The Effect of Labor Market Tightness on Recruiting Levers: Evidence from US Employers during Covid-19*

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Abstract

How do employers' recruitment strategies adapt to labor shortages? Do they relax their skill requirements to draw from a potentially larger pool of candidates, or do they raise wages offered to price out competitors? This paper uses the unexpected and heterogeneous impact of Covid-19 across industries to estimate the elasticity of employers' posted wages and skill demand to labor market tightness. Taking advantage of the granularity of online job postings data, we propose a precise measure of local labor market tightness whose variation relies on an industry-based shift-share IV approach. We find that, during the pandemic years, tightness caused a statistically significant decline in the likelihood of employers listing education and experience requirements on job ads, but conditional on posting, they increased the levels listed. There is evidence of complementarity in recruiting levers for low-wage, low-skill jobs, particularly exposed to tightness, where years of education and experience required by employers are constrained by a lower bound. For these positions, tightness also led to a statistically significant increase in advertised salaries, a response that contributed to explain the reduction in wage inequality observed in post-pandemic US labor markets.

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1 Introduction

Labor market tightness ebbs and flows with the business cycle boom and bust. This cyclicality makes it hard to isolate and study the effect of a change in labor market tightness on employers' behavior due to concurrent economic changes biasing our estimate. However, the nature of the Covid-19 pandemic in 2020 led to variation in labor market tightness across industries. For example, sectors like *Health Care and Social Assistance* faced a shortage of workers at the onset of the pandemic, whereas others like *Arts, Entertainment, and Recreation* had a surplus of workers that remained inactive. *Accommodation and Food Services* saw a sudden decline in demand with the introduction of stay-at-home orders, followed by a rapid surge in demand as well as labor shortages due to workers resigning and reallocating away from those jobs. Meanwhile, *Professional Services*, *Management* or jobs in tech and finance experienced much milder swings with the widespread expansion of remote work. This paper leverages pre-pandemic variation in industrial composition across local labor markets and Covid-19 heterogeneous impact across industries to estimate the effect of (Covid-induced) labor market tightness on employers' skill demand and wages.

This is an important question both because there are compelling reasons to believe that tight labor markets will persist well beyond pandemic years, and because there is theoretical ambiguity about employers' response to it. The restriction of global mobility during the height of the pandemic, and for a while thereafter, has led to significant migrant shortages in US markets. Similarly, the onset of the pandemic caused labor force to plummet by as much as 3 percentage point as well as catalyzed the anticipated retirement of the baby boomers. Well-documented declines in fertility rates and in native labor force internal mobility are further exacerbating employers' difficulty of filling their openings. Together these trends point towards persistently higher levels of labor markets tightness, which we indeed observe. Theoretically, faced with tight labor markets, employers can adopt one of two recruitment strategies. One strategy is to adjust and/or lower their hiring standards. For example, an opening listing that would normally require someone with five years of experience, might now accept applicants with three years of experience. Another strategy is to improve job compensation and benefits to attract the limited number of qualified workers in the market. This could take the form of higher wages, health insurance, and/or providing more flexible work options such as hybrid or remote work.[1]

This paper empirically tests both hypotheses by estimating the effect of Covid-induced labor market tightness variation on employers' posted skills and wages, and asks whether the impact was different for a group of low-wage and low-skill jobs particularly affected by tightness. To observe firms' hiring behavior, we use Lightcast online job posting data, a database collected from roughly 50,000 websites covering the near universe of online job postings for all metropolitan statistical areas (MSAs) in the US, which we have available from 2018 through 2022. These job ads in turn

[1] While we appreciate that non-wage amenities are an important component of compensation packages and some workers highly value them, in this paper we focus on advertised wages only.

have detailed information on listed education, experience, skills and wages, which will be our outcomes of interest in the analysis. We construct extensive and intensive margin measures for education, experience and wages in job postings at the occupation-commuting zone-year level. The extensive margin measure captures the share of postings that list, for instance, an education requirement, whereas the intensive margin measures captures the level required, for instance the years of education, for those postings including education as requirement. To build our measure of tightness we then complement online job posting data Local Area Unemployment Statistics (LAUS) data. We improve on demand-driven measures of tightness by devising a more precise shift-share instrument obtained by interacting nation-wide growth in online job postings for each 3-digit NAICS industry with pre-pandemic local industry shares from the American Community Survey (ACS) 5-year file for 2015-2019, which allows us to construct a more exogenous measure of local labor market tightness. We benchmark our measure with that proposed by Autor, Dube, and McGrew (2023) and find high levels of correlation between the two.

Prior to beginning our analysis, we undertake two steps. First, we validate the evidence of a national downskilling trend over the course of the pandemic provided by the literature, but we also highlight that this decline mostly arose at the onset of pandemic. In contrast, local labor market tightness was the highest in 2021 and 2022, relative to 2019. Second, we identify low-wage, low-skill service and blue collar jobs by combining different attempts in the literature to define the lowest rungs of the job ladder as we believe tightness might have a different effect on those positions.[2] We assign to this group the low-skill service and blue collar occupations (SOC 35 to 39 and 412 for the former; SOC 33 and 45 to 53 for the latter) that fall within the bottom tercile of the US wage distribution in the pre-pandemic years derived with ACS data.[3] Crucially, job postings for these positions in 2019 featured much fewer years of education and experience, constraining employers who wished to lower the skill level required, thus establishing a lower bound.

We identify three main findings. First, focusing on the local dimension of tightness, and including occupation fixed effects to control for composition of job ads, our 2SLS estimates show that higher local labor market tightness had a negative and statistically significant effect on the share of job ads listing an education or experience requirement. In other words, employers facing hiring difficulties primarily resorted to removing skill requirements from their job postings. Second, in terms of level of skills, we find that tightness increased average years of education and experience, even though these estimates are not statistically significant, except for the education margin of low-wage, low-skill jobs. Assuming that postings without a listed education or experience don't require any, our interpretation of this result is that tighter labor markets lead employers to completely remove their requirements for some jobs, while raising requirements for a subset of others where they need

[2] Recent works has showed that some of these occupations show a slightly larger downskilling and that workers in these jobs, historically vulnerable, saw more tightness-induced competition after the pandemic, which spurred quits and reallocation.

[3] We follow Forsythe, Kahn, Lange, and Wiczer (2022) in choosing the SOC codes to identify these occupations.

management or supervision staff to oversee less trained or under-skilled workers. Third, as an alternative or complementary mechanism, our results also show that local labor market tightness caused employers to increase the salaries advertised in their postings, with the effect being larger and statistically significant for the low-wage, low-skill group of jobs. Overall, our findings show that employers rely on multiple levers to attract new candidates when filling vacancies becomes challenging, including offering higher wages. Such evidence contributes to explain the compression in US wage distribution observed after the pandemic.

This paper relates to three strands of the literature. First, our work contributes to a large literature on the effect of the Covid-19 pandemic on labor markets. Thus far, the literature has explored many outcomes such as changing labor force composition (Albanesi and Kim, 2021), wage compression (Larrimore, Mortenson, and Splinter, 2023), native mobility (Peri and Zaiour, 2023) and reallocation (Barrero, Bloom, Davis, and Meyer, 2021). Most closely related to this project is work by Gu and Zhong (2023) and Forsythe et al. (2022) who also use Lightcast online job openings data to think about the effect of the pandemic on posted skills. Using spatial variation in duration of stay-at-home-orders, Gu and Zhong (2023) find suggestive evidence that longer stay-at-home orders shifted demand from "people-oriented" to "operation-oriented" management. Focusing on low-skill occupations, Forsythe et al. (2022) document the evolution of skills requirements at the national level across different waves of Covid-19. They observe that during the pandemic employers were more likely to list education and experience requirements, but conditional on listing, they required fewer years of education and experience.

Our paper differs from these two cited papers in three ways. First, we isolate the role of tightness to explain changes in skills, rather than using Covid-related policies or time indicators that capture Covid waves as explanatory variables. Second, our shift-share Bartik instrument empirical approach allows us to recover a casual estimate by using variation in industrial composition across commuting zones and Covid-19 differential impact on labor market tightness across industries. This contrasts with state variation in labor market tightness used by Autor et al. (2023) and the focus on the evolution of skills for the US market as a whole, as discussed in Forsythe et al. (2022). Third, this paper connects research documenting Covid-19 effect on wages (e.g. Autor et al. (2023)) and skill demand (e.g. Forsythe et al. (2022)) by bringing these two outcomes into the same framework as margins employers leverage and evaluating their complementarity.

Second, this paper is closely related to the budding literature on skill demand cyclicality. Studying the effect of slack labor markets following the Great Recession, Hershbein and Kahn (2018) and Modestino, Shoag, and Ballance (2020) find that employers persistently increase their skill requirements, i.e., upskill. On the flip side, faced with tight labor markets during the fracking boom, Modestino, Shoag, and Ballance (2016) find that employers reduce their education and experience requirements, i.e., downskill.[4] Our paper expands this literature by studying the effect of a labor

[4] Modestino et al. (2016) use change in local unemployment as their right hand side variable to capture tightening

demand –not labor supply– shock on employers hiring strategy. It is also the first study to evaluate the persistence in upskilling after a boom fades.

Third, our paper contributes to the labor market tightness literature, which studies the effect of labor market tightness on different outcomes like wage growth (Autor et al., 2023) and union activity (Pezold, Jäger, and Nüss, 2023). Our paper contributes to this literature by introducing and validating a more granular measure of labor market tightness. In the absence of Lightcast online job posting data, prior work has relied on using the Job Openings and Labor Turnover Survey (JOLTS), the primary government source on US job openings, to construct a measure of labor market tightness. However, JOLTS is publicly available only at aggregate levels, such as 2-digit NAICS industries or states (Peri and Zaiour, 2023). Using Lightcast online job postings, we proxy for the increase in vacancies using growth in number of online job postings for each industry and construct our labor market tightness as a ratio of online job postings to postings plus employment. This novel approach circumvents measurement error concerns surrounding temporary lay-offs and pandemic headline unemployment numbers.[5]

The remainder of this paper proceeds as follows. Section 2 introduces the data; Section 3 illustrates recent trends in job postings and their content as well as the characteristics of postings and workers in the low-wage, low-skill group; Section 4 presents our methodology, discussing the empirical framework, our measure of tightness and the shift-share IV approach; Section 5 presents our main results. Finally, Section 6 concludes.

2 Data and Samples

In this paper, we define local labor markets at the commuting zone (CZ) level and leverage variation across industries to study change in employers' hiring strategy. Given our setting, we rely on various data sources to answer our research question. For our outcome variables as well as the shift component of our shift-share IV approach, we use Lightcast online job posting data. For our right hand side variables and to build the shares of our shift-share IV, we rely on the US Census public use microdata as available from IPUMS (Ruggles, Genadek, Goeken, Grover, and Sobek, 2015) and on the US Bureau of Labor Statisitics Local Area Unemployment Statistics program (LAUS).

2.1 Lightcast Overview

The key data for observing employers' posted skills and wages comes from Lightcast online job posting data, which was previously circulated as Burning Glass Technologies. Lightcast (LC) is a data analytics company that scrapes roughly 50,000 websites, including job boards and company pages to build a dataset of the near-universe of online job postings from 2010 to 2022 for all MSAs in the United States.[6] Their algorithm identifies newly posted job ads, removes duplicates, and

labor markets.

[5]We expand this discussion on methods in Section 4.1 and Appendix A.

[6]Job postings are available at the establishment level, or the specific physical branch of a firm.

standardizes common information across postings. For each job posting, we have information on the education level, field of study and experience requirements as well as an average of nine skills extracted from the posting's open-text. We also have advertised wages for approximately 30% of all postings. This breadth and detail of LC's vacancy data makes it uniquely suited to help us unpack the black box of firm demand margin within and across occupations and industries.

Using Lightcast job openings data offers two advantages over using the Job Openings and Labor Turnover Survey (JOLTS), the primary government source on US job openings. First, Lightcast is available at a more granular industrial and geographical level, which is essential to our identification strategy since our "treatment" happens at the commuting zone level. JOLTS data is the product of surveying a nationally representative sample of 21,000 US business establishments across all non-agricultural industries in the public and private sectors for all 50 States and the District of Columbia. However, vacancies are typically only available at aggregate levels (disaggregated by states or by 17 mutually exclusive broad sectors of the economy, representing 2-digit NAICS industries) whereas LC provide vacancy-level information on city and county along with 6-digit NAICS industry. Second, Lightcast data has a richer set of job posting characteristics, which allows us to examine various margins of skill demand, which would be otherwise difficult to observe.

Unfortunately, LC data advantages come at the cost of two potential drawbacks. First, as a by-product of relying on online voluntary postings to capture job openings, LC over-represents white collar jobs (Hershbein and Kahn, 2018; Babina, Fedyk, He, and Hodson, 2020). This white-collar bias does not pose a serious threat to our results for two reasons. First, as of 2020, high-skilled jobs make up 60% of the entire US workforce so that, even in the worst (and, as we will discuss, unfounded) scenario of severe bias, our findings will help us understand hiring demands for a significant share of the labor force.[7] Second, and most importantly, a growing share of job ads has moved to online platforms over time, including those for low-skill jobs. If present, a bias detected for the Great Recession years is very likely to be much smaller nowadays. Indeed, recent validation exercises proved that the sample provided by Lightcast is well-aligned with JOLTS openings for the private sector (Chetty, Friedman, Stepner et al., 2020; Dalton, Kahn, and Mueller, 2020).[8] The second downside of using LC data is that vacancies represent stated but not necessarily realized firm demand. For a complete picture, one would also like to see characteristics and wages of workers eventually hired. However, this paper doesn't claim to recover general equilibrium effects. Instead, it concerns itself with understanding the dynamics of partial equilibrium as driven by firms' decisions.

Our main LC sample is the subset of postings with populated location (county), industry and occupation from 2018 to 2022. We drop postings from Alaska and Hawaii to focus on the contiguous

[7]Source: The Department for Professional Employees' 2021 Fact Sheet, which relies on data derived from US Census Bureau and Bureau of Labor Statistics.

[8]Other validation exercises conducted and made available by Lightcast provide additional reassuring evidence, both for the time series and in geographic terms (see Figure 13 in Appendix C).

United States. We only keep non-farm, non-military private sector postings and we further restrict our sample to in-person job postings only, in order to purge our estimates from skill changes due to Covid-induced shifts to remote jobs. Our final sample includes about 162 million postings in total.

2.2 Lightcast Skills

For each skill, we define an extensive and intensive margin measure, similarly to what described in Gu and Zhong (2023). First, to measure the *extensive* margin, we compute the fraction of job postings that require skill s in commuting zone c at time t. Second, to measure the *intensive* margin, we compute the average level of skill s in commuting zone c at time t focusing only on postings that require said skill. For example, when looking at the effect of labor market tightness on education requirement, our extensive margin variable will capture the share of postings in commuting zone c at time t that list an education requirement. Conversely, our intensive margin variable will capture the change in average years of education listed say from 16 years (Bachelor's) to 14 years (Associate's degree) for postings that list an education level.

Our main outcomes of interest are the intensive and extensive margin variables of education, experience and posted wages. Of secondary interest, we create a *software* variable, which captures the share of postings requiring knowledge of a specific software, encompassing without distinction basic knowledge of Microsoft Office to advanced programming skills like Python and SQL. We also create a measure of demand for cognitive skills as defined by Hershbein and Kahn (2018) where a posting is said to require cognitive skills if it includes any of the following keyword or phrase: *research, analy..., decision, solving, math, statistic, thinking*.[9]

2.3 Employment, Shares and Controls: ACS and LAUS

As we will illustrate in Section 4, our main explanatory variable, labor market tightness, is built as the ratio between vacancies and total available jobs (i.e., the sum of vacancies and filled jobs). While we capture vacancies using Lightcast online job postings, we need a measure of local employment over time. We rely on the US Bureau of Labor Statistics Local Area Unemployment Statistics program (LAUS) to obtain monthly employment figures at the county level.[10]

Given standard endogeneity concerns, we will instrument for local labor market tightness using a shift-share IV approach. We use changes in the number of online job postings to build the shift component of our instrument, but for information on local employment across industries to build the industry shares we rely on US Census public use American Community Survey (ACS) microdata as available from IPUMS (Ruggles, Genadek, Goeken, Grover, and Sobek, 2015). We

[9]Inspired by Deming and Kahn (2018) and Deming and Noray (2020), we also create other variables capturing demand for social skills (i.e., including the following keyword: *communicat..., team, collaborat..., negotiat..., present, persuasion*), for "fastest-growing software" skills (such as those including the following keyword: *python, r, apache, hadoop, revit*), and other categories. We plan to explore the impact on these dimensions soon.

[10]Since our geographical unit of analysis is commuting zones (CZs), we aggregate county and PUMA level data from ACS, LAUS and Lightcast to CZs using Autor and Dorn (2013)'s crosswalk.

employ the 2015-2019 5-year data, which build a 5% sample around 2017, to compute pre-Covid employment-based 3-digit NAICS industry shares in each commuting zone.

We also use this dataset to identify the occupations within the group of low-wage, low-skill workers and compute their demographics. In particular, our low-wage, low-skill group includes low-skill service (SOC 35 to 39 and 412) and blue collar (SOC 33 and 45 to 53) occupations in the bottom tercile of the US pre-Covid wage distribution (2015-2019 ACS, after converting wages to 2017 US dollars). We follow Forsythe et al. (2022) in the selection of SOC codes defining the low-skill service and blue collar occupation, and we then decide to intersect them with the bottom tercile of US wages, as this is the portion of distribution scrutinized by Autor et al. (2023).[11]

Finally, we acknowledge that there are many factors that affect static and dynamic local skill composition, which we can't observe and control for. We use ACS data to create control variables that account for local demographic composition observed across commuting zones. These control variables include share of foreign-born population, women in employment, manufacturing employment and college-educated population. We also measure the share of employment that can be done remotely per commuting zone at the 3-digit NAICS code following Dingel and Neiman (2020)'s method.[12]

3 Descriptive Statistics

3.1 Aggregate

In this section we aim to characterize changes in US job postings in the time surrounding the pandemic up to the end of 2022, as our sample spans 2018 to 2022. We start by showing the surge in the number job ads posted online in Figure 1. Panel A displays the monthly deviation in the number of postings relative to the average across months in 2019, after we apply the sample restrictions described in 2.1. After an initial drop at the beginning of the pandemic, the number of job postings consistently rose above the pre-pandemic monthly average, reaching the highest level in the first half of 2022, with a peak of over 1.2 million job ads in excess of the 2019 average. As one can expect, the share of job postings for remote or hybrid positions increased after the onset of the pandemic, as documented by the increasing distance between the solid blue line (in-person postings only) and the lighter dashed line (remote or hybrid job postings). In order to avoid confounding effects coming from skill changes due to remote work, we drop those postings to focus on in-person postings in our analysis. Panel B reports the percentage change in the number of job postings by 2-digit NAICS industry relative to the industry-specific average across months in 2019. A clear heterogeneity emerges. While Arts, Entertainment, and Recreation (NAICS 71) has been the most affected sector at the beginning of the pandemic, registering the largest drop, Accommodation

[11] Autor et al. (2023) use monthly CPS data to compute the 2019 wage distribution and isolate low-wage occupations whose workers' dynamics during the pandemic period are then examined.

[12] Estimates are publicly available at: `https://github.com/jdingel/DingelNeiman-workathome`.

and Food Services (NAICS 72) has been one of the main drivers behind the overall rebound and surge observed in Panel A, with a staggering 75% increase at the beginning of 2022. This industry heterogeneity will be crucial in motivating the choice of our instrument.

Next, we ask whether the content, not just the number, of online postings has changed in this period. In particular, we look at changes in our two main outcome variables, education and experience, inspecting whether they display a sufficient degree of variation to motivate our analysis on employers' recruiting responses. Panel A and Panel B of Figure 2 display the national change in the intensive and the extensive margin with respect to the average across 2019 months, respectively. On the intensive margin, we observe a sudden sizeable drop at the beginning of the pandemic. By the end of summer 2020, employers were requiring between 0.4 and 0.5 years less in terms of both education and experience. This drop is not negligible since a Bachelor's degree is coded as 16 years of education and a high school diploma as 12 years of education. Thus, considering that the 2019 national average was slightly higher that 14 years of education, this change moved the national average much closer to high school diploma. For education (solid blue line), since mid-2021 the average level of years required started to increase again, re-gaining more than half of the decline observed since the onset of Covid-19. In contrast, the decline in experience appears to be more persistent since the average level of years required (red solid line) remains close to its lowest point of mid-2020.

On the extensive margin, we observe a small drop at the beginning of the pandemic and a quick recovery back to 2019 levels by the end of 2020. Interestingly, by the end of 2022, around 47% of employers were including an experience requirement, up by 2 percentage points relative to the 45% average across 2019 months. Hence, on average, more employers chose to include an experience requirement but, conditional on asking, they required fewer years of experience. While these preliminary observations might be greatly affected by compositional changes, we interpret these national trends as evidence of aggregate downskilling during and after the pandemic.

Since our analysis utilizes spatial variation to understand the impact of local tightness, we next explore whether and, if so, how our variables differ across local labor markets, approximated by 722 commuting zones (CZs) covering the contiguous US. The two panels of Figure 3 show the change in average years of education and experience required between 2019 and 2022 for each commuting zone. It is immediate to realize that previously discussed national time series hide a great deal of geographic heterogeneity. Some commuting zones reported an increase in the average years of education well above 1 year (darkest blue areas in Panel A), while others reported a decrease well below 1 year (darkest red areas). In line with the evidence from the national time series, Panel B shows that the majority of commuting zones report a decline for this. Commuting zones in states like California, Florida and Virginia are almost all reporting drops in average years of experience.[13]

We now want to explore whether labor market tightness also displays geographic heterogeneity.

[13] A similar figure for the extensive margin will be added in the Appendix.

Table 1 lists the top and bottom five commuting zones with the largest and smallest changes in our measure of tightness between 2019 and any of the subsequent three years. To contextualize these changes in terms of size of commuting zones, the last column reports the percentile of CZ population in 2017. While tightness increased and decreased the most in smaller commuting zones, larger CZs also displayed quite large swings, as showed in Panel B where we restrict the exercise to CZs whose population is equal or above the 90^{th} percentile of the population distribution.[14]

Finally, after showing that skill demand changed over this period, we conclude this section by turning our attention to salaries advertised in job postings in Figure 4. We report the evolution of the average share of postings advertising a salary (black solid line, y-axis on the left) and of the average level of salaries after controlling for inflation (gray solid line, y-axis on the right).[15] The share of job postings containing salary information doubled by the end of 2022, increasing by roughly 20 percentage points relative to the average across 2019 month. The average real salary advertised decreased markedly at the beginning of the pandemic instead, but re-gained the decline and by the end of 2022 was back around its 2019 average.[16]

3.2 Group-specific: Focus on low-wage, low-skill occupations

Armed with evidence from the literature that skill demand saw significant changes for low-skill service occupations (Forsythe, Kahn, Lange, and Wiczer, 2022), and that historically vulnerable workers, such as low-wage, young non-college workers, saw a rapid relative wage growth due to tightness after the pandemic (Autor, Dube, and McGrew, 2023), we want to explore whether employers' recruitment in terms of skills and salaries behaved differently than for the rest of the market. First, we begin by characterizing jobs in the set of low-wage, low-skill occupations. Figure 5 explores the industry (3-digit NAICS) and occupation (3-digit SOC) composition of online job postings in 2019 for this group. Panel A shows that job ads for these occupations posted prior to the pandemic belonged mostly to accommodation and food services (over 21% combined), passenger transportation (20%), administrative and support services (15%), and health care and social assistance (over 6%). In terms of occupations, Panel B shows that 43% of postings are for food-related jobs (cooking, serving, preparing or processing food), while cleaning-related jobs (janitors, cleaners, landscapers, etc.) account for another 13% of postings, and transportation-related openings (freight, stock, and material hand-movers, truck and tractor operators, truck and tractor operators, parking and passenger attendants, aircraft service attendance, etc.) for slightly more than 20%.

In Figure 6 we compare skills and wages of workers employed in this set of occupations relative to the rest. Panel A highlights some important differences in terms of education attainment and labor market experience. Almost two-thirds of workers employed between 2015 and 2019 in low-wage,

[14]We report another metric of the variation of labor market tightness at the CZ-level also in Figure 15 in Appendix C.

[15]For this figure and throughout the paper, salary figures have been converted to December 2019 USD dollar using CPI data by the BLS.

[16]We are not controlling for compositional changes in the pool of vacancies.

low-skill occupations don't have any college education (around 20% have no high school degree and around 40% have a high school degree as their highest degree completed), as opposed to less than one-third of workers in the rest of occupations. Workers in low-wage, low-skill occupations also tend to have less experience. Over 15% of them have less than 5 years of experience, while more than 30% have less than 10.[17] Not surprisingly, low-wage, low-skill jobs pay substantially lower wages than the rest, as Panel B clearly shows for 2015-2019 years.

Turning to skill demand for these jobs, in Figure 7 we show the national evolution of skill requirements compared to the rest. Panel A shows that required years of both education and experience were back to the pre-Covid averages by the end of 2022 for low-wage, low-skill jobs, whereas years required for other occupations were still below pre-Covid averages. It is important to consider baseline levels here. Average years of required education and experience for low-wage, low-skill jobs in 2019 were 12.4 and 1.6, respectively. This makes clear that employers recruiting for these jobs don't have large room for downskilling if they can't find workers with suitable skills, as asking less than 12 years of education would imply explicitly asking for less than a high school degree, while asking for less than 1 year of experience would amount to explicitly asking for no experience. It might well be employers choose instead not to post any requirement when the requirement would amount to 0. Practically by low-skill definition, the average requirements for low-wage, low-skill jobs in 2019 were around 2 less years of required education and experience compared to the rest.

Panel B adds to the different response of skill demand across groups by showing the profoundly different dynamics of the extensive margin across groups. At the onset of the pandemic, employers recruiting for low-wage, low-skill jobs were more likely to list an education and experience requirement (up by between 6% and 8% percentage points compared to 2019), but while the extensive margin for experience remained well above the pre-pandemic average (dashed red line), education declined rapidly since the start of 2019, falling below 2019 average (solid red line). Conversely, for the rest of occupations, the share of employers posting a skill requirement declined slightly to below 2019 averages for the last three quarters of 2020, and then remained around the pre-pandemic averages (blue lines).

Figure 8 completes the picture by showing that posted salaries also reacted differently across groups over time. Specifically, while employers have become more likely to advertise a salary for both groups compared to pre-Covid, even though more so for low-wage, low-skill jobs (Panel B), the average salary level in real terms increased for low-wage, low-skill jobs, especially in 2021 and 2022 (Panel A). At the end of 2021, average real salary advertised increased by 5% for these occupations relative to before the pandemic. This evidence from the employer-side is in line with equilibrium results on wage compression found by Autor et al. (2023). We will explore whether demand-driven labor market tightness had any role in explaining these salary dynamics.

[17]We impute labor market experience by subtracting education attainment to individual age, and we then aggregate workers into 5-year bins, starting from 1-5 years of experience up to 35-40 years.

4 Methodology

4.1 Empirical Framework, Tightness Measure and Shift-Share IV

We use a shift-share IV approach that leverages the interaction of Covid-19 heterogeneous effect on labor demand across industries with pre-pandemic variation in industrial composition across commuting zones. The intuition is as follows. The Orlando and surrounding Orange county (FL) area, characterized by a high share of employment in the leisure and hospitality industry, with facilities like Universal Studios and Disney World, might initially experience slack labor markets followed by a rapid surge in tightness. Due to a Covid-induced drop in demand for leisure workers at the onset of the pandemic, areas with many workers in front-line, customer-facing services saw a disproportionate share of layoffs and sharp drops in employment. However, with the lifting of stay-at-home orders and the reopening of economic activities, the dramatic rebound in labor demand increased tightness levels in areas with a similar industry composition, fueled by job quits and unfilled openings for jobs characterized by low pays as well as disamenities in the form of greater disease exposure risk and thinner staffing level. In contrast, the San Jose-Sunnyvale-Santa Clara area (CA) might experience much milder swings in employment and demand given the high share of employment in the tech industry, where well-paid highly-educated workers benefited from the rapid rise of remote work arrangements. Given the sudden and unexpected nature of the pandemic, neither location could change their industrial composition ex-ante, and thus experience very different levels of labor market tightness during and after the pandemic. We use this variation to answer the question: how does local labor market tightness affect employers' posted skills and wages?

To answer this question, we use commuting zones as our geographic unit of analysis. We approximate local labor markets with commuting zones, accounting for cities that span several counties and include non-metropolitan areas in our analysis.[18] We further look at outcomes within occupation to account for variation in posted wages and skills due to local compositional changes in jobs. Thus, we define our outcome variables as change in outcome y in occupation o in commuting zone c in year t relative to 2019, the last year before the pandemic. Running a standard OLS model, we have the following specification:

$$\begin{aligned} y_{o,c,t} - y_{o,c,2019} = \alpha &+ \beta_1 \Delta^{t-2019}\text{Tightness}_{ct} * S_o + \beta_2 \Delta^{t-2019}\text{Tightness}_{ct} * (1 - S_o) \\ &+ S_o + \boldsymbol{X}_{c,2019} + \rho_r + \phi_t + \psi_o + \epsilon_{o,c,t} \end{aligned} \tag{1}$$

where Tightness_{ct} is a measure of pandemic-induced local labor market tightness, and S_o is an indicator for occupations belonging to the low-wage, low-skill group of jobs that we have defined. In other words, we allow both the level and impact of tightness to differ by group (low-wage, low-skill jobs and the rest of jobs). β_1 and β_2 will be our coefficients of interest, capturing how

[18]Commuting zones by construction are clusters of counties that are characterized by strong within-cluster and weak between-cluster commuting ties and are often used in the literature to think about local labor markets.

a percentage change in tightness in commuting zone c in year t changes our outcome y relative to 2019. We add a set of commuting zone-level controls along with Census division dummies to absorb region-specific factors (ρ_r), year fixed effects (ϕ_t), and occupation fixed effects (ψ_o).[19] We cluster standard errors at commuting zone-level to address potential serial correlation within an area. Finally, we weight observations by the commuting zone share of national population in 2019, allowing us to upweight larger areas while fixing weights at pre-pandemic level.

To construct our measure of labor market tightness, Tightness_{ct}, we deviate from the traditional Beveridge curve method of estimating a ratio of vacancy rate to unemployment rate ($\frac{v}{u}$). There are many reasons for this choice, which we expound upon in Appendix A, but this is due primarily to the fact that the pandemic induced an usual scale of temporary layoffs, which rendered traditional measures of unemployment imprecise.[20] Therefore, we opt to create a measure of labor market tightness following the spirit of Peri and Zaiour (2023)'s job vacancy rate, constructed as the total number of the vacancies divided by the sum of total employment and vacancies, obtaining information on vacancies from JOLTS and on employment from CPS. It amounts to:

$$\text{Tightness}_t = \left(\frac{Vacancy}{Vacancy + Employment} \right)_t \tag{2}$$

They also build a Bartik measure by state and year of this sector-driven demand growth using vacancies for the shift component. However, by substituting JOLTS vacancies with Lightcast online job postings, we can improve on such measures taking advantage on the higher granularity of our data in terms of industry and geography.[21] First, we can create a measure of changes, after taking the log, in local tightness in commuting zone c between year t and 2019 by using job posting and employment available at the county level from Lightcast and LAUS, respectively, which we then map to commuting zones. Our main explanatory variable then is as follows:

$$\Delta^{t-2019}\text{Tightness}_{c,t} = \ln \left(\frac{Postings}{Postings + Employment} \right)_{c,t} - \ln \left(\frac{Postings}{Postings + Employment} \right)_{c,2019} \tag{3}$$

Crucially, we can then exploit the detailed industry information for job postings, available at 6-digit NAICS level and aggregated at 3-digit NAICS, to build a more precise Bartik measure in order to

[19]Our list of controls referring to 2019 includes the share of foreign-born population; share of employed women; share of employment in manufacturing; and share of college-educated population. We also include a measure of the share of jobs that can be done remotely in each CZ c to account for the fact that openings might not accurately reflect local tightness, even if remote postings have been dropped, in areas where teleworkable industries are popular. This variable is measured as share of jobs in industry i that are estimated to be feasible from remote (Dingel and Neiman (2020)) interacted with pre-Covid employment in local industry i as a share of CZ's population.

[20]In Appendix A we will also benchmark our proposed measure of tightness with the measure by Autor et al. (2023), based on the employment-to-employment separation rate and the unemployment rate, and find a high correlation between the two.

[21]While the concepts of job posting and vacancy are not the same, previous studies have established that Lightcast sample is well-aligned with JOLTS openings (Chetty et al. (2020); Dalton et al. (2020)). See further validation exercises alleviating this concern in Appendix C. The literature has also used job postings to proxy for vacancies. For instance, see Forsythe, Kahn, Lange, and Wiczer (2020).

purge regression estimates of equation (1) from the potential endogeneity and reverse causality. We therefore propose the following Bartik product to predict changes in labor market tightness due to industry-level vacancies:

$$\Delta \widehat{Postings}_{c,t} = \sum_i \pi_{i,c,2017} \times \mathscr{P}^{\text{US-wide}}_{i,t-19} \tag{4}$$

where π_{ic} is 2017 3-digit NAICS industry shares summing to 1 across industries for each commuting zone c and $\mathscr{P}_i$ is the national industry i shift in job postings for each observed year t relative to 2019. We also compute the leave-one-out version (we refer to it as "LOO"). We finalize our shift-share instrument by standardizing changes in postings by CZ pre-Covid working population and taking the log to obtain is:

$$Z_{c,t} \equiv \ln\left(\frac{\Delta \widehat{Postings}_{c,t}}{WorkingAgePop_{c,2017}}\right) \tag{5}$$

Our shift-share instrument has three appeals. First, vacancy count at the local level, especially in small locations, may be measured with some error, whereas our measure allows for more precision. Second, while first differences absorb some of the unobserved variables, actual vacancy growth could potentially reflect location-specific time-varying shocks, which might be problematic if correlated to hiring standards. Third, the use of shares measured years prior to Covid to apportion vacancies, along with the unexpected nature of the pandemic, solves the reverse causality issue stemming from location-by-industry employment responding to changes in skills occurring during or due to Covid-19. Using the instrument in equation (5), we then predict $\Delta^{t-2019}\text{Tightness}_{ct}$ defined in equation (3) with the following first stage:

$$\Delta^{t-2019}\text{Tightness}_{ct} = \alpha + \beta_1 Z_{ct} + \beta_2 S_o + \boldsymbol{X}_{c,2019} + \rho_r + \phi_t + \psi_o + \epsilon_{o,c,t} \tag{6}$$

and then insert our predicted values of labor market tightness into our second-stage equation.

4.2 IV validity

To address instrument validity, we discuss the two standard IV assumptions: relevance and exclusion restriction. As for the former, we report in Table 3 estimates from first-stage regressions and show the first-stage F-statistics, which all pass the conventional threshold levels. As expected our instrument is positively and significantly associated with our measure of labor market tightness, regardless of the set of controls included. Our preferred specification for subsequent analysis is Column (7) where we use occupation-level observations, we employ the leave-one-out version of our shift share instrument, and we include the full set of controls, dummies for census divisions regions, year and occupation fixed effects, weighting the sample by CZ share of national population in 2019.

As for the latter, it is hard to think of how 2017 local industry shares might directly affect *changes* in skill requirements in 2022 except through the impact of the pandemic on demand for jobs, once we remove remote postings. Plus, the unexpected timing and random nature of the pandemic supports the assumption that employers did not change their location in anticipation of a pandemic. We don't require that the shares predict nothing in levels, but simply that the shares only predict changes through the causal channel emphasized by our design.

As a sanity check, Figure 9 shows the top-5 industries in terms of Rotemberg weights and the relationship between weights and first-stage F-statistic. The 5 industries, which are those driving our 2SLS estimator, are: Transit and Ground Passenger Transportation, Educational Services, Ambulatory Health Care Services, Food Services and Drinking Places, and Hospitals, (closely followed by Accommodation).[22] This evidence is reassuring since all these industries are industries that we expect to have experienced a significant change in demand during the pandemic. In Appendix B we provide a broader discussion and additional evidence on the validity of the instrument proposed.

5 Results

We begin the analysis by validating the main results of Forsythe et al. (2022). Table 2 reports estimates from regressions of posting-level skill requirements on indicators for Covid waves and interactions with postings for low-skill service occupations. "Covid 1" equals one if the date of the postings is between March 2020 and March 2021, "Covid 2" if the date is between April 2021 and June 2022, whereas "Service" takes value one if the posting belongs to low-skill service occupations (SOC 35–39, 412), and "Low-wage" if it belongs to our previously defined low-wage, low-skill set of occupations. While our data only span 2018 to 2022, Columns 1 to 4 that include sector-by-occupation-by month fixed effects reproduce pretty closely results by Forsythe et al. (2022), who have information since 2015. Indeed, similar to their conclusions for the intensive margins, coefficients on both Covid phases show significant downskilling and low-skill service occupations saw slightly larger declines, showing that employers are more likely to ask for a skill requirement than before the pandemic for a similar type of job, but, conditional on asking, they request fewer years. This evidence looks aligned with the national evolution of skill demand displayed in Figure 2. In Column 5 to 8 we run the same specifications but substitute low-skill service with our newly-defined group of low-wage, low-skill service and blue collar jobs in the interaction terms.

We turn now the attention to our main results to capture the role played by labor market tightness in driving skill demand. Table 4 shows the effect of changes in commuting zone-level labor market tightness on the share of postings listing education or experience (extensive margin). Even columns pertain to education, while odd columns to experience. Columns 1 and 2 report OLS estimated, columns 3 and 4 report 2SLS estimates using the shift-share IV described in 4.1, and columns 5 to 8 using the leave-one-out version of the IV. All regressions use CZ share of national population as weight and include dummies for Census divisions as well as year fixed effects. Columns 7 and 8, which represent our preferred specification, also include occupation fixed effects. The negative,

[22] These industries are those with the five highest Rotemberg weights, which can be interpreted as sensitivity-to-misspecification parameters and reveal which variation our instrument is using the most.

statistically significant coefficients indicate that tighter labor markets decrease the probability of posting job ads listing education and experience requirements. For education, the negative impact is larger for low-wage, low-skill jobs, while for experience the impact is similar through the occupation groups. Since our outcomes are percentage point changes relative to 2019, we can interpret the result on education as follows: a one percentage point increase in the change of CZ's tightness is predicted to decrease the change in the share of job postings requiring some level of education by 0.336 percentage points.

Table 5 has the same structure of Table 4 but examines the effect of labor market tightness on the average years of schooling and experience listed (intensive margin). Columns 7 and 8 show that, while labor market tightness didn't significantly affect average years of experience listed, it affected the level of education required for low-wage, low-skill jobs. The intensive margin outcomes are measured as changes in years, so that a one percentage point increase in the change of CZ's tightness is predicted to increase average years of education listed by 0.55 years in postings for low-wage, low-skill positions.

We want to understand if these changes in skill demand translated into changes in the salaries advertised. In Table 6 we examine how labor market tightness affected the share of postings advertising a salary (extensive margin in odd columns) and the level of those offers (intensive margin in even columns, after controlling for inflation and taking the log). An increase in local labor market tightness causes an increase in the level of salary advertised for low-wage, low-skill jobs, but not for the rest of occupations.

In rationalizing these findings it is important to remember that, while labor markets were already pretty tight before Covid, the main surge in tightness occurred through 2021 and 2022 with the gradual re-openings of activities and the lifting of stay-at-home orders, when average skill requirements were already well below their pre-Covid levels. In some industries, especially those featuring many of these low-wage low-skill jobs, employers had significant difficulties in filling their vacancies due to sudden demand growth and reallocation of workers to different jobs (better paid and less exposed to risk of contagion). Tightness hit particularly hard those industries, as it can be seen by the increase of postings in Figure 14, but employers willing to hire in those position were constrained by a lower bound in terms of skill, given that demand for those positions required very low levels of education and experience. With the option of downskilling limited by the nature of those jobs, some employers adopted the strategy of simply removing any requirement, as we see with the decrease in the extensive margin, while listing higher requirements for some positions (likely managerial or supervisory roles to deal with less-qualified new hires). As an alternative or complementary strategy to attract candidates, employers for these jobs also increased advertised wages, spurring and contributing to a wage compression that reduced inequality in US labor markets.

6 Conclusion

In this paper, we examine the effect of labor market tightness on changes in employers' skill demand and advertised salaries by utilizing the heterogeneous effect of Covid-19 across industries combined with pre-pandemic variation in industrial composition across commuting zones. To track changes in demand for education and experience, we use information from Lightcast online job postings data and, improving on Peri and Zaiour (2023) methodology, we exploit job postings to construct a measure for local labor market tightness and a shift-share instrument. We then employ a long differences model to study changes in our main variables between 2019, and years leading up to and including 2022.

Our analysis showed that local labor market tightness affected low-wage, low-skill service and blue collar occupations differently from the rest of the labor market. While tightness caused employers to decrease the share of postings listing a requirement, employers aiming to recruit for low-wage, low-skill positions faced the constraint of not being able to decrease skill requirements further. Some decided to increase requirements, education in particular, but also increased advertised salaries, as complementary strategy to attract candidates to fill their vacancies. This would further support the evidence of tightness-induced wage compression found by Autor et al. (2023).

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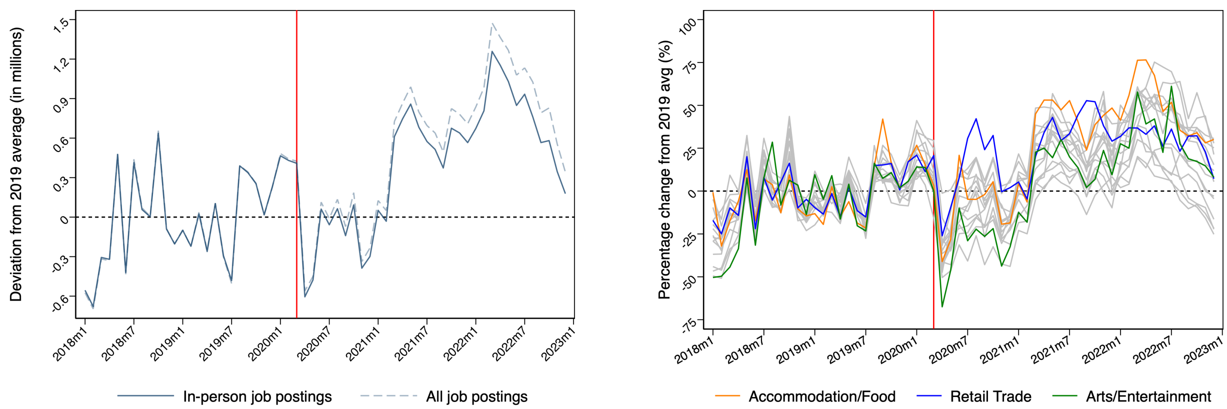
Figure 1: Time series of job postings

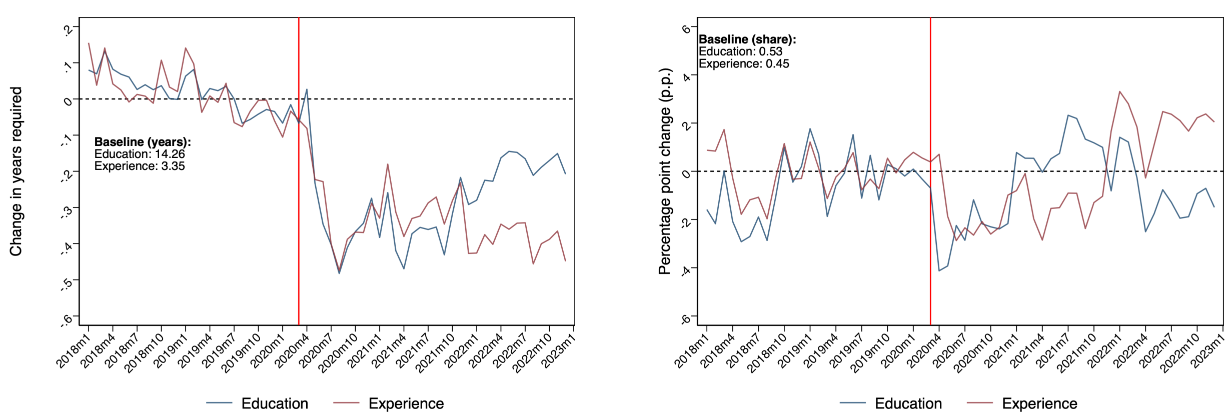
(a) Time series (b) Time series by industry



Notes: This figure displays the evolution of online job postings over time relative to averages across 2019 months. We restrict the sample to postings that report valid information for industry, occupation and location (county). We drop postings from Alaska and Hawaii. We only keep non-farm, non-military private sector postings. In Panel B we further restrict to in-person job postings only, aggregating postings at the 2-digit NAICS level and showing percentage changes relative to industry-specific average across 2019 months. This will be our sample for the analysis.
Source: Lightcast online job postings.

Figure 2: National evolution of skill requirements in job postings

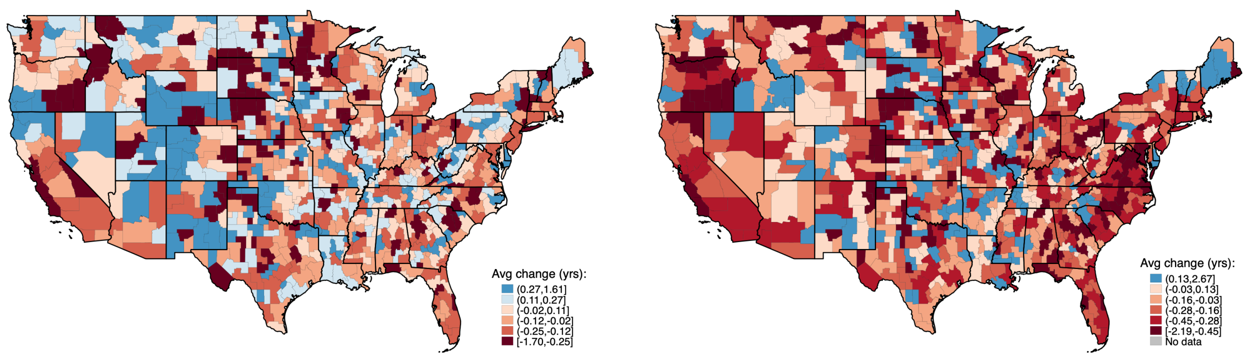
(a) Intensive margin (b) Extensive margin



Notes: This figure displays the evolution of education and experience requirements in online job postings over time. Panel A displays changes in average years required relative to 2019 average across months, while Panel B changes in the share of postings posting a requirement required relative to 2019 average across months. In both panel we restrict the sample to postings that report valid information for industry, occupation and location (county). We drop postings from Alaska and Hawaii. We only keep non-farm, non-military private sector postings, and we further restrict to in-person job postings only. This coincides with our sample for the analysis.
Source: Lightcast online job postings.

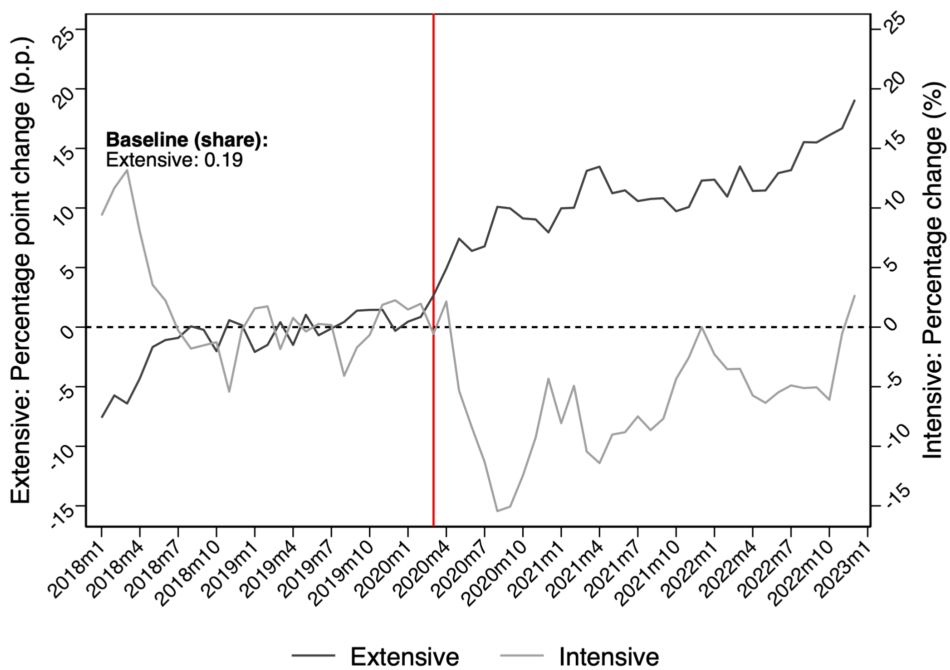
Figure 3: Changes in intensive margin across commuting zones

(a) Education (b) Experience



Notes: This figure displays changes at the commuting zone level in years of education and experience required in online job postings between 2019 and 2022. Usual set of restrictions applied. Changes reported by sextiles of their distribution over commuting zones.
Source: Lightcast online job postings.

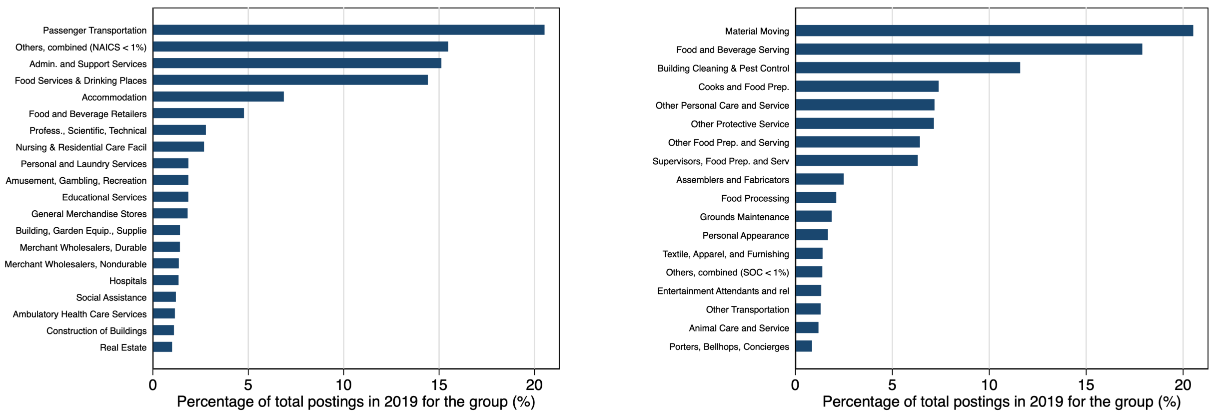
Figure 4: National evolution of intensive and extensive margin for posted salary



Notes: This figure displays the evolution of the intensive and extensive margin for posted salary over time. It reports both the change in percentage point of the share of postings listing a salary (black line, y-axis on the left) and the percentage change in the level of salaries advertised (gray line, y-axis on the right). Salaries have been converted to December 2019 US dollars using the CPI multiplier provided by BLS. Both changes are computed relative to averages across 2019 months.
Source: Lightcast online job postings.

Figure 5: Composition of job postings for the low-wage low-skill group

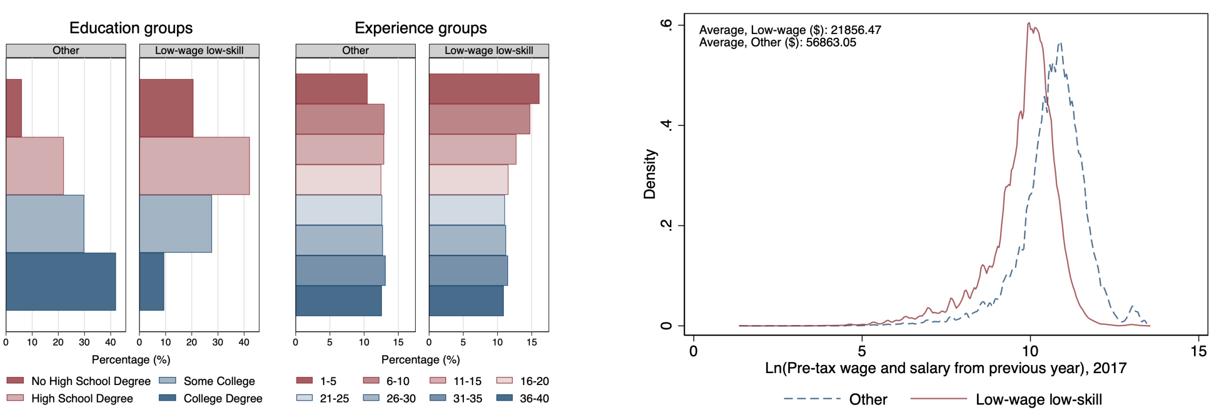
(a) Industry (b) Occupation



Notes: This figure displays the composition of job postings in 2019 for the low-wage low-skill group in terms of industries (3-digit NAICS) and occupations (3-digit SOC). Restrictions to job postings are applied. Low-wage low-skill group includes low-skill service (SOC 35 to 39 and 412) and blue collar occupations (SOC 33 and 45 to 53) in the bottom tercile of the US pre-Covid wage distribution (2015-2019 5-year ACS data).
Source: Lightcast online job postings.

Figure 6: Realized education, experience and wage of low-wage, low-skill workers

(a) Skill (b) Wage

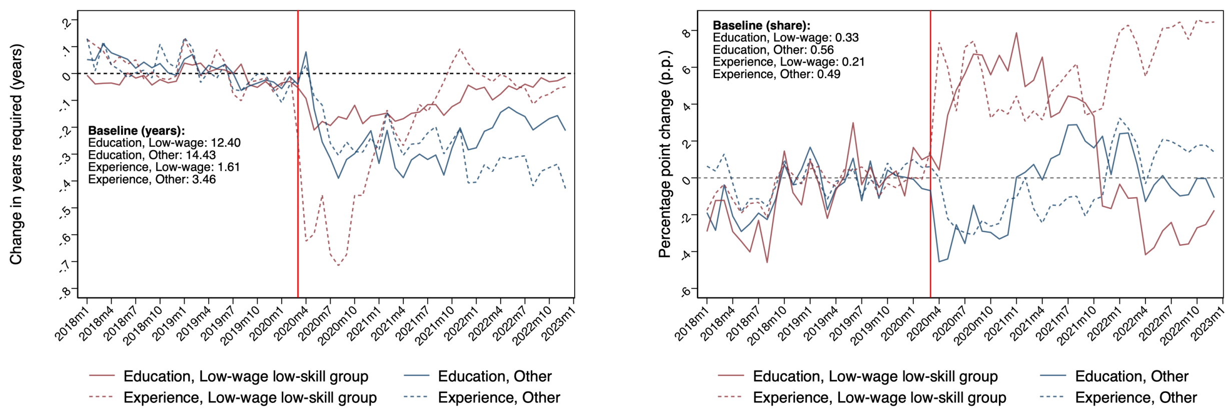


Notes: This figure displays the composition of workers in the low-wage, low-skill group in 2015-2019 in terms of educational attainment (four groups), experience in the labor market (imputed by subtracting years of education to reported age of the individual and divided in eight groups with range of 5-year range), and pre-tax wages (adjusted for inflation to 2017). We only keep working-age (18 to 65 years of age) individuals residing in non group-quarters who are non-enrolled in school. Low-wage, low-skill group includes low-skill service (SOC 35 to 39 and 412) and blue collar occupations (SOC 33 and 45 to 53) in the bottom tercile of the US pre-Covid wage distribution (2015-2019 5-year ACS data).
Source: 2015-2019 5-year ACS data (dowloaded from IPUMS).

Figure 7: National evolution of skill requirements in job postings by group

(a) Intensive margin

(b) Extensive margin

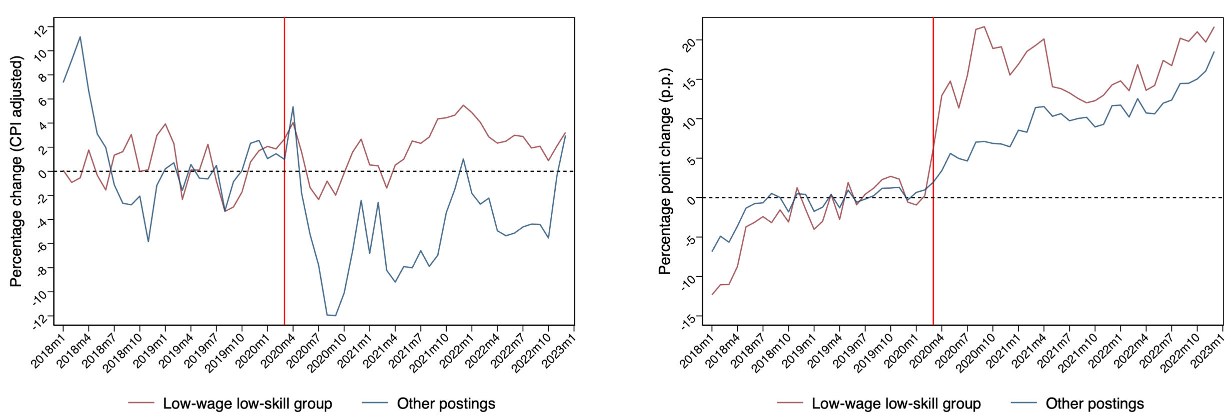


Notes: This figure displays the evolution of education and experience requirements in online job postings over time by group (low-wage, low-skill vs. all other postings). Panel A displays changes in average years required relative to the group-specific average across 2019 months, while Panel B changes in the share of postings posting a requirement required relative to group-specific average across 2019 months. Restrictions on sample of postings are applied.
Source: Lightcast online job postings.

Figure 8: National evolution of intensive and extensive margin for posted salary by group

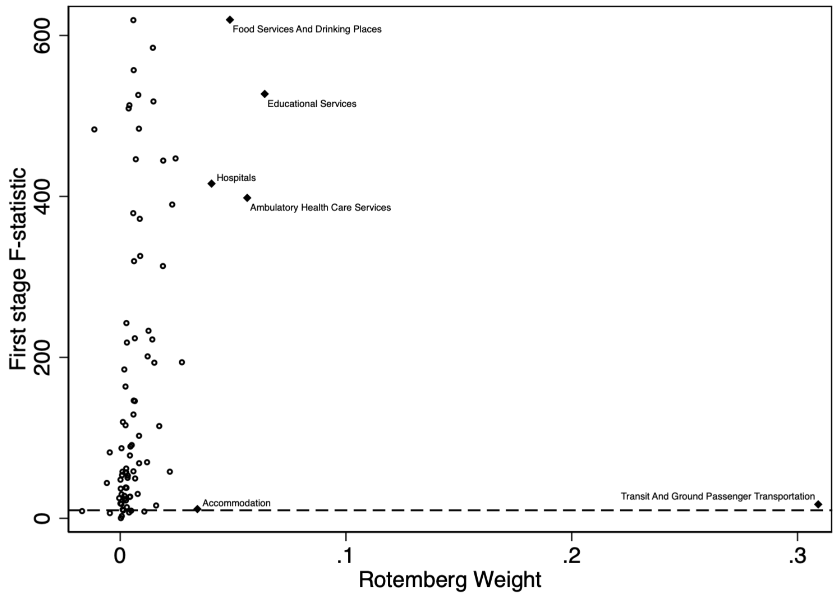
(a) Intensive margin

(b) Extensive margin



Notes: This figure displays the evolution of the intensive and extensive margin for posted salary over time by group (low-wage, low-skill vs. all other postings). Panel A displays percentage changes in posted salary (converted to December 2019 US dollars using the CPI multiplier provided by BLS) relative to group-specific average across 2019 months, while Panel B changes in the share of postings posting salary information relative to group-specific average across 2019 months. Restrictions on sample of postings are applied.
Source: Lightcast online job postings.

Figure 9: Relationship between the Rotemberg weights and the first-stage F-statistic



Notes: This figure plots each industry-specific instrument's Rotemberg weight against the first stage F-statistic.

Table 1: Changes in measure of labor market tightness by commuting zone-year pair

	CZ code	$\Delta_{t-19} \ln(\frac{Postings}{Postings+Emp})$	Year	Working-age Pop (pct, 2017)
Panel A: Top and Bottom year-CZ pairs				
Sheridan County, MT	26407	-1.22	2022	2
Big Rapids-Ludington, MI	12002	-0.72	2020	33
Bonners Ferry, ID	34501	-0.67	2022	9
Big Rapids-Ludington, MI	12002	-0.60	2022	33
Big Rapids-Ludington, MI	12002	-0.58	2021	33
Garden County, NE	28303	1.23	2020	0
Wichita Falls, TX	32604	1.28	2022	17
Phillipsburg, KS	28603	1.33	2021	6
Phillipsburg, KS	28603	1.50	2022	7
Sheridan County, MT	26407	1.50	2022	2
Panel B: Top and Bottom year-CZ pairs for large CZs				
San Jose, CA	37500	-0.13	2020	96
Glens Falls, NY	18600	-0.12	2020	91
Portland, OR	38801	-0.11	2020	96
New York-Nassau-Suffolk, NY	19400	-0.11	2020	99
Glens Falls, NY	18600	-0.10	2022	91
West Palm Beach, FL	7100	0.46	2020	94
Lancaster-Reading, PA	19100	0.46	2022	92
Hartford-New Haven-Bridgeport-Stamford, CT	20901	0.48	2021	97
Fort Myers-Cape Coral-Naples, FL	7200	0.48	2022	90
San Jose, CA	37500	0.50	2022	96

Notes: Percentiles 25, 50 and 75 of the main statistic are 0.08, 0.23 and 0.40, respectively.

Table 2: Skill requirements in job postings and Covid indicators

VARIABLES	(1) Education Intensive	(2) Education Extensive	(3) Experience Intensive	(4) (Experience Extensive	(5) Education Intensive	(6) Education Extensive	(7) Experience Intensive	(8) Experience Extensive
Covid 1	-0.127***	0.00546	-0.0207*	-0.00402*	-0.115***	-0.000323	-0.00532	0.00228
	(0.0105)	(0.00329)	(0.0109)	(0.00215)	(0.0102)	(0.00330)	(0.0111)	(0.00229)
Covid 1 * Service	0.0348***	0.0186***	-0.148***	0.0243***				
	(0.00795)	(0.00407)	(0.0201)	(0.00567)				
Covid 1 * Low-wage					-0.0810***	0.0613***	-0.468***	-0.0120*
					(0.0184)	(0.00340)	(0.0363)	(0.00651)
Covid 2	-0.152***	0.0261***	-0.109***	0.0281***	-0.137***	0.0226***	-0.102***	0.0260***
	(0.00783)	(0.00256)	(0.00915)	(0.00308)	(0.00756)	(0.00241)	(0.00920)	(0.00334)
Covid 2 * Service	0.116***	-0.0157***	-0.120***	-0.0249***				
	(0.00594)	(0.00430)	(0.0166)	(0.00543)				
Covid 2 * Low-wage					-0.0297*	0.00797	-0.296***	-0.0140**
					(0.0162)	(0.00515)	(0.0376)	(0.00614)
Constant	14.23***	0.515***	3.287***	0.446***	14.23***	0.515***	3.290***	0.446***
	(0.00506)	(0.00154)	(0.00656)	(0.00137)	(0.00512)	(0.00153)	(0.00671)	(0.00138)
Observations	79,195,070	150,645,678	68,450,302	150,645,678	79,195,070	150,645,678	68,450,302	150,645,678
R-squared	0.385	0.136	0.271	0.107	0.385	0.136	0.271	0.107
Model	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Period	2018-2022	2018-2022	2018-2022	2018-2022	2018-2022	2018-2022	2018-2022	2018-2022
Sector-Occ.-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports estimates from regressions of posting-level skill requirements on indicators for Covid waves (”Covid 1” equals one if the date is between March 2020 and March 2021, while ”Covid 2” equals one if the date is between April 2021 and June 2022). ”Service” is an indicator for postings belonging to low-skill service occupations as defined in Forsythe et al. (2022). ”Low-wage” is an indicator for postings belonging to our low-wage, low-skill group as defined above. Robust standard errors are clustered at the year-month level. All models include sector-by-occupation-by month fixed effects (two-digit NAICS and two-digit SOC level). Columns 1-4 validate the main regression results from Forsythe et al. (2022) (unlike their regressions, employing Lightcast job postings data starting from 2015, our period spans 2018 to 2022).

Table 3: Proposed Instrument Strongly Predicts Labor Market Tightness

VARIABLES	(1) Δ LM Tightness	(2) Δ LM Tightness	(3) Δ LM Tightness	(4) Δ LM Tightness	(5) Δ LM Tightness	(6) Δ LM Tightness	(7) Δ LM Tightness
Ln Δ Postings (std)	0.0498***	0.0369***	0.0380***	0.0294***	0.0110		
	(0.00492)	(0.00370)	(0.00541)	(0.00620)	(0.00691)		
Ln Δ Posting LOO (std)						0.0282***	0.0285***
						(0.00600)	(0.00578)
Remote Work Share of Pop.		-1.252***	-1.807***	-1.246**	-0.224	-1.242**	-1.391**
		(0.295)	(0.299)	(0.546)	(0.470)	(0.546)	(0.621)
Foreign-Born (%)				-0.00557	-0.489***	-0.0222	-0.00385
				(0.0977)	(0.164)	(0.0976)	(0.0963)
College-Educated (%)				-0.514***	0.122	-0.523***	-0.475**
				(0.175)	(0.210)	(0.174)	(0.186)
Employment among Women (%)				0.609**	-0.0662	0.617**	0.609**
				(0.244)	(0.232)	(0.241)	(0.260)
Employment in Manufacturing (%)				0.324	1.441***	0.313	0.187
				(0.229)	(0.219)	(0.227)	(0.236)
Low-wage group			0.657**	0.619**	0.319**	0.595**	-0.000576***
			(0.268)	(0.263)	(0.155)	(0.265)	(0.000210)
Constant	0.319***	0.464***	0.393***	-0.0282	0.124	-0.0327	0.136
	(0.0206)	(0.0436)	(0.0586)	(0.130)	(0.122)	(0.129)	(0.130)
Observations	1,953	1,953	1,933	1,933	1,933	1,935	107,969
R-squared	0.326	0.359	0.417	0.438	0.175	0.440	0.485
Model	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Instrument	Baseline	Baseline	Baseline	Baseline	Baseline	LOO	LOO
Census Divisions	No	No	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occ. FE	-	-	-	-	-	-	Yes
Weights	Yes	Yes	Yes	Yes	No	Yes	Yes
F-stat	102.3	99.51	49.16	22.45	2.520	22.08	24.38

Notes: Weighted regressions are weighted by start of period commuting-zone share of national population. Robust SE in parentheses are clustered on commuting zone. Significance levels: *** for p<0.01, ** for p<0.05, * for p<0.1.

Table 4: Share of posting with education and experience requirements: Extensive margin and labor market tightness

VARIABLES	(1) Education	(2) Experience	(3) Education	(4) Experience	(5) Education	(6) Experience	(7) Education	(8) Experience
Δ LM Tightness * Other	-0.0294***	-0.0246***	-0.269***	-0.154***	-0.261***	-0.155***	-0.225***	-0.147***
	(0.00926)	(0.00837)	(0.0561)	(0.0362)	(0.0622)	(0.0365)	(0.0573)	(0.0361)
Δ LM Tightness * Low-wage	-0.0613***	0.0145	-0.350***	-0.0860**	-0.347***	-0.0885**	-0.336***	-0.109***
	(0.0124)	(0.0115)	(0.0588)	(0.0369)	(0.0632)	(0.0369)	(0.0575)	(0.0370)
Remote Work Share of Pop.	0.0574	0.0967	-0.231	-0.0672	-0.210	-0.0646	-0.155	-0.0649
	(0.115)	(0.0872)	(0.223)	(0.138)	(0.224)	(0.138)	(0.207)	(0.138)
Foreign-Born (%)	0.0232	0.0360***	-0.0218	0.0164	-0.0207	0.0160	-0.0186	0.0169
	(0.0145)	(0.0133)	(0.0315)	(0.0208)	(0.0310)	(0.0208)	(0.0282)	(0.0204)
College-Educated (%)	0.0190	0.00476	-0.179**	-0.0772*	-0.183**	-0.0818*	-0.176***	-0.0813*
	(0.0338)	(0.0285)	(0.0724)	(0.0468)	(0.0728)	(0.0478)	(0.0662)	(0.0474)
Employment among Women (%)	0.0320	0.0115	0.196**	0.0807	0.203**	0.0861	0.184**	0.0843
	(0.0444)	(0.0384)	(0.0931)	(0.0579)	(0.0924)	(0.0586)	(0.0846)	(0.0578)
Employment in Manufacturing (%)	0.0290	0.0522	0.0621	0.0732	0.0549	0.0708	0.0603	0.0729
	(0.0470)	(0.0362)	(0.0809)	(0.0482)	(0.0799)	(0.0475)	(0.0740)	(0.0475)
Constant	-0.0455*	-0.0389*	-0.0380	-0.0259	-0.0458	-0.0287	-0.0563	-0.0531**
	(0.0242)	(0.0209)	(0.0420)	(0.0264)	(0.0425)	(0.0259)	(0.0393)	(0.0254)
Observations	118,587	118,587	107,780	107,780	107,969	107,969	107,969	107,969
R-squared	0.014	0.038		0.022		0.022	0.109	0.142
Model	OLS	OLS	2SLS	2SLS	2SLS LOO	2SLS LOO	2SLS LOO	2SLS LOO
Census Divisions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occ. FE	No	No	No	No	No	No	Yes	Yes
Weights	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-Stage F-stat					24.29	24.29	24.38	24.38

Notes: Weighted regressions are weighted by start of period commuting-zone share of national population. Robust SE in parentheses are clustered on commuting zone. Significance levels: *** for p<0.01, ** for p<0.05, * for p<0.1.

Table 5: Years of education and experience required: Intensive margin and labor market tightness

VARIABLES	(1) Education	(2) Experience	(3) Education	(4) Experience	(5) Education	(6) Experience	(7) Education	(8) Experience
Δ LM Tightness * Other	-0.0480	0.0251	0.150	0.350*	0.236	0.405**	0.223	0.213
	(0.0300)	(0.0439)	(0.168)	(0.205)	(0.151)	(0.206)	(0.146)	(0.191)
Δ LM Tightness * Low-wage	0.128**	0.0212	0.595***	0.410*	0.654***	0.489**	0.551***	0.328
	(0.0556)	(0.0616)	(0.175)	(0.232)	(0.180)	(0.227)	(0.151)	(0.204)
Remote Work Share of Pop.	0.167	-0.374	0.491	-0.0675	0.586	0.0223	0.494	-0.205
	(0.361)	(0.465)	(0.474)	(0.604)	(0.490)	(0.618)	(0.484)	(0.566)
Foreign-Born (%)	-0.189***	0.0994*	-0.155***	0.120*	-0.138**	0.131*	-0.116**	0.136**
	(0.0519)	(0.0532)	(0.0525)	(0.0693)	(0.0540)	(0.0725)	(0.0542)	(0.0644)
College-Educated (%)	-0.276**	0.0413	-0.191	0.290	-0.124	0.324	-0.108	0.246
	(0.125)	(0.162)	(0.157)	(0.243)	(0.163)	(0.246)	(0.159)	(0.226)
Employment among Women (%)	0.233	0.236	0.119	0.105	0.0539	0.0816	0.0678	0.185
	(0.165)	(0.213)	(0.197)	(0.262)	(0.202)	(0.270)	(0.199)	(0.247)
Employment in Manufacturing (%)	0.0444	-0.0275	-0.0511	-0.0839	-0.0553	-0.105	-0.0571	-0.0865
	(0.130)	(0.224)	(0.158)	(0.257)	(0.167)	(0.264)	(0.165)	(0.241)
Constant	-0.168*	-0.171	-0.183*	-0.216*	-0.181*	-0.227*	-0.258**	-0.172
	(0.0910)	(0.113)	(0.100)	(0.115)	(0.103)	(0.117)	(0.106)	(0.114)
Observations	115,439	111,539	104,948	101,427	105,136	101,615	105,136	101,615
R-squared	0.008	0.009	0.005	0.004	0.003	0.003	0.070	0.061
Model	OLS	OLS	2SLS	2SLS	2SLS LOO	2SLS LOO	2SLS LOO	2SLS LOO
Census Divisions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occ. FE	No	No	No	No	No	No	Yes	Yes
Weights	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-Stage F-stat					24.29	24.29	24.38	24.38

Notes: Weighted regressions are weighted by start of period commuting-zone share of national population. Robust SE in parentheses are clustered on commuting zone. Significance levels: *** for p<0.01, ** for p<0.05, * for p<0.1.

Table 6: Posted salaries: Intensive and extensive margin and labor market tightness

VARIABLES	(1) Salary Ext	(2) Ln(Salary)	(3) Salary Ext	(4) Ln(Salary)	(5) Salary Ext	(6) Ln(Salary)
Δ LM Tightness * Other	0.0543***	-0.0276	-0.145	0.0691	-0.143	0.0933
	(0.0120)	(0.0171)	(0.0906)	(0.0681)	(0.0886)	(0.0671)
Δ LM Tightness * Low-wage	0.0649***	0.0666***	-0.148	0.196**	-0.145	0.229***
	(0.0140)	(0.0221)	(0.0944)	(0.0819)	(0.0894)	(0.0733)
Remote Work Share of Pop.	-0.433**	0.159	-0.661***	0.342	-0.664***	0.370
	(0.186)	(0.218)	(0.254)	(0.247)	(0.248)	(0.249)
Foreign-Born (%)	0.00696	-0.0427*	-0.0398	-0.0254	-0.0387	-0.0203
	(0.0256)	(0.0234)	(0.0387)	(0.0266)	(0.0386)	(0.0274)
College-Educated (%)	0.229***	-0.0236	0.0882	0.0459	0.0960	0.0699
	(0.0702)	(0.0677)	(0.124)	(0.0919)	(0.125)	(0.0928)
Employment among Women (%)	0.0937	0.0856	0.249**	-0.00209	0.239**	-0.0247
	(0.0733)	(0.0794)	(0.101)	(0.0891)	(0.100)	(0.0896)
Employment in Manufacturing (%)	-0.0250	-0.00718	-0.00944	-0.0166	-0.00440	-0.0175
	(0.0561)	(0.0786)	(0.0848)	(0.0835)	(0.0840)	(0.0860)
Constant	-0.0473	-0.0720*	-0.0542	-0.0705	-0.0498	-0.0677
	(0.0460)	(0.0430)	(0.0581)	(0.0467)	(0.0574)	(0.0473)
Observations	118,587	102,626	107,780	93,157	107,969	93,344
R-squared	0.201	0.098	0.154	0.095	0.156	0.094
Model	OLS	OLS	2SLS	2SLS	2SLS LOO	2SLS LOO
Census Divisions	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Occ. FE	Yes	Yes	Yes	Yes	Yes	Yes
Weights	Yes	Yes	Yes	Yes	Yes	Yes
First-Stage F-stat					24.38	24.38

Notes: Weighted regressions are weighted by start of period commuting-zone share of national population. Robust SE in parentheses are clustered on commuting zone. Significance levels: *** for p<0.01, ** for p<0.05, * for p<0.1.

A Data and Measures

A.1 Industry crosswalk

In order to take advantage on industry-level information from both ACS and Lightcast sources, we map industry information of Census code contained in ACS data to the North American Industry Classification System (NAICS) code used by Lightcast by using publicly-provided crosswalks.[23] For situations of one-to-many mapping we choose to employ equal weights. Our analysis relies on industries at the 3-digit NAICS level, giving us 86 different industries.

A.2 Tightness measures

As described in Section 4.1 we decide to build a measure of labor market tightness that does not rely on unemployment for two main reasons. First, standard measures involving unemployment rate would greatly underestimate tightness during some phases of the pandemic due to the explosion of temporary-layoff unemployment. Many workers that were laid off expected to be recalled by their previous employers so that they did not engage in usual search behaviors, making the distinction between temporary-layoff unemployment and jobless unemployment extremely important (Hall and Kudlyak, 2022). Second, we devise an empirical strategy that relies on industry heterogeneity to measure local tightness and, if we wanted to use unemployment, it would be hard to find a conceptual link between unemployment and specific industries as, once workers become unemployed, they likely apply to a broad range of jobs in different industries.

Therefore, we opt to build a measure that uses vacancies, which we proxy with job postings, and can take advantage of the granularity of Lightcast data. While vacancies measured by the Job Openings and Labor Turnover Survey (JOLTS) of the US Bureau of Labor Statistics are only available disaggregated by 17 mutually exclusive broad sectors of the economy, which would greatly limit the granularity of the analysis, we can use 86 industries, after aggregating 6-digit NAICS into 3-digit NAICS industries.[24] Importantly, we benchmark our methodology of capturing changes in tightness with changes in the measure proposed by Autor et al. (2023) in Figure 10. While we can construct our measure at the commuting zone level, we bring it to the state level in order to compare the two. Reassuringly enough, our measure built on local online job postings and employment tracks particularly well their measure based on state-level employment-to-employment separation rate from LEHD/J2J data paired with the state-level unemployment rate from LAUS.

Alternative measures of tightness, mostly available at the national level only, are computed by online job boards such as LinkedIn and Indeed. These platforms exploit the fact that they can observe applicants to job postings to claim they have a more precise measure of job search activity. Unfortunately, we don't observe "clicks" or applications made per posting in Lightcast data.

[23] `https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html`.

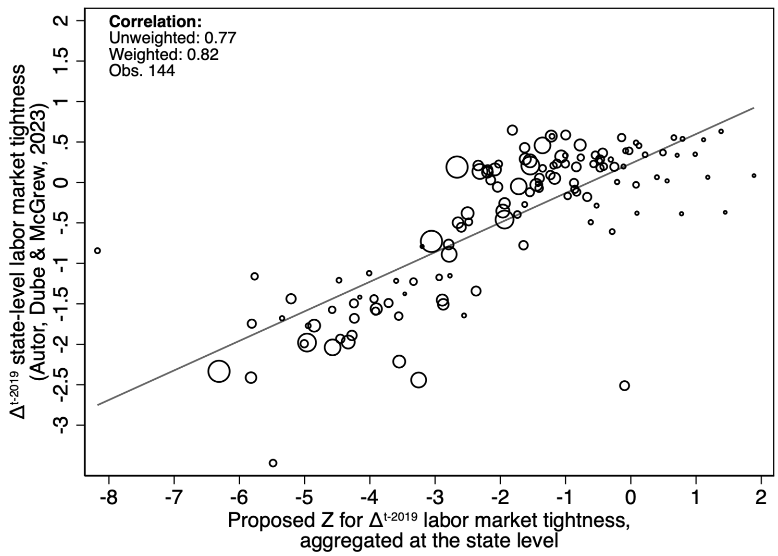
[24] In the JOLTS such disaggregation by sector is unavailable at the state level, or at any smaller geographical level, further limiting the scope of the analysis in geographical terms. On the contrary, we observe the county code for each job posting, allowing us to build our measure at the commuting zone level.

However, Lightcast is able to capture the almost entirety of openings for the US, providing us with details on crucial dimensions of postings, and we highly value this advantage. At the same time, there is no guarantee that application activity on a platform captures job search accurately as users are likely to be only a subset of the whole population of job seekers.

A.3 More on heterogeneity

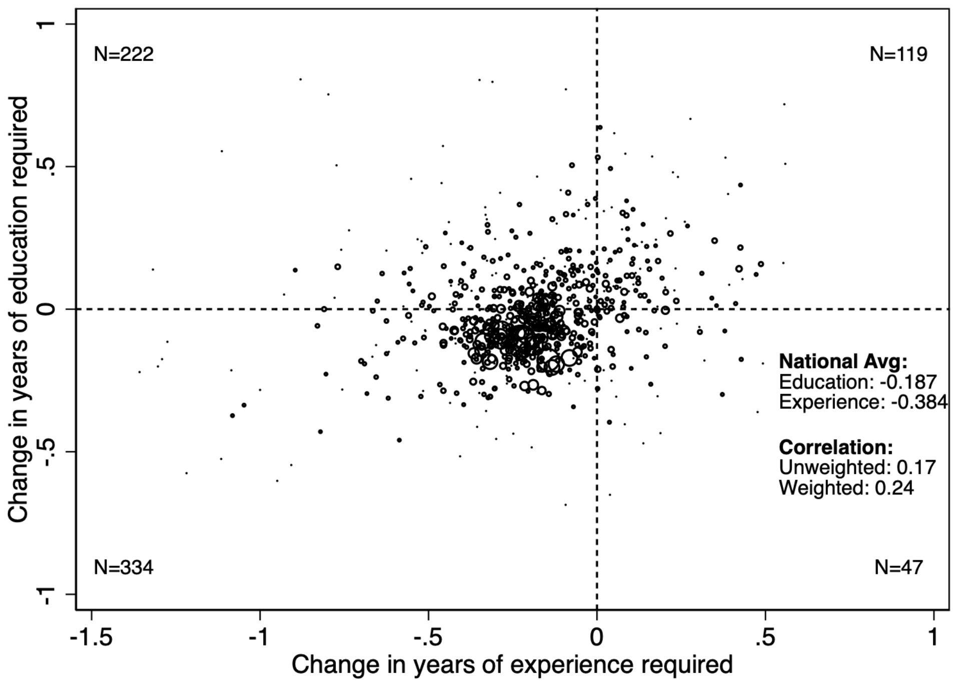
While we observe a great degree of heterogeneity across locations, it is hard to comment on the correlation between the changes in education and experience from previous figures. Hence, in Figure 11, we plot the correlation between the changes in the two intensive margins for the 722 commuting zones of the contiguous US. 46% of commuting zones display a decline in both and are located in the third quadrant. The correlation coefficient between the changes is 0.17 but it goes up to 0.24 once we weight by the 2019 population of each commuting zone. As a benchmark for interpreting this heterogeneity, national average changes in the intensive margins between 2019 and 2022 are reported.

Figure 10: Changes in Autor et al. (2023)'s labor market tightness vs. our proposed instrument



Notes: This figure benchmarks changes in Autor et al. (2023)'s proposed measure of labor market tightness to our instrument for local tightness. While our instrument captures changes in yearly tightness at the commuting zone (CZ) level from online postings, their measure is built as the average of state-level employment-to-employment separation rate and negative unemployment rate (both standardized), and it is available biannually at the state level. To make the two measures comparable, we start by aggregating ours to the state level using the crosswalk provided by Autor and Dorn (2013) and weighting by the 2019 population of each CZ. Then, we take the average of the two 6-month levels of their measure for each year and state. Since our instrument captures changes in tightness relative to 2019, we also take the difference of their annualized measure in 2020, 2021 and 2022 with its 2019 level. As usual, we exclude Alaska and Hawaii. Changes in tightness are not available for Arkansas, Mississipppi, and Tennesse, and as a result, these states do not appear in the graph. Each point represents a state-by-year observation. Size of the marker represents the state's share of national population in 2019. We report weighted and unweighted correlation coefficients.
Source: Calculations by Autor et al. (2023), Lightcast, LAUS.

Figure 11: Correlation between 2019-2022 changes in intensive margins by commuting zone



Notes: This figure shows the relationship between 2019-2022 changes in the average intensive margins (years of education on the y-axis, years of experience on the x-axis) by commuting zone. Each point represents a commuting zone, and the size of the marker represents 2019 population. Commuting zones with changes below the 1 percentile and above the 99 percentile of the distribution of changes are not displayed.
Source: Lightcast online job postings.

B Validity of the shift-share instrument

This section aims at strengthening the credibility of our empirical design by conducting some of the validity tests prescribed by Goldsmith-Pinkham, Sorkin, and Swift (2020). The Bartik estimator can be decomposed into a weighted sum of the just-identified instrumental variable estimators that use each industry share (π_{jk}) as a separate instrument. The weights, called Rotemberg weights, can be interpreted as sensitivity-to-misspecification parameters, and tell us how sensitive the over-identified estimate of our coefficient of interest is to misspecification (i.e., endogeneity) in any instrument. In order words, they describe the research design: by telling us which exposure design gets more weight in the overall estimate, and thus which of these identifying assumptions is most worth testing, they make clear which variation in the data the estimator is using. In this setting, important comparisons are across places with greater and smaller shares of top 5 industries according to the weights. Hence, testing the specification validity for the sub-sample of industry-specific shares that affect the most the overall 2SLS estimation will reassure on the general validity of our estimations.

We start by computing the Rotemberg weights for each industry to identify the top 5 industries in terms of weights. Panel C in Table 7 lists these industries: *Transit And Ground Passenger Transportation*, *Educational Services*, *Ambulatory Health Care Service*, *Food Service and Drinking Places*, and *Hospitals*. The top 5 instruments together receive almost exactly half of the absolute weight of the estimator (0.518/1.044). Since these instruments refer to the industries that should motivate the empirical strategy, we are reassured to see that they are well-aligned with our expectations. According to our narrative, in these industries, firms should have difficulty in hiring and filling their vacancies during and after the pandemic due to declines or surges of demand. It should be plausible that a labor shortage was the main shock hitting the industry rather than, for instance, simultaneous technological innovations increasing demand (and ultimately affecting changes in skills). It would have been particularly problematic if, for instance, industries prone to secular technological changes had received large weights (as in the case of Autor, Dorn, and Hanson (2013)). In addition to that, we can see in Panel A that the share of industries with negative weights is pretty low.

Importantly, Panel B shows that the national growth rates g_k provide a pretty reliable guide to which industries drive estimates, as the shocks g_k explain an important portion of the variance of the Rotemberg weights (see the correlation between α_k and g_k). Panel B also highlights that weights are not very related to the variation in industry shares across locations ($var(z)$). This does not come as a surprise since our top 5 are not examples of tradables, which by definition have industry shares that vary a lot across locations.

We conclude by showing the relationship between each industry-specific IV's β_i and the first-stage F-statistic in Figure 12. The dispersion in the point estimates among the high-powered industries is low and the high-weight industries appear to be clustered closely to the overall point estimate.

Table 7: Summary of Rotemberg weights

Panel A: Negative and positive weights

	Sum	Mean	Share
Negative	-0.044	-0.007	0.040
Positive	1.044	0.013	0.960

Panel B: Correlations of Industry Aggregates

	α_k	g_k	β_k	F_k	$\mathrm{Var}(z_k)$
α_k	1				
g_k	0.689	1			
β_k	-0.002	0.133	1		
F_k	0.079	0.224	-0.125	1	
$\mathrm{Var}(z_k)$	0.185	0.129	-0.029	0.002	1

Panel C: Variation across years in α_k

	Sum	Mean
2020	0.061	0.001
2021	0.256	0.003
2022	0.683	0.008

Panel D: Top 5 Rotemberg weight industries

	$\hat{\alpha}_k$	g_k	$\hat{\beta}_k$	95 % CI	
Transit And Ground Passenger Transportation	0.309	1.34e+06	0.717	(0.700,0.900)	0.610
Educational Services	0.064	3.67e+05	0.741	(0.700,0.700)	9.787
Ambulatory Health Care Services	0.056	8.61e+05	0.661	(0.600,0.600)	5.324
Food Services And Drinking Places	0.049	7.69e+05	0.619	(0.600,0.600)	6.237
Hospitals	0.040	3.92e+05	0.679	(0.600,0.700)	5.375

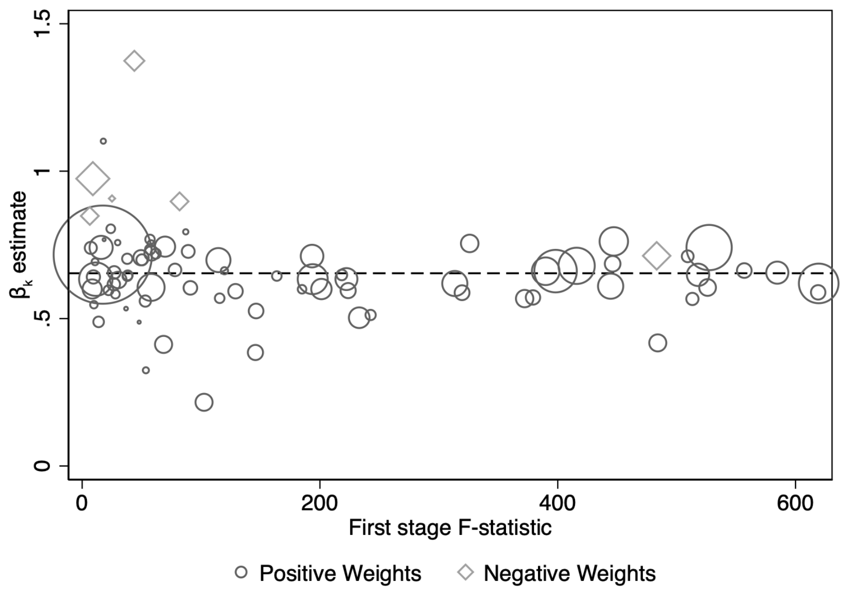
Panel E: Estimates of β_k for positive and negative weights

	α-weighted Sum	Share of overall β	Mean
Negative	-0.041	-0.063	0.952
Positive	0.695	1.063	0.632

Notes: This table reports results from the Rotemberg decomposition. We use the change in the (log of) posted salaries, i.e. intensive margin, as outcome of interest.

While there are negative Rotemberg weights, these industries are few and only small share of the overall weight.

Figure 12: Relationship relationship between each industry-specific IV's β_k and first stage F-stat

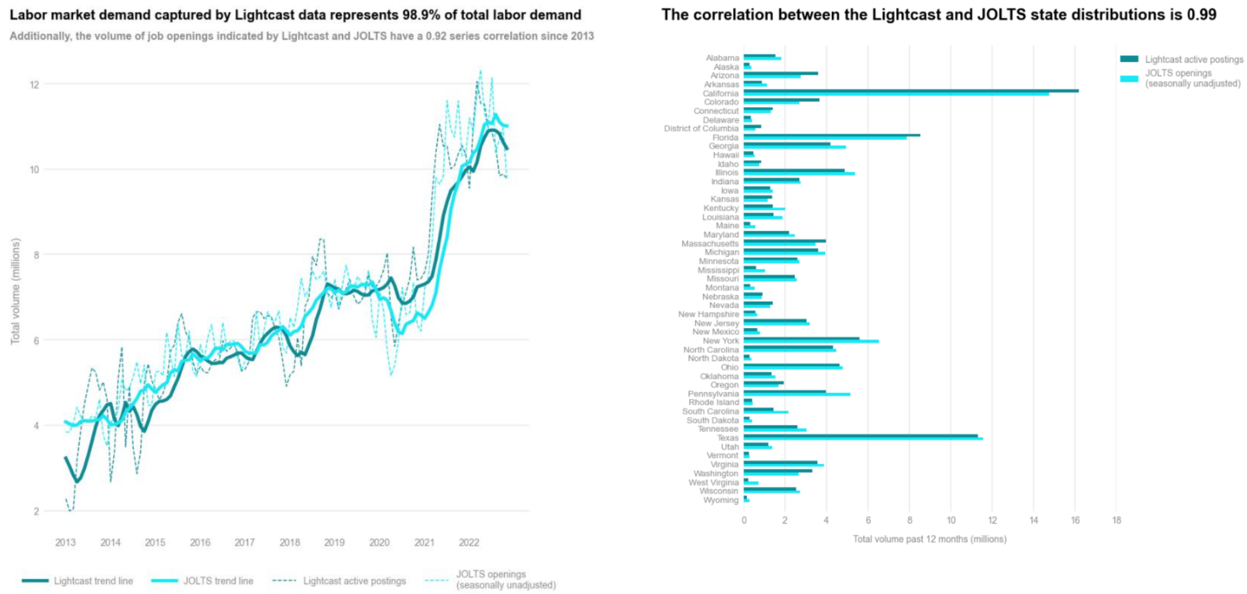


Notes: This figure shows the relationship between each industry-specific IV's β_k and first stage F-stat. Each point is a separate instrument's estimates (industry share). The figure plots the estimated β_k for each instrument on the y-axis and the estimated first-stage F-statistic on the x-axis. The size of the points areflects the magnitude of the Rotemberg weights, with the circles denoting positive Rotemberg weights and the diamonds denoting negative weights. The horizontal dashed line is plotted at the value of the overall $\hat{\beta}$. Only instruments with F above 5 are reported.

C Complementary evidence

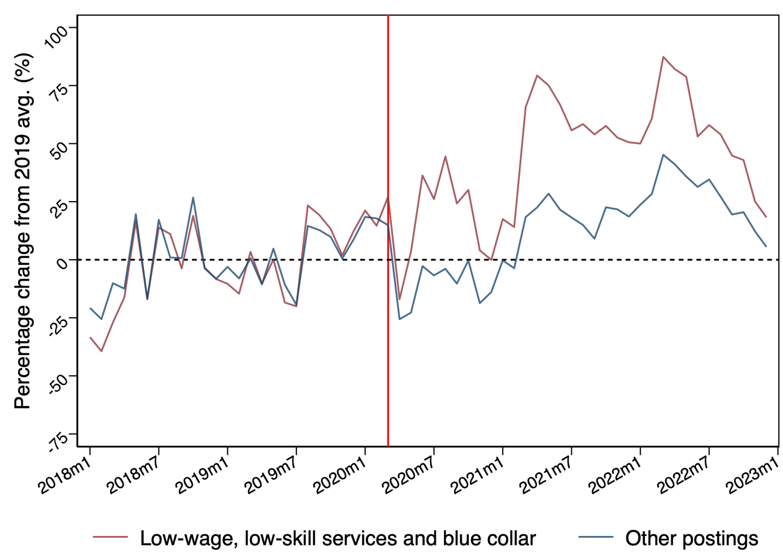
Figure 13: Representativeness of Lightcast sample of online job postings

(a) Time (b) Geography



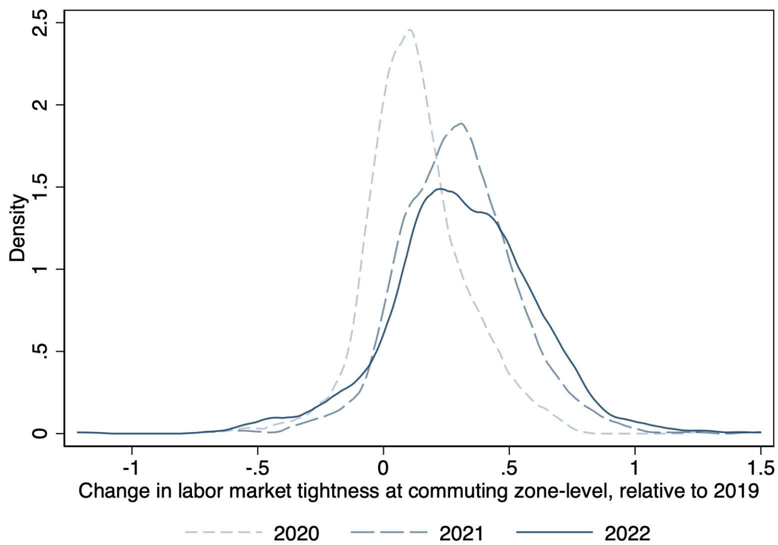
Source: Lightcast.

Figure 14: Time series of job postings by group



Notes: This figure displays the evolution of online job postings over time relative to averages across 2019 months by group. We restrict the sample to postings that report valid information for industry, occupation and location (county). We drop postings from Alaska and Hawaii. We only keep non-farm, non-military private sector postings.
Source: Lightcast online job postings.

Figure 15: Labor market tightness over time



Notes: This figure displays the probability density estimation of the change in labor market tightness relative to 2019 across commuting zones, our main regressor described in equation (3). We plot the density separately for the 2019-2020 (short dashed light blue line), the 2019-2021 (dashed blue line), and the 2019-2022 (solid dark blue line) changes.
Source: Lightcast, LAUS.