$)	1				
National Growth Rate (g_o)	-0.0597	1			
Just-Identified Coefficient ($\hat{\eta}_o$)	-0.1327	0.0859	1		
First-Stage F Statistic ($\hat{F}_o$)	0.5562	-0.0785	-0.0892	1	
Variance of Shares ($\sqrt{var(z_o)}$)	0.5520	-0.0386	-0.0776	0.4288	1

Panel C: Rotemberg Weights by Years		
	Sum	Mean
2012 - 2014	0.3282	0.0003
2013 - 2015	0.3080	0.0003
2014 - 2016	0.2336	0.0002
2015 - 2017	0.2164	0.0002
2016 - 2018	0.2739	0.0003
2017 - 2019	0.1839	0.0002

Panel D: Top Five Occupations by Rotemberg Weights					
	$\hat{\alpha}_o$	g_o	$\hat{\eta}_o$	$\hat{F}_o$	Occ. Share
Sale Workers (II)	0.1971	0.3826	-0.1788	11,318	6.2581
Bankers (II)	0.1201	0.1336	-0.0711	10,004	1.4968
Farmers (I)	0.1187	-0.1799	-0.0657	2704.6	0.2859
Chimney Sweeps (II)	0.0745	-0.6519	-0.0035	2210.8	0.0320
Construction Workers (I)	0.0735	0.2912	0.0967	1733.2	1.0320

Panel E: Just-Identified Coefficients by Negative and Positive Rotemberg Weights			
	$\hat{\alpha}$-Weight.		
	Sum	Share	Mean
Positive	-0.0234	0.5714	1.9699
Negative	-0.0069	0.1681	1.1189
Overall	-0.0302	0.7395	1.7323

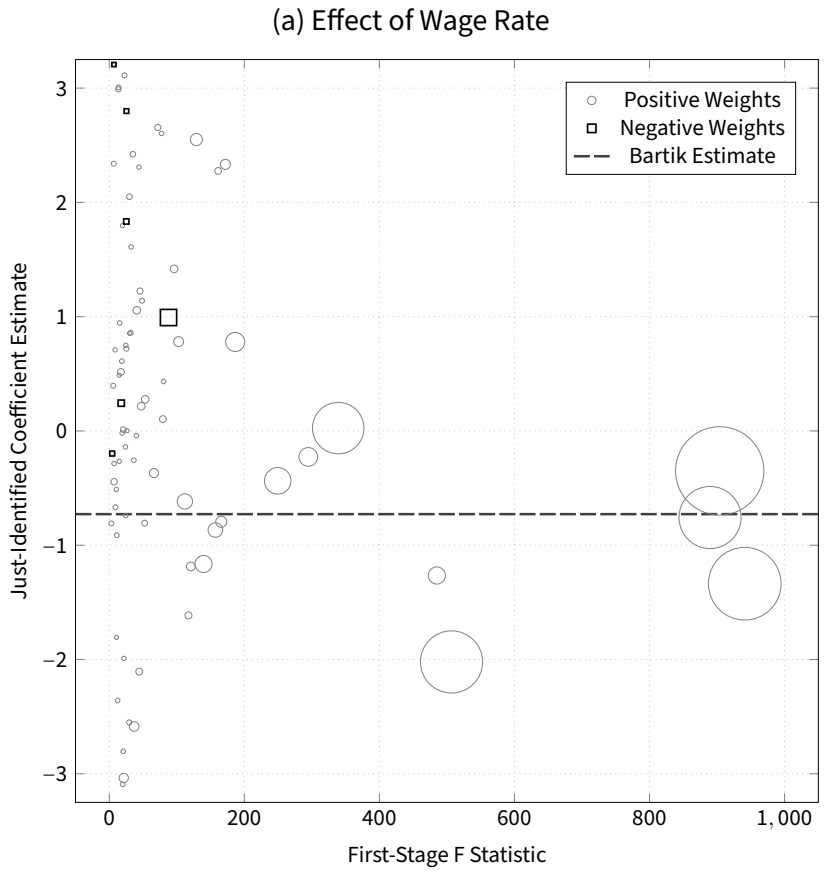
NOTE. — The table displays statistics about the Rotemberg weights underlying our estimated effect of labor market tightness on labor demand. For ease of computation, we derive the statistics by running specification (3) in Table 2 on a random 50 percent sample of firms. In all cases, we report statistics about the aggregated weights with normalized growth rates (i.e., we subtract the per-period average across occupations). Panel A reports the share, mean, and sum by negative and positive Rotemberg weights. For the occupations with the 100 highest absolute Rotemberg weights, Panel B delivers correlations between the Rotemberg weights, the normalized national two-year growth rates, the just-identified coefficient estimates, the first-stage F statistics of the occupational employment share in the base year, and the standard deviations in the occupational employment shares across firms. Panel C displays the sum of Rotemberg weights across years (in terms of two-year intervals). Panel D describes the top five occupations with the largest Rotemberg weights, including the occupational employment share in the overall labor market (multiplied by 100 for legibility). The Roman number (in parentheses) denotes the level of skill requirements: helpers (I), professionals (II), specialists (III), or experts (IV). Panel E shows how the values of the just-identified coefficients vary by positive and negative Rotemberg weights. CI = Confidence Interval. Occ. = Occupation. Weight. = Weighted. Sources: Integrated Employment Biographies + Official Statistics of the German Federal Employment Agency + IAB Job Vacancy Survey, 1999-2019.

Summary of Rotemberg Weights (Cont.)
(c) Effect of Labor Market Tightness: Job Seeker Instrument

Panel A: Negative and Positive Rotemberg Weights					
	Sum	Mean	Share		
Positive	0.2088	0.0004	0.0773		
Negative	-0.7527	-0.0011	0.2787		
Overall	-0.5439	-0.0005	0.3560		
Panel B: Correlations					
	$\hat{\alpha}_o$	g_o	$\hat{\eta}_o$	$\hat{F}_o$	$\sqrt{var(z_o)}$
Rotemberg Weight ($\hat{\alpha}_o$)	1				
National Growth Rate (g_o)	0.0242	1			
Just-Identified Coefficient ($\hat{\eta}_o$)	0.0715	0.1770	1		
First-Stage F Statistic ($\hat{F}_o$)	-0.7440	-0.0082	-0.0327	1	
Variance of Shares ($\sqrt{var(z_o)}$)	-0.3690	-0.0857	-0.1714	0.4148	1
Panel C: Rotemberg Weights by Years					
	Sum	Mean			
2012 - 2014	-0.0804	-0.0001			
2013 - 2015	-0.0932	-0.0001			
2014 - 2016	-0.0914	-0.0001			
2015 - 2017	-0.1411	-0.0001			
2016 - 2018	-0.0854	-0.0001			
2017 - 2019	-0.0524	-0.0000			
Panel D: Top Five Occupations by Rotemberg Weights					
	$\hat{\alpha}_o$	g_o	$\hat{\eta}_o$	$\hat{F}_o$	Occ. Share
Sale Workers (II)	-0.0996	-0.1982	-0.2532	11,975	6.2581
Masons (II)	-0.0459	-0.4563	-0.0613	2166.7	0.9448
Truck Drivers (II)	-0.0423	-0.2329	0.0105	3957.7	3.1550
Bankers (II)	-0.0366	-0.1941	-0.1385	8205.3	1.4968
Gardeners (II)	-0.0360	-0.4321	0.0268	488.95	0.7031
Panel E: Just-Identified Coefficients by Negative and Positive Rotemberg Weights					
	$\hat{\alpha}$-Weight.				
	Sum	Share	Mean		
Positive	-0.0069	0.0149	-3.5825		
Negative	-0.1133	0.2456	0.0219		
Overall	-0.1202	0.2605	-1.4997		

NOTE. — The table displays statistics about the Rotemberg weights underlying our estimated effect of labor market tightness on labor demand. For ease of computation, we derive the statistics by running specification (3) in Table 2 on a random 50 percent sample of firms. In all cases, we report statistics about the aggregated weights with normalized growth rates (i.e., we subtract the per-period average across occupations). Panel A reports the share, mean, and sum by negative and positive Rotemberg weights. For the occupations with the 100 highest absolute Rotemberg weights, Panel B delivers correlations between the Rotemberg weights, the normalized national two-year growth rates, the just-identified coefficient estimates, the first-stage F statistics of the occupational employment share in the base year, and the standard deviations in the occupational employment shares across firms. Panel C displays the sum of Rotemberg weights across years (in terms of two-year intervals). Panel D describes the top five occupations with the largest Rotemberg weights, including the occupational employment share in the overall labor market (multiplied by 100 for legibility). The Roman number (in parentheses) denotes the level of skill requirements: helpers (I), professionals (II), specialists (III), or experts (IV). Panel E shows how the values of the just-identified coefficients vary by positive and negative Rotemberg weights. CI = Confidence Interval. Occ. = Occupation. Weight. = Weighted. Sources: Integrated Employment Biographies + Official Statistics of the German Federal Employment Agency + IAB Job Vacancy Survey, 1999-2019.

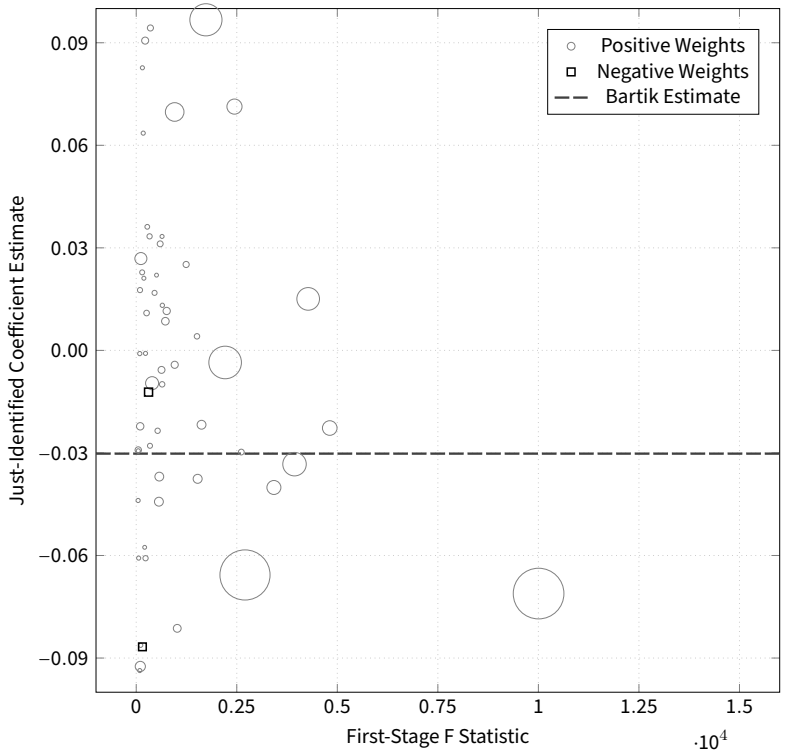
Figure D1: Heterogeneity of Just-Identified Coefficient Estimates



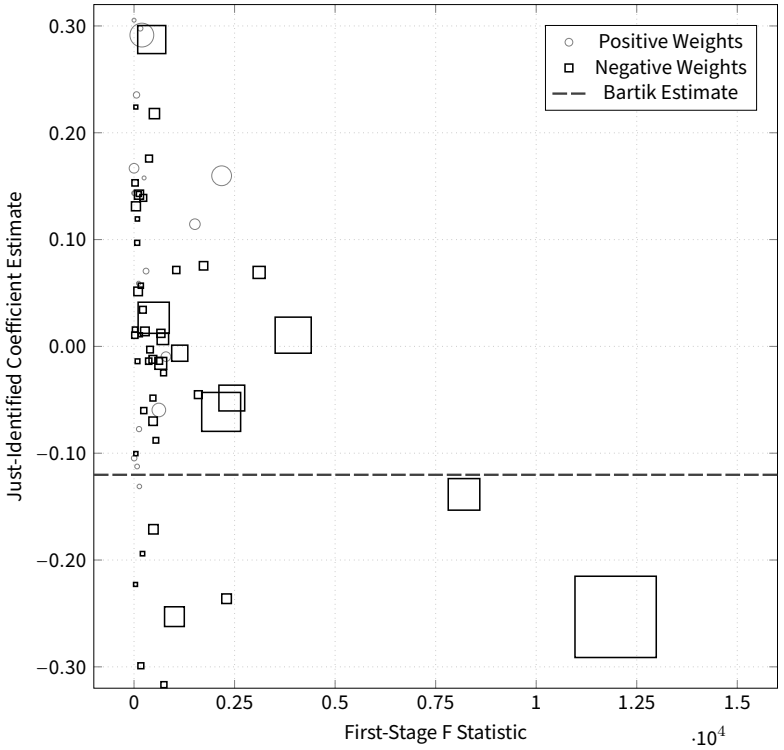
NOTE: — The figure visualizes the relationship between each instruments just-identified coefficient estimate, the first-stage F statistics, and the Rotemberg weights. Each marker refers to a separate instruments estimates (occupation share). The figure plots the estimated just-identified coefficents for each instrument (i.e., occupational employment share in the base year) against the respective first-stage F statistic. The size of the markers are proportional to the the absolute value of the Rotemberg weights, with the circles denoting positive weights and the squares denoting negative weights. The horizontal dashed line reflects the overall Bartik estimate. For reasons of parsimony, the figure includes only the 50 instruments with the highest absolute Rotemberg weights, which account for 78.1 percent of the sum of absolute weights. Sources: Integrated Employment Biographies + Official Statistics of the German Federal Employment Agency + IAB Job Vacancy Survey, 1999-2019.

Heterogeneity of Just-Identified Coefficient Estimates (Cont.)

(b) Effect of Labor Market Tightness: Vacancy Instrument



(c) Effect of Labor Market Tightness: Job Seeker Instrument



NOTE: — The figure visualizes the relationship between each instruments just-identified coefficient estimate, the first-stage F statistics, and the Rotemberg weights. Each marker refers to a separate instruments estimates (occupation share). The figure plots the estimated just-identified coefficents for each instrument (i.e., occupational employment share in the base year) against the respective first-stage F statistic. The size of the markers are proportional to the the absolute value of the Rotemberg weights, with the circles denoting positive weights and the squares denoting negative weights. The horizontal dashed line reflects the overall Bartik estimate. For reasons of parsimony, the figure includes only the 100 occupations with the highest absolute Rotemberg weights, which account for 78.9 percent (vacancies) and 52.4 percent (job seekers) of the sum of absolute weights. Sources: Integrated Employment Biographies + Official Statistics of the German Federal Employment Agency + IAB Job Vacancy Survey, 1999-2019.

Table D1: Shifters of Demand and Supply for Employment Shares of Top 5 Rotemberg Occupations
(a) Effect of Wage Rate

Employment Share of ...	(1) Gastronomy Workers	(2) Medical Assistants	(3) Hairdressers	(4) Cooks	(5) Farmers
Log Productivity	-0.855***	-0.051	-0.581**	-0.988***	-1.077*
	(0.250)	(0.387)	(0.233)	(0.289)	(0.560)
Log Investments	0.010	-0.538*	0.097	0.188	0.819***
	(0.102)	(0.313)	(0.166)	(0.217)	(0.228)
Business Expectations	0.002	-0.001	0.00006	0.002	-0.024***
	(0.003)	(0.014)	(0.00390)	(0.008)	(0.009)
Female Share	1.675***	14.20***	2.456***	2.952***	-3.322***
	(0.428)	(1.851)	(0.880)	(0.846)	(1.077)
Foreign Share	6.842***	2.262	2.032	7.613***	-1.661
	(2.321)	(2.467)	(1.823)	(0.846)	(1.420)
Firm Size	Yes	Yes	Yes	Yes	Yes
F: Productivity	11.7***	0.02	6.23**	11.7***	3.70*
F: Demand Shifters	0.15	1.50	0.25	0.38	7.32***
F: Supply Shifters	11.7***	29.4***	4.17**	8.55***	4.84***
Observations	4,728	4,728	4,728	4,728	4,728
Identifying Variation	0.118	0.096	0.082	0.082	0.067
2015 Minimum Wage Bite	0.620	0.143	0.546	0.313	0.460

NOTE: — The table displays weighted least squares regressions of the top five occupational employment shares (in the firms' base year), as defined by column titles, on explanatory variables in the year after the predetermined share was fixed. Apart from productivity, the set of covariates includes variables that are likely to shift labor demand (investments and business expectations) or labor supply (share of female or foreign workers). In all specifications, we control for ten firm size categories. The F Statistics refer to tests of (joint) significance of the productivity variable, the set of labor demand variables, or the set of labor supply variables. The last row delivers the occupations' relative weight in the Bartik estimator. * = p<0.10. ** = p<0.05. *** = p<0.01. Sources: Integrated Employment Biographies + IAB Establishment Panel, 1999-2019.

Shifters of Demand and Supply for Employment Shares of Top 5 Rotemberg Occupations (Cont.)
(b) Effect of Labor Market Tightness: Vacancy Instrument

Employment Share of ...	(1) Sales Workers	(2) Bankers	(3) Farmers	(4) Chimney Sweeps	(5) Construction Workers
Log Productivity	-0.567 (0.469)	0.047 (0.034)	-1.077* (0.560)	-0.443** (0.212)	-0.009 (0.140)
Log Investments	-0.247 (0.306)	-0.036 (0.026)	0.819*** (0.228)	-0.041 (0.192)	0.064 (0.148)
Business Expectations	-0.007 (0.011)	-0.0005 (0.0003)	-0.024*** (0.009)	-0.006* (0.004)	-0.0003 (0.004)
Female Share	9.686*** (1.544)	0.146 (0.132)	-3.322*** (1.077)	-1.443** (0.690)	-2.876*** (0.715)
Foreign Share	-3.585* (1.869)	-0.035 (0.046)	-1.661 (1.420)	-1.801** (0.711)	2.506 (2.183)
Firm Size	Yes	Yes	Yes	Yes	Yes
F: Productivity	1.46	1.90	3.70*	4.35*	0.00
F: Demand Shifters	0.63	1.33	7.32***	1.51	0.13
F: Supply Shifters	21.9***	0.74	4.84***	3.21**	8.09***
Observations	4,728	4,728	4,728	4,728	4,728
Identifying Variation	0.113	0.069	0.068	0.043	0.042

NOTE: — The table displays weighted least squares regressions of the top five occupational employment shares (in the firms' base year), as defined by column titles, on explanatory variables in the year after the predetermined share was fixed. Apart from productivity, the set of covariates includes variables that are likely to shift labor demand (investments and business expectations) or labor supply (share of female or foreign workers). In all specifications, we control for ten firm size categories. The F Statistics refer to tests of (joint) significance of the productivity variable, the set of labor demand variables, or the set of labor supply variables. The last row delivers the occupations' relative weight in the Bartik estimator. * = p<0.10. ** = p<0.05. *** = p<0.01. Sources: Integrated Employment Biographies + IAB Establishment Panel, 1999-2019.

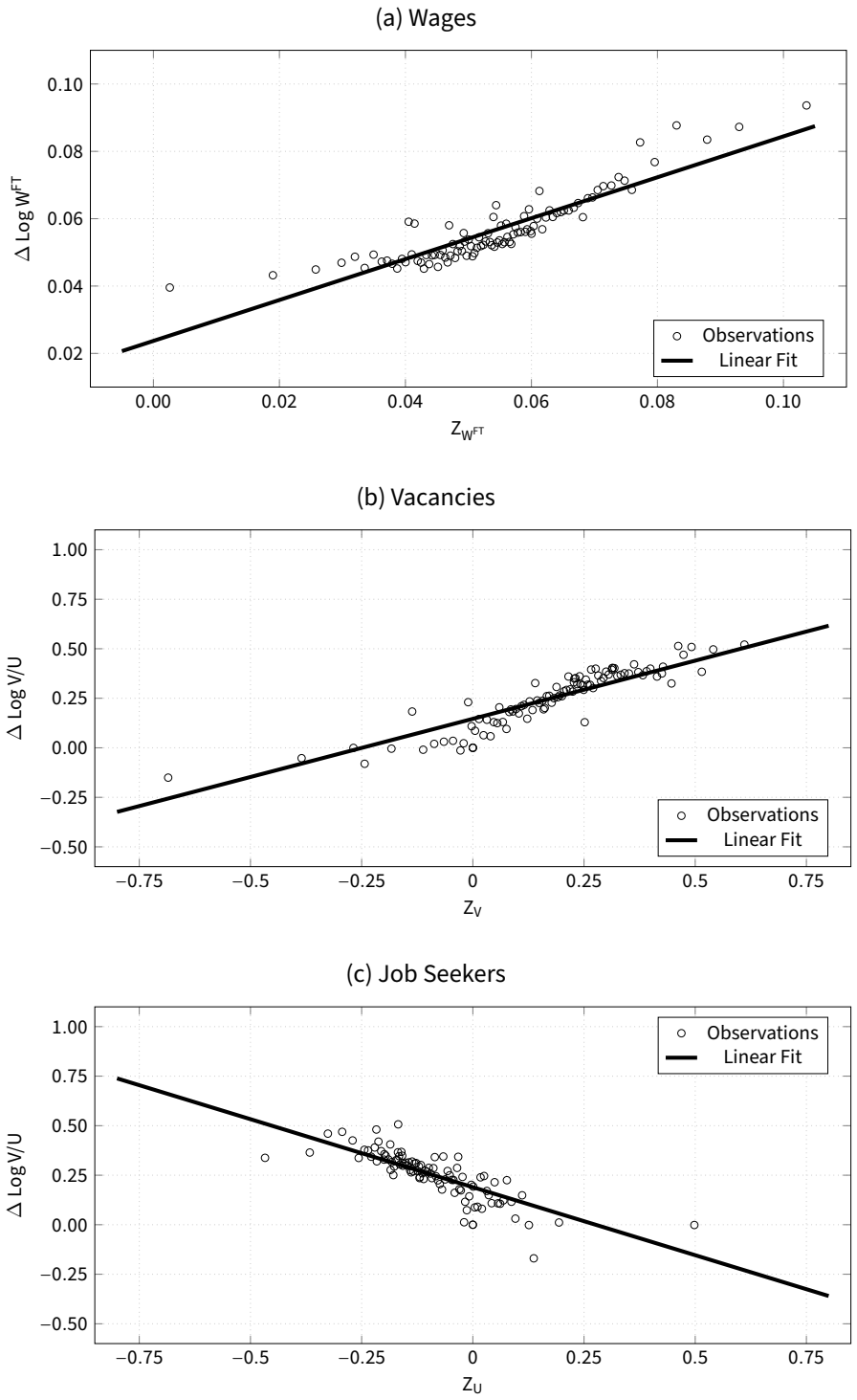
Shifters of Demand and Supply for Employment Shares of Top 5 Rotemberg Occupations (Cont.)
(c) Effect of Labor Market Tightness: Job Seeker Instrument

Employment Share of ...	(1) Sales Workers	(2) Masons	(3) Truck Drivers	(4) Bankers	(5) Gardeners
Log Productivity	-0.567	-0.309	-0.769*	0.047	-0.767
	(0.469)	(0.281)	(0.421)	(0.034)	(0.526)
Log Investments	-0.247	-0.454	1.783***	-0.036	0.356
	(0.306)	(0.340)	(0.319)	(0.026)	(0.251)
Business Expectations	-0.007	0.001	-0.032**	-0.0005	-0.019**
	(0.011)	(0.005)	(0.012)	(0.0003)	(0.009)
Female Share	9.686***	-4.025***	-6.231***	0.146	-1.516
	(1.544)	(1.150)	(0.948)	(0.132)	(1.131)
Foreign Share	-3.585*	-0.668	-0.572	-0.035	0.324
	(1.869)	(1.858)	(2.060)	(0.046)	(1.948)
Firm Size	Yes	Yes	Yes	Yes	Yes
F: Productivity	1.46	1.21	3.34*	1.90	2.13
F: Demand Shifters	0.63	1.11	15.6***	1.33	2.49*
F: Supply Shifters	21.9***	5.25***	22.8***	0.74	0.91
Observations	4,728	4,728	4,728	4,728	4,728
Identifying Variation	0.104	0.048	0.044	0.038	0.037

NOTE: — The table displays weighted least squares regressions of the top five occupational employment shares (in the firms' base year), as defined by column titles, on explanatory variables in the year after the predetermined share was fixed. Apart from productivity, the set of covariates includes variables that are likely to shift labor demand (investments and business expectations) or labor supply (share of female or foreign workers). In all specifications, we control for ten firm size categories. The F Statistics refer to tests of (joint) significance of the productivity variable, the set of labor demand variables, or the set of labor supply variables. The last row delivers the occupations' relative weight in the Bartik estimator. * = p<0.10. ** = p<0.05. *** = p<0.01. Sources: Integrated Employment Biographies + IAB Establishment Panel, 1999-2019.

E. Regression Results: Further Evidence

Figure E1: First-Stage Regressions



NOTE. — The figures show binned scatterplots with 100 hundred markers to visualize the underlying variation of the first-stage regressions. L = Employment. FT = Full-Time. U = Jobs Seekers. V = Vacancies. W = Average Daily Wages. Z = Shift-Share Instrument. Sources: Integrated Employment Biographies + Official Statistics of German Federal Employment Agency + IAB Job Vacancy Survey, 1999-2019.

Table E1: Reduced-Form Regressions

	(1) Δ Log L^{FT}	(2) Δ Log L^{FT}	(3) Δ Log L^{FT}	(4) Δ Log L^{FT}
$Z_{W^{FT}}$	-0.466***			-0.455***
	(0.013)			(0.013)
Z_V		-0.014***		-0.011***
		(0.001)		(0.001)
Z_U			0.061***	0.059***
			(0.002)	(0.002)
Fixed Effects	Year	Year	Year	Year
Observations	7,993,993	7,993,993	7,993,993	7,993,993
Clusters	1,801,671	1,801,671	1,801,671	1,801,671

NOTE. — The table displays the underlying reduced-form regressions of the IV estimations in Columns (2), (3), and (4) from Table 2. The instrumental variables refer to shift-share instruments of biennial national changes in occupations in occupations weighted by past occupational employment in the respective establishment. The lag difference is two years. Labor markets are combinations of 5-digit KldB occupations and commuting zones. Standard errors (in parentheses) are clustered at the establishment level. L = Employment. U = Job Seekers. V = Vacancies. Z = Shift-Share Instrument. * = p<0.10. ** = p<0.05. *** = p<0.01. Sources: Integrated Employment Biographies + Official Statistics of the German Federal Employment Agency + IAB Job Vacancy Survey, 1999-2019.

Table E2: Labor Demand Effects by Lag Difference

	(1) Δ Log L^{FT}	(2) Δ Log L^{FT}	(3) Δ Log L^{FT}
Δ Log W^{FT}	-0.617***	-0.730***	-0.772***
	(0.022)	(0.022)	(0.023)
Δ Log V/U	-0.023***	-0.051***	-0.058***
	(0.002)	(0.002)	(0.002)
Fixed Effects	Year	Year	Year
Instruments	$Z_{W^{FT}}$, Z_V, Z_U	$Z_{W^{FT}}$, Z_V, Z_U	$Z_{W^{FT}}$, Z_V, Z_U
Lag Difference	1 Year	2 Years	3 Years
Observations	9,988,682	7,993,993	6,277,010
Clusters	2,057,324	1,801,671	1,600,914
F: Δ Log W^{FT}	2,790	3,322	3,344
F: Δ Log V/U	24,539	30,380	29,733

NOTE. — The table displays IV regressions of differences in log employment (of regular full-time workers) per establishment on differences in the log of average daily wages and the log of labor market tightness. The instrumental variables refer to shift-share instruments of national changes in occupations weighted by past occupational employment in the respective establishment. The lag of the first-differences estimator (in years) differs across specifications. Labor markets are combinations of 5-digit KldB occupations and commuting zones. Standard errors (in parentheses) are clustered at the establishment level. F = F Statistics of Excluded Instruments. FT = Full-Time. KldB = German Classification of Occupations. L = Employment. U = Job Seekers. V = Vacancies. W = Average Daily Wages. Z = Shift-Share Instrument. * = p<0.10. ** = p<0.05. *** = p<0.01. Sources: Integrated Employment Biographies + Official Statistics of the German Federal Employment Agency + IAB Job Vacancy Survey, 1999-2019.

Table E3: Labor Demand Effects by Specification

	(1) Δ Log L^{FT}	(2) Δ Log L^{FT}	(3) Δ Log L^{FT}	(4) Δ Log L^{FT}
Δ Log W^{FT}	-0.748***	-0.719***	-0.717***	-0.759***
	(0.046)	(0.022)	(0.022)	(0.022)
Δ Log V/U	-0.088***	-0.050***	-0.052***	-0.046***
	(0.003)	(0.002)	(0.002)	(0.002)
Fixed Effects	Year $\times$ Industry	Year $\times$ CZ	Year	Year
Instruments	$Z_{W^{FT}}$, Z_V, Z_U	$Z_{W^{FT}}$, Z_V, Z_U	$Z_{W^{FT}}$, Z_V, Z_U	$Z_{W^{FT}}$, Z_V, Z_U
Wage Measure	Mean	Mean	P50	Mean
Vacancy Measure	Overall	Overall	Overall	Registered
Observations	7,993,993	7,993,993	7,993,993	7,993,993
Clusters	1,801,671	1,801,671	1,801,671	1,801,671
F: Δ Log W^{FT}	804	3,431	3,209	3,321
F: Δ Log V/U	12,919	30,048	30,380	27,826

NOTE. — The table displays IV regressions of differences in log employment (of regular full-time workers) per establishment on differences in the log of average daily wages and the log of labor market tightness. The instrumental variables refer to shift-share instruments of biennial national changes in occupations weighted by past occupational employment in the respective establishment. Standard errors (in parentheses) are clustered at the establishment level. Industry refers to 2-digit Classification of Economic Activities in the European Community (NACE). of CZ = Commuting Zone. F = F Statistics of Excluded Instruments. FT = Full-Time. L = Employment. P50 = Median. U = Job Seekers. V = Vacancies. W = Average Daily Wages. Z = Shift-Share Instrument. * = $p<0.10$. ** = $p<0.05$. *** = $p<0.01$. Sources: Integrated Employment Biographies + Official Statistics of the German Federal Employment Agency + IAB Job Vacancy Survey, 1999-2019.

Table E4: Labor Demand Effects by Establishment Size

	(1) Δ Log L^{FT}	(2) Δ Log L^{FT}	(3) Δ Log L^{FT}	(4) Δ Log L^{FT}
Δ Log W^{FT}	-0.830***	-0.518***	-0.906***	-0.760***
	(0.115)	(0.027)	(0.040)	(0.196)
Δ Log V/U	-0.054***	-0.045***	-0.082***	-0.059***
	(0.011)	(0.002)	(0.003)	(0.011)
Fixed Effects	Year	Year	Year	Year
Instruments	$Z_{W^{FT}}, Z_V, Z_U$	$Z_{W^{FT}}, Z_V, Z_U$	$Z_{W^{FT}}, Z_V, Z_U$	$Z_{W^{FT}}, Z_V, Z_U$
Weighted Regression	Yes	No	No	No
Sample	All Establishments	Small Establishments	Medium-Sized Establishments	Large Establishments
Observations	7,993,993	4,976,471	2,735,624	281,898
Clusters	1,801,671	1,215,334	535,843	50,494
F: Δ Log W^{FT}	628	1,631	2,121	178
F: Δ Log V/U	1,814	18,406	11,645	1,304

NOTE. — The table displays IV regressions of differences in log employment (of regular full-time workers) per establishment on differences in the log of average daily wages and the log of labor market tightness. The instrumental variables refer to shift-share instruments of biennial national changes in occupations weighted by past occupational employment in the respective establishment. The lag difference is two years. Labor markets are combinations of 5-digit KldB occupations and commuting zones. Regression weights reflect the number of workers of an establishment. We calculate time-constant establishment size categories from the unit-specific median of employees across available years: small (1-9 workers), medium (10-99 workers), and large (at least 100 workers). Standard errors (in parentheses) are clustered at the establishment level. F = F Statistics of Excluded Instruments. FT = Full-Time. KldB = German Classification of Occupations. L = Employment. U = Job Seekers. V = Vacancies. W = Average Daily Wages. Z = Shift-Share Instrument. * = $p<0.10$. ** = $p<0.05$. *** = $p<0.01$. Sources: Integrated Employment Biographies + Official Statistics of the German Federal Employment Agency + IAB Job Vacancy Survey, 1999-2019.

Table E5: Labor Demand Effects by Territory and AKM Effects

	(1) Δ Log L^{FT}	(2) Δ Log L^{FT}	(3) Δ Log L^{FT}	(4) Δ Log L^{FT}
Δ Log W^{FT}	-0.657***	-0.842***	-0.641***	-0.351***
	(0.027)	(0.033)	(0.034)	(0.041)
Δ Log V/U	-0.049***	-0.058***	-0.028***	-0.070***
	(0.002)	(0.004)	(0.003)	(0.002)
Fixed Effects	Year	Year	Year	Year
Instruments	$Z_{W^{FT}}, Z_V, Z_U$	$Z_{W^{FT}}, Z_V, Z_U$	$Z_{W^{FT}}, Z_V, Z_U$	$Z_{W^{FT}}, Z_V, Z_U$
Sample	West Germany	East Germany	Low AKM Effects	High AKM Effects
Observations	6,566,797	1,427,196	3,817,245	4,176,748
Clusters	1,486,423	321,747	911,127	890,545
F: Δ Log W^{FT}	2,146	1,732	1,030	1,418
F: Δ Log V/U	26,326	4,687	12,906	17,812

NOTE. — The table displays IV regressions of differences in log employment (of regular full-time workers) per establishment on differences in the log of average daily wages and the log of labor market tightness. The instrumental variables refer to shift-share instruments of biennial national changes in occupations weighted by past occupational employment in the respective establishment. The lag difference is two years. Labor markets are combinations of 5-digit KldB occupations and commuting zones. We separate employers into low- and high-productivity firms depending on whether their respective AKM wage effect lies below or above the median. Standard errors (in parentheses) are clustered at the establishment level. F = F Statistics of Excluded Instruments. FT = Full-Time. KldB = German Classification of Occupations. L = Employment. U = Job Seekers. V = Vacancies. W = Average Daily Wages. Z = Shift-Share Instrument. * = p<0.10. ** = p<0.05. *** = p<0.01. Sources: Integrated Employment Biographies + Official Statistics of the German Federal Employment Agency + IAB Job Vacancy Survey, 1999-2019.

F. Discussion: Further Evidence

In this section, we discuss the implications of our findings in three further analyses. In the first analysis, we examine the wage and employment effects of the 2015 introduction of a statutory minimum wage in Germany in the light of our regression results. In the second analysis, we calculate the employment effect from the doubling in labor market tightness between 2012 and 2019. In the third analysis, we explore whether firms made concessions in terms of lower wages and skills to reduce search frictions that originate from higher labor market tightness.

Minimum Wage Introduction in 2015. For the first time, Germany introduced a national minimum wage on January 1, 2015. The minimum wage was set at 8.50 Euro per hour and strongly bit into the wage distribution, raising wages of about 17.8 percent of the workforce. In fact, the minimum wage was introduced mid-way during our period of analysis. Hence, variation from the minimum wage introduction is part of the variation leading to our elasticity estimates. In line with our Bartik-style identification strategy, the minimum wage caused an effective wage shift that strongly differed by occupation (Friedrich, 2020).

We use our estimated labor demand elasticities to predict employment effects from minimum wage induced wage changes in simulation exercises. Such a simulation of employment effects is particularly helpful for an assessment of policy effects before a minimum wage is introduced or raised. Prior to the minimum wage introduction in Germany, the simulation by Knabe/Schöb/Thum (2014) has had the most controversial impact in the scientific and public debate, especially since their results predicted substantial disemployment effects ranging between 425,000 and 910,000 jobs depending on the postulated market structure.[32] In their influential study, they provide a careful description of the wage distribution before the wage floor came into effect. They take the relative wage gaps for bins of workers which were paid below the minimum wage. To calculate employment effects for these group of workers, the authors interact the wage gaps with a uniform own-wage elasticity of labor demand of -0.75, which is retrieved from early reviews on elasticity estimates for Germany (Sinn et al., 2006; Ragnitz/Thum, 2007). In fact, the debate on the ex-ante simulation by Knabe/Schöb/Thum (2014) still continues since ex-post evaluations do not detect disemployment effects of the predicted size (Ahlfeldt/Roth/Seidel, 2018; Caliendo et al., 2018; Bossler/Gerner, 2020; Dustmann et al., 2022).

[32] In an alternative simulation, Müller/Steiner (2013) arrive at a negative employment effect of 490,000 workers in their preferred scenario. Arni et al. (2014) predict a loss of 570,000 jobs. Moreover, Henzel/Engelhardt (2014) gauge the disemployment effect to range between 470,000 and 1.4 million workers, depending on the underlying own-wage elasticity of labor demand (-0.1 vs. -0.8).

While the assumed labor demand elasticity (-0.75) in the study of Knabe/Schöb/Thum (2014) is strikingly similar to our baseline own-wage elasticity at the firm level (-0.71), we can expand their simulation approach in various aspects: First, we can account for observed wage effects after the minimum wage introduction. In doing so, we account for non-compliance and spillovers which, of course, were not available when ex-ante simulations were debated. Second, we can apply separate own-wage elasticities of labor demand for full-time and part-time employment, which turns out to be an important distinction given the heterogeneities in Table 4. Third, as the national statutory minimum wage applies to all employers in Germany, it will affect aggregate labor demand. As suggested by our results, such aggregated changes will alter labor market tightness via search externalities. Hence, building on our aggregate own-wage elasticity of labor demand, we can incorporate the feedback mechanism that limits employment effects of the minimum wage.

To simulate the aggregated employment effect, we need to estimate the causal wage effect of the minimum wage introduction, which we will then multiply by the own-wage elasticity of labor demand. A naive difference-in-difference estimation would likely overestimate the wage effect as low-wage workers may feature more positive earnings growth than high-wage workers. Hence, we estimate the wage effect from the following worker-level difference-in-difference-in-difference (DiDiD) specification:

$$\Delta^{t+2} ln\, W_{jt} = \beta_0 + \beta_1 \cdot \text{bite}_{jt} + \beta_2 \cdot \text{cohort}_{jt} + \beta_{DiDiD} \cdot \text{bite}_{jt} \cdot \text{cohort}_{jt} + \varepsilon_{jt} \qquad \text{(F.1)}$$

The dependent variable is the change in log hourly wages over the upcoming two years of individual j in cohort t, which is either the year 2012 or 2014. The bite variable measures the percentage difference between the wage of affected workers (in either 2012 or 2014) and the 2015 minimum wage level. The bite is zero for wages of unaffected workers above the minimum wage level. The coefficient β_1 captures general wage growth of affected workers, irrespective of the minimum wage introduction. The cohort dummy takes the value 1 for workers in 2014, when the minimum wage was upcoming, and 0 for workers in 2012. The coefficient β_2 captures wage growth of the 2014 cohort relative to the 2012 cohort independent of the minimum wage bite. We are interested in β_{DiDiD} which is the wage growth of workers affected by the minimum wage (i) relative to the wage growth of unaffected workers and (ii) relative to wage growth from before the minimum wage introduction. Hence, β_{DiDiD} yields the causal wage effect of the minimum wage on the treated workers.

We estimate Equation (F.1) by OLS on the universe of administrative employment records in Germany (see Section 4).[33] The estimated DiDiD wage effect is 0.396 log points (standard

[33] The only difference in terms of data to our analysis in Section 6 is a restriction to workers with a single job. This restriction is required to calculate worker-level wage growth.

error: 0.002) for affected full-time workers and 0.341 log points (standard error: 0.002) for affected part-time workers. These effects closely match the wage effects of Bossler/Schank (2022), who identify wage effects of the minimum wage introduction from regional variation with a size of 0.4 log points. While the estimated wage effects are treatment effects on the treated (i.e., effects for workers who received an hourly wages below the threshold prior to the minimum wage introduction), we are interested in the aggregate wage effect. We calculate the aggregate wage effect of the minimum wage by multiplying the DiDiD-based wage effects with the average bite of the respective group of workers (1.7 percent for full-time and 9.6 percent for part-time workers): $\hat{\beta}_{DiDiD} \cdot \overline{\text{bite}}_{t=2014}$. We arrive at an aggregate wage growth of 0.7 and 3.3 percent for full-time and part-time workers, respectively.

Given the aggregate minimum wage effects on wages along with our estimated own-wage elasticities of labor demand, we simulate aggregated employment effects of the minimum wage introduction from the following equation:

$$\underbrace{\Delta L}_{\substack{\text{aggregate}\\ \text{minimum wage effect}\\ \text{on employment}}} = \underbrace{\tilde{\eta}_W^L}_{\substack{\text{aggregate}\\ \text{own-wage elasticity}\\ \text{of labor demand}}} \cdot \underbrace{\left(\beta_{DiDiD} \cdot \overline{\text{bite}}_{t=2014} \right)}_{\substack{\text{aggregate}\\ \text{minimum wage effect}\\ \text{on wages}}} \cdot \underbrace{L_{t=2014}}_{\text{workforce}} \qquad \text{(F.2)}$$

Table F1 delivers the simulation results. Whereas Columns (1) and (2) display simulated minimum wage effects based on own-wage elasticities of labor demand at the firm level (i.e., without applying the feedback cycle), Columns (3) and (4) use the estimated aggregate own-wage elasticities of labor demand to account for search externalities. In both cases, we estimate separate effects for full- and part-time workers. As the own-wage elasticities of labor demand and the aggregate wage effects are estimated statistics, we draw the parameters from the underlying effect distributions. Based on 10,000 draws, we simulate standard errors of the predicted employment effects.

The baseline simulation absent search externalities yields a negative effect on full-time employment of -96,432 workers, which is broadly in line with Knabe/Schöb/Thum (2014) who report disemployment effects of 160,000 (competitive model) and 40,000 (monopsony model) for full-time workers. In Table F2, we compare heir findings with the results from our simulation in more detail. However, we find a much smaller effect on part-time employment that is only -29,867 and statistically insignificant, which stems from the small own-wage elasticity of labor demand of this group. In total, our simulation yields a disemployment effect of 126,299 workers. Crucially, however, this effect disregards that an aggregate decline in labor demand reduces labor market tightness.

When incorporating the feedback mechanism, the aggregate decline reduces to 66,757 full-time and 21,087 part-time workers, which adds up to an overall disemployment effect of

Table F1: Employment and Wage Effects of the German Statutory Minimum Wage

	(1) L^{FT}	(2) L^{PT}	(3) L^{FT}	(4) L^{PT}
Individual-Firm WELD	-0.713***	-0.067		
	(0.021)	(0.060)		
Aggregate WELD			-0.494***	-0.046
			(0.022)	(0.042)
Minimum Wage Effects on Wages	0.0069***	0.0328***	0.0069***	0.0328***
	(0.00004)	(0.0003)	(0.00004)	(0.0003)
Minimum Wage Effects on Employment	-96,432***	-29,867	-66,757***	-21,087
	(2,916)	(27,054)	(3,053)	(19,008)
Minimum Wage Effects on Total Employment	-126,299***		-87,844***	
	(27,216)		(19,218)	

NOTE. — The table presents simulation results for employment effects of the 2015 introduction of the nationwide minimum wage in Germany. Following Equation (F.2), we interact the individual-firm or aggregate own-wage elasticity of labor demand (first and second row) from Table 4 and Equation (11) with aggregate minimum wage effects on wages from Equation (F.1) (third row). Columns (1) and (2) use individual-firm own-wage elasticities of labor demand whereas Columns (3) and (4) incorporate the aggregate own-wage elasticities of labor demand, for full- and part-time workers respectively. We retrieve standard errors of the simulated employment effects by drawing 10,000 realizations from the underlying effects distributions of the estimated own-wage elasticities of labor demand and the estimated minimum wage effect on wages. FT = Full-Time. L = Employment. PT = Part-Time. WELD = Own-Wage Elasticity of Labor Demand. * = p<0.10. ** = p<0.05. *** = p<0.01. Source: Integrated Employment Biographies, 2012-2016.

87,844 workers. This much smaller disemployment effect mirrors evidence from ex-post evaluations of the minimum wage (Bruttel, 2019; Caliendo/Schröder/Wittbrodt, 2019). While our effects are somewhat smaller than the estimates in Caliendo et al. (2018), they slightly exceed the estimated aggregated employment effect in Bossler/Gerner (2020). Dustmann et al. (2022) argue that most of the firm-level employment reduction is offset by job mobility to competing employers. Thus, their finding closely matches our reasoning about search externalities, namely that a labor demand reduction facilitates employment expansions at other firms.

The literature offers several explanations to rationalize the absence of large negative employment effects of minimum wages with theory (Schmitt, 2015). Analyses in terms of headcount employment (extensive margin) may underestimate the overall employment effect when minimum wages spark off reductions in working hours (intensive margin). Product price increases can buffer higher personnel cost (Aaronson/French/MacDonald, 2008). An increasing labor productivity may enable firms to pay the minimum wage (Riley/Bondibene, 2017). Moreover, a fraction of firms may not comply with the minimum wage legislation (Ashenfelter/Smith, 1979). In monopsonistic labor markets, modest wage floors can even stimulate employment (Stigler, 1946). Our analysis provides an additional explanation for this puzzle: aggregate reductions in employment lower labor market tightness through search externalities which in turn facilitates recruitment for firms that

Table F2: Comparison of Minimum Wage Simulations

	Full-Time Employment	Part-Time Employment	Overall Employment
WELD = -0.75 Ex-Ante Wage Gap (SOEP)	-160,203	-750,514	-910,717
WELD = -0.75 Ex-Post Wage Effect (IEB)	-102,596	-340,147	-442,743
Estimated Invididual-Firm WELDs Ex-Post Wage Effect (IEB)	-96,432	-29,867	-126,299
Estimated Aggregate WELDs Ex-Post Wage Effect (IEB)	-66,757	-21,087	-87,843

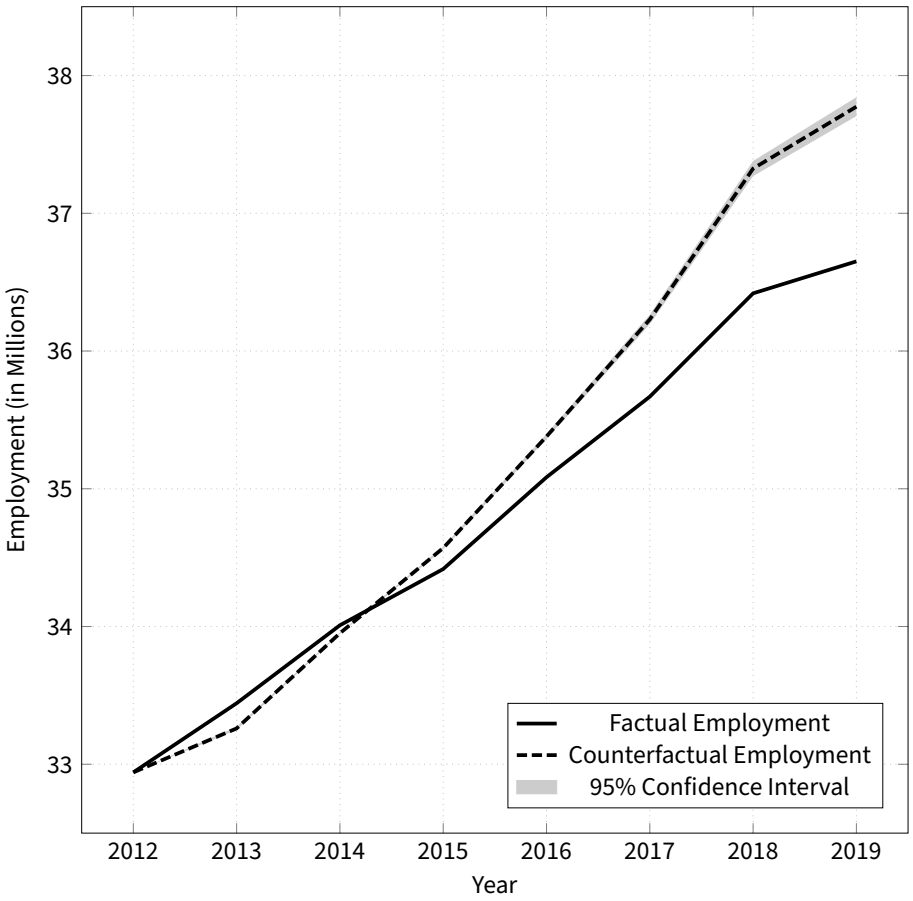
NOTE. — The table displays the employment effects from different simulations of the 2015 national minimum wage introduction in Germany. The first row presents the results from the simulation in Knabe, Schöb, and Thum (2014, Table 9a). The study is based on a single own-wage elasticity of -0.75 and assumes that wage increases mirror ex-ante wage gaps prior to the minimum wage introduction (based on SOEP data). In the second row, we apply the approach from Knabe/Schöb/Thum (2014) to observed minimum wage effects on wages (based on IEB data). In the third row, we instead make use of our estimated individual-firm own-wage elasticities of labor demand for full-time (-0.71) and part-time workers (-0.08). The last row mirrors our preferred simulation from Table F1 in which we replace the individual-firm elasticities by our estimates for the aggregate own-wage elasticities for full- (-0.50) and part-time workers (-0.06). IEB = Integrated Employment Biographies. SOEP = German Socio-Economic Panel. WELD = Own-Wage Elasticity of Labor Demand. Sources: Knabe/Schöb/Thum (2014) + Integrated Employment Biographies, 2012-2016.

want to hire. We demonstrate that this channel reduces the disemployment effect of minimum wages by about thirty percent.

Employment Trends and Labor Market Tightness. In a second application, we quantify the overall impact of the doubling of labor market tightness between 2012 and 2019 on aggregate employment. Such a quantification is highly relevant as there was an emerging public opinion that the increased tightness was posing a severe problem to the German labor market. To the best of our knowledge, there is no causal evidence on the employment effects of the increased labor market tightness.

In a counterfactual analysis, we compare the observed aggregated employment growth with a hypothetical scenario in which labor market tightness did not change. For the counterfactual, we use our estimated tightness effects on labor demand and simulate the development of aggregate employment conditional on an unchanged labor market tightness during the period of analysis (i.e., we fix the ratio of vacancies to job seekers at the level of 2012). In this hypothetical scenario, for each year, we multiply the observed relative change in tightness by our estimated elasticities of labor demand with respect to tightness (separately for full- and part-time workers), and subtract the respective sum from the factual stock of employment.

Figure F1: Labor Market Tightness and Employment Trends



NOTE. — The figure contrasts the factual trend of total employment in Germany with a hypothetical trend that simulates employment if labor market tightness was fixed at its 2012 level. We simulate full- and part-time employment separately and add them up to predict total employment. We draw 10,000 realizations from the distribution of the estimated labor demand elasticity with respect to labor market tightness to calculate standard errors for the simulated employment effect. The grey shade indicates 95 percent confidence intervals. Employment refers to the number of jobs (as opposed to individual workers) which are subject to social security contributions. This number refers to the total number of jobs minus civil servants, family workers, apprentices, and people in partial retirement schemes. Sources: Integrated Employment Biographies + Official Statistics of the German Federal Employment Agency + IAB Job Vacancy Survey, 2012-2019.

Figure F1 displays the factual and counterfactual development of total employment, which is the sum of full- and part-time jobs.[34] While observed total employment rose from 32.9 million employees in 2012 to 36.7 million jobs in 2019, it could have risen to 37.8 million jobs if labor market tightness had not changed. Thus, in the absence of increasing labor market tightness, employment could have grown by an additional 1.1 million jobs until 2019. Figure F1 delivers a separate analysis of full-time and part-time employment, showing that the growth of both kinds of employment was slowed by the increase in labor market tightness between 2012 and 2019. In sum, our results imply that the increase in labor

[34] Given the IEB data, employment refers to the number of jobs (as opposed to individual workers) that are subject to social security contributions. This number refers to the total number of jobs minus civil servants, family workers, apprentices, and people in partial retirement schemes.

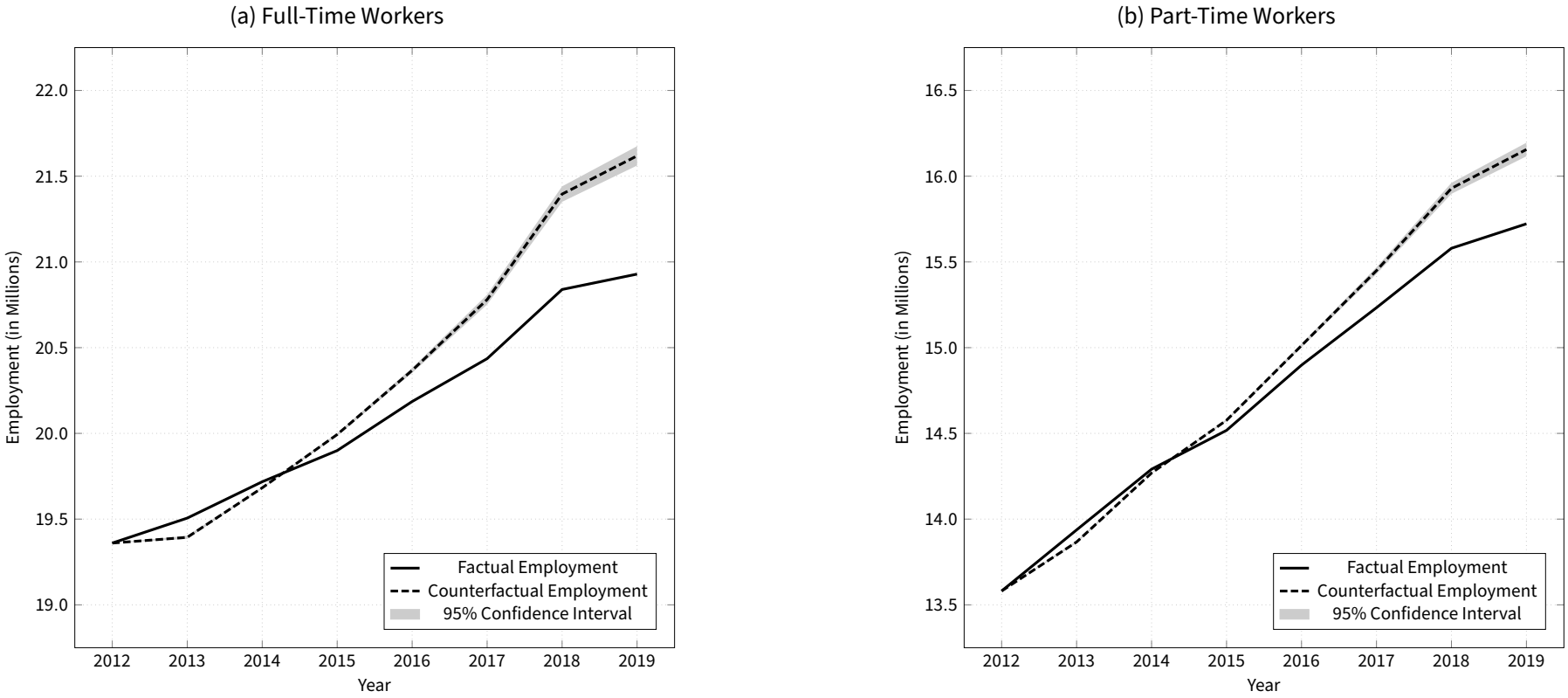
market tightness considerably dampened the positive trend in labor demand, underlining the importance of search frictions in tight labor markets.

As labor market tightness is not solely a market outcome, our finding of labor shortage raises the question of potential policy interventions. First, at given labor market tightness, improvements in the matching efficiency would result in more hires (e.g., better public and private employment services). Second, given our negative tightness effect, any measures that lift the number of job seekers (relative to vacancies) would stimulate employment. In the short and medium run, appropriate policies could i) encourage inactive individuals to search for jobs, ii) stimulate female labor supply, iii) allow for immigration of workers, or iv) raise the effective retirement age. In the long run, higher birth rates would have a positive effect on the working population. Apart from policy measures, firms can partly circumvent labor shortage by i) substituting labor by capital (e.g., machines), ii) increasing productivity or working hours of incumbent workers, iii) reducing outflow of workers (e.g., by raising wages or improving non-wage job amenities), or iv) making wage or skill concessions upon hiring.

Wage and Skill Concessions. In practice, firms facing higher labor market tightness do not necessarily have to settle for lower employment levels. Instead, these firms could still manage to expand or retain the workforce by making concessions, e.g., by raising wages or by recruiting workers with lower skills. The theoretical literature discusses extensively the positive effect of higher labor market tightness on wages, which is commonly referred to as the "wage curve" (Blanchflower/Oswald, 1995; Card, 1995). First, in search-and-matching models, employers pay higher wages as the value of a filled position increases with labor market tightness (Mortensen/Pissarides, 1999). Second, in bargaining models, high labor market tightness enables workers to extract a larger fraction of the overall surplus due to more outside options (Nash, 1950; Nickell/Andrews, 1983). Third, according to the efficiency wage hypothesis, firms may raise wages above market-clearing levels to retain incumbent workers and attract hires (Stiglitz, 1974; Yellen, 1984).

We empirically address the conjecture that firms need to make concessions to maintain their employment (growth) in tight labor markets. Building on the same instrumental variable approach as in our analysis of labor demand, we regress the average wage level of firms and the fraction of unskilled workers in a firm on our measure of firm-specific labor market tightness. Table F3 shows the respective results for full-time and part-time employment. In Columns (1) and (2), we observe a positive effect of higher labor market tightness on the wage level in a firm: on average, the doubling in tightness (i.e., a 100 percent increase in the vacancy-to-job-seekers ratio) raises mean wages of full-time (part-time) workers in a firm by 0.9 (0.5) percent. Although the wage response is significantly positive for both groups of workers, the magnitude of these effects is fairly small: wages of full-time workers only increased by about a fifth of the negative

Figure F2: Labor Market Tightness and Employment Trends by Labor Outcome



NOTE. — The figure contrasts factual trends of employment in Germany with hypothetical trends that simulate employment if labor market tightness was fixed at its 2012 level. We simulate trends separately for full-time and part-time employment. Part-time employment encompasses regular part-time and marginal part-time workers. We draw 10,000 realizations from the effect distribution of the respective labor demand elasticity with respect to tightness to calculate standard errors for the simulated employment effects. The grey shade indicates 95% confidence intervals. Employment refers to the number of jobs (as opposed to individual workers) which are subject to social security contributions. This number refers to the total number of jobs minus civil servants, family workers, apprentices, and people in partial retirement schemes. Sources: Integrated Employment Biographies + Official Statistics of the German Federal Employment Agency + IAB Job Vacancy Survey, 2012-2019.

employment response and only by a tenth when looking at part-timers. This result mirrors a relatively flat but positively sloped wage curve, which is in line with previous findings from Germany (Baltagi/Blien/Wolf, 2009; Bellmann/Blien, 2001). Rather than tightness, these studies relate wages only to the unemployment rate, which is a less comprehensive measure for workers' outside options. Our flat wage curve indicates an only limited role of outside options in the bargaining process, which can be rationalized on two grounds. First, firms may rely on wage posting instead of wage bargaining. Second, both parties may resume rather than terminate unsuccessful negotiations (Hall/Milgrom, 2008) in the consensus-based system of industrial relations in Germany (Dustmann et al., 2014).

We cross-validate our finding of relatively small wage increases by examining additional information from the IAB Job Vacancy Survey on whether firms were willing to accept wage concessions upon hiring. Between 2012 and 2019, employers report wage concession in 15.7 percent of all hires. A naive regression of a binary variable for wage concessions on log labor market tightness suggests that the doubling of tightness raised the probability of a wage concession upon hiring by only 3.4 percentage points.

Columns (3) and (4) display the regressions for the fraction of unskilled workers. We define unskilled workers as employees who neither have completed vocational training nor hold a university degree. In 2012, the average share of unskilled workers in full-time and part-time employment across firms was 6.4 and 9.5 percent, respectively. The results imply that wage increases lowered the share of unskilled workers in full-time employment, reflecting positive returns to skills. For the effect of labor market tightness, we arrive at a significantly positive semi-elasticity of 0.003 for full-time workers and 0.001 for part-time workers. Hence, firms were willing to make some skill concessions. The massive increase in labor market tightness (by 100 percent) resulted in an increase in the share of unskilled workers in full-time (part-time) employment by 0.3 (0.1) percentage points.[35] According to the IAB Job Vacancy Survey, firms hired workers with lower skills than originally demanded in 9.9 percent of new matches between 2012 and 2019. In line with little skill concessions, pooled OLS regressions imply that the doubling of labor market tightness raised the probability of hiring a worker with lower skills by only 1.8 percentage points.

Our estimates suggest that the extent of firms' wage and skills concession was fairly small in practice, providing an explanation for the markedly negative effect of labor market tightness on employment. Crucially, however, the results do not shed light on whether profit-maximizing firms were not willing or, alternatively, were not able to make substantial concessions. On the one hand, firms with monopoly or monopsony power dispose of rents but have an incentive to stay small. On the other hand, firms without rents would incur losses when raising wages above the worker's marginal value product.

[35] Similarly, Kölling (2020) finds that German establishments which report labor shortages between 2004 and 2014 employ ceteris paribus more low- and medium-skilled but less high-skilled workers.

Table F3: Wage and Skill Concessions

	(1) Δ Log W^{FT}	(2) Δ Log W^{PT}	(3) Share of Unskilled in FT Workers	(4) Share of Unskilled in PT Workers
Δ Log W^{FT}			-0.031***	
			(0.006)	
Δ Log W^{PT}				-0.062***
				(0.023)
Δ Log V/U	0.009***	0.005***	0.003***	0.001**
	(0.001)	(0.002)	(0.001)	(0.001)
Fixed Effects	Year	Year	Year	Year
Instruments	Z_V, Z_U	Z_V, Z_U	$Z_{W^{FT}}$, Z_V, Z_U	$Z_{W^{PT}}$, Z_V, Z_U
Observations	7,993,993	11,448,610	7,589,549	10,107,198
Clusters	1,801,671	2,693,588	1,693,188	2,407,445
F: Δ Log W^{FT}			2,825	
F: Δ Log W^{PT}				61
F: Δ Log V/U	45,522	46,424	28,327	27,168

NOTE. — The table displays IV regressions of differences in measures of wage and skill concessions per establishment on differences in the log of average hourly wages and the log of labor market tightness. The instrumental variables refer to shift-share instruments of biennial national changes in occupations weighted by past occupational employment in the respective establishment. The lag difference is two years. Labor markets are combinations of 5-digit KldB occupations and commuting zones. Full-time employment includes regular full-time workers whereas part-time employment encompasses regular part-time and marginal part-time workers. Unskilled workers have neither completed vocational education nor have acquired a university degree. Standard errors (in parentheses) are clustered at the establishment level. F = F Statistics of Excluded Instruments. FT = Full-Time. KldB = German Classification of Occupations. L = Employment. PT = Part-Time. U = Job Seekers. V = Vacancies. W = Average Hourly Wages. Z = Shift-Share Instrument. * = p<0.10. ** = p<0.05. *** = p<0.01. Sources: Integrated Employment Biographies + Official Statistics of the German Federal Employment Agency + IAB Job Vacancy Survey, 1999-2019.

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