Recruitment Competition and Labor Demand for High-Skilled Foreign Workers

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Abstract

This paper estimates the causal effect of recruitment competition on the labor demand for high-skilled foreign workers. I assemble a new data set, combining a firm-level panel of all Labor Condition Applications (LCAs) submitted as a first step to obtaining H-1B visas between 2010 and 2019 with online job vacancies and data on venture capital (VC) investments. I use plausibly quasi-exogeneous variation in VC investments in start-ups to instrument yearly changes in recruitment competition at the local labor market level. I find that a one standard deviation increase in the number of job postings advertised by start-ups yields an 8 percent increase in the number of LCAs submitted by employers in the market and a 3 percent increase in the wages advertised in these LCAs. Estimates are only significant for computer occupations. These results support the role of labor market tightness in explaining the absence of the crowding-out effect from H-1B workers against close native substitutes.

Keywords: Labor Market Tightness; Skilled Workers; H-1B

JEL Classification Numbers: F22; J23; J61

1 Introduction

"Do immigrants crowd out native workers?" This is one of the most important questions in the economic literature on migration. According to the canonical model of competitive labor demand and supply, an influx of foreign workers is theorized to negatively impact the employment of native workers with similar skills. However, when considering high-skilled immigrants, empirical evidence does not support this prediction. The US context gives a perfect example of the absence of empirical evidence to support this crowding-out effect. Focusing on the H-1B visa program,the main employment-based type of visa for college-educated foreign workers in the United States,Peri et al. (2015) document a positive effect of H-1B inflows on total native employment. Kerr et al. (2015) focus on the effect on skilled native employment growth at the firm level, showing that this effect is positive for younger natives but null for older ones. Doran et al. (2022) provide causal evidence of the crowding-out effect of H-1B workers against other foreign workers but do not show any effect against native workers. This paper does not attempt to estimate this crowding-out effect; rather, it posits that labor market tightness can explain the lack of a crowding-out effect from high-skilled immigrants against native workers in previous empirical research.

Employers recruiting H-1B workers often claim that their recruitment of skilled foreign workers results from their search for the "very best talent." In a testimony before the US Congress Committee on Science and Technology on March 12, 2008, Microsoft Chairman Bill Gates urged policymakers to take actions "to address the shortage of scientists and engineers." He proposed relaxing immigration policy constraints in general and in particular to increase the H-1B visa quota to help "companies to attract and retain the very best talent, regardless of nationality and citizenship."

This argument suggests that these employers are recruiting in tight labor markets, where labor demand cannot be filled with US workers alone. Tight labor markets might partly explain the absence of evidence of a crowding-out effect against native workers. In an ideal experiment to identify the crowding-out effect of H-1B workers against close native substitutes, one would randomly draw two groups of firms searching to recruit for similar positions. Only the treatment group would be authorized to recruit H-1B workers. In a frictionless labor market, one would expect that firms in the control group would recruit native workers to fill their vacancies. The crowding-out effect would be identified by comparing changes in native employment between both groups. In a tight labor market, employers from the control group might not succeed in recruiting native workers, leaving some of these vacancies unfilled. In this context, the difference in changes in native employment would be smaller than in a frictionless labor market, thereby reducing the estimated crowding-out effect.

In this paper, I investigate the effect of an increase in recruitment competition on firms' labor demand for high-skilled foreign workers. Therefore, this analysis explores whether tight labor markets can explain the absence of evidence of the crowding-out effect. I focus on the H-1B visa program, the largest US temporary visa program for highly skilled workers who have attained at least a bachelor's degree. I assemble a new data set by combining a firm-level panel of all Labor Condition Applications (LCAs) ever submitted as a first step to obtaining H-1B visas between 2010 and 2019 with online job vacancies and data on venture capital (VC) investments in start-ups. I structure the data across cells defined by employer, six-digit Standard Occupational Classification (SOC) code, and year. For each cell, I observe the number of LCAs submitted. I also measure the exposure of each cell to recruitment competition from local start-ups. This corresponds to the total number of vacancies advertised by start-ups recruiting on the same local labor market as defined by county, six-digit SOC code, and year. To account for endogeneity and omitted variable biases, I use plausibly quasi-exogeneous residual VC investments in start-ups to instrument yearly variation in the recruitment competition generated by the corresponding innovative companies.

Accurately measuring labor market tightness is challenging. This likely explains why only a few studies have investigated the aforementioned labor market tightness narrative despite its importance in the immigration debate over the past decades (Raux, 2021; Signorelli, 2022). Labor market tightness reflects imbalances between labor demand and labor supply. Job search models refer to this concept as the ratio between the number of job vacancies on a given labor market and the number of available workers in this market. Measuring the denominator of this ratio raises several challenges. First, job search models approximate the number of available workers with the number of unemployed, a method that becomes problematic when focusing on high-skilled labor markets where unemployment is less prevalent and job-to-job transitions are more frequent. Second, measuring labor supply at a granular level is particularly challenging, as it requires imputing the type of occupations in which each worker can potentially be recruited. This cannot be done without introducing strong assumptions and measurement errors.

I address this challenge by focusing on variation in recruitment competition, which is not subject to these measurement issues. I use the total number of job postings advertised each year by start-ups in each local labor market as a proxy for recruitment competition. Focusing on start-up job postings rather than considering the vacancies advertised by all other employers in the local labor market has two advantages. Because the instrumental variable (IV) leverages variation in only start-up job postings, restricting the measure of recruitment competition to start-ups better highlights the ordinary least squares (OLS) bias corrected by the IV. In addition, this restriction emphasizes the specific variation exploited with the IV. The relationship between the labor demand for H-1B workers and recruitment competition can be interpreted in terms of labor market tightness if variation in the labor supply is held constant in the specification. I include a series of fixed effects in some specifications to eliminate variations associated with changes in the labor supply.

Assessing whether employers seek to recruit H-1B workers in response to tight labor markets is a causal question. A naïve OLS regression of the number of LCAs on the number of job postings advertised by local start-ups might be affected by several biases, prohibiting a causal interpretation. Omitted variables affecting both the labor demand for H-1B workers and the total labor demand from start-ups generate a bias. The first source of bias relates to omitted local labor market conditions. For example, a positive shock to the local economy might increase employers' labor demand, which might translate into an increase in both the number of job postings advertised by local start-ups and the number of LCAs submitted by other employers. A second source of bias relates to the unobserved changes in the labor supply of US workers. An increase in the number of available US workers in the local labor market might decrease the labor demand for H-1B workers, while start-ups in this market might view this as a recruitment opportunity, thereby increasing their number of advertised vacancies. One of the main contributions of this paper is to provide an IV approach allowing for a causal interpretation of the relationship between recruitment competition and the labor demand for H-1B workers.

The identification strategy instruments the changes in the number of job postings advertised by local start-ups with VC investments in these start-ups. The relevance of this IV builds on both the data and the literature. Haltiwanger et al. (2013) document that start-up recruitment accounts for a significant portion of US job creation. Consistently, I find that, on average, vacancies advertised by start-ups represent 10 percent of all the job postings advertised by local labor markets for management, business, computer, and engineer occupations. In addition, Bertoni et al. (2011) show the positive causal impact of VC investments on start-ups' employment growth. I predict the total number of vacancies advertised by start-ups using the plausibly quasi-exogeneous component of VC investments received by these start-ups, after controlling for county-by-year fixed effects. This prediction is orthogonal to time-varying shocks affecting the local economy. I document a positive and significant correlation between residual VC investments and the number of vacancies advertised by these start-ups, establishing that such an instrument is plausibly exogenous and reasonably strong.

The main findings are as follows. First, I find that a one standard deviation increase in the number of job postings advertised by start-ups in the local labor market increases the number of LCAs submitted by employers recruiting in this market by 8 percent. It also increases the wages advertised in these LCAs by 3 percent. Second, I find that these results only hold for LCAs submitted for computer occupations. Estimates associated with other types of occupations are both smaller in magnitude and insignificant. These results are consistent with a labor market tightness narrative where employers increase their labor demand for H-1B workers when the supply of US workers in the local labor market becomes tighter. Therefore, they provide an additional explanation for the absence of a crowding-out effect from H-1B workers against close native substitutes.

Previous literature has documented three other mechanisms that partly explain the absence of the crowding-out effect. First, foreign and US workers of similar education might supply varied skills and be considered imperfect substitutes (Ottaviano and Peri, 2012; Peri and Sparber, 2009; Peri and Sparber, 2011). Second, high-skilled foreign workers generate long-run productivity gains and economic growth (Hunt and Gauthier-Loiselle, 2010; Kerr and Lincoln, 2010; Moser et al., 2014; Peri et al., 2015). Each of these arguments provides a reason to explain how immigration inflows might positively affect native employment in some contexts. However, they seem insufficient to explain the short-run absence of the crowding-out effect from H-1B workers at the firm level.[1]

Third, firms respond to negative immigration shocks by adapting their production inputs through offshoring (Ottaviano et al., 2013; Olney, 2012; Glennon, 2023), technology adoption (Lewis, 2011; Clemens et al., 2018) or by recruiting other immigrant workers (Sparber, 2019; Mayda et al., 2020; Abramitzky et al., 2023). These papers suggest that employers that cannot recruit H-1B workers use one of these adjustments rather than recruiting US workers, which may explain the absence of a crowding-out effect. Labor market tightness might be one reason explaining this choice. My results complement this literature by documenting this channel, which is particularly relevant in the H-1B context.

This paper also contributes to the literature studying firms' implications of labor scarcity, which mostly considers the effect of labor scarcity on technology adoption (Capretttini et al., 2022; Franck, 2022), firm performance (Sauvagnat and Schivardi, 2023; D'Acunto et al., 2020; Mayda et al., 2020; Barbanchon et al., 2022), and recruitment strategies (Sparber, 2019; Mayda et al., 2020). My paper complements the latter. To the best of my knowledge, I am the first to document the causal impact of an increase in recruitment competition on firms' labor demand for high-skilled foreign workers.

Finally, this paper relates to the broad literature on the labor market impact of immigration. Dustmann et al. (2016) propose a survey of this literature. More precisely, it complements the vast body of research on the labor market implications of the H-1B visa program (Mithas and Lucas, 2010; Kerr et al., 2015; Peri et al., 2015; Bound et al., 2015; Aobdia et al., 2018; Mayda et al., 2018; Mayda et al., 2020; Doran et al., 2022).

[1] US and H-1B workers are likely to be perfect substitutes because a majority of the latter has also graduated from US universities and benefited from the same education as US workers (Beine et al., 2023)

The rest of the paper is organized as follows. Section 2 presents the different sources of data. Section 3 details the identification strategy. Section 4 presents the results, and Section 5 concludes.

2 Data

One of this paper's main contributions is the creation of a new database that allows me to tackle the two identification challenges presented in the introduction. First, it provides a granular-level measure of recruitment competition for high-skilled occupations. Second, it enables me to implement a new IV strategy to causally interpret the results. This database gathers administrative data with information from two big online data sources. It combines exhaustive data on employers that have started the administrative process to obtain H-1B visas with online-collected measures of recruitment competition and VC investments in start-ups.

2.1 Data on LCAs

The first source of data gathers LCAs from the US Department of Labor. The initial step of the administrative process to sponsor a foreign worker under the H-1B visa program is to submit an LCA to ensure the job is eligible for the program. The data include detailed information on the position associated with each LCA (six-digit SOC code, advertised wage for the job) as well as identifying information on each sponsoring employer including its name, city, and industry.

This data set enables me to observe the exhaustive pool of employers that have started the administrative process to obtain H-1B visas between 2010 and 2019. In the context of this paper, an employer corresponds to an establishment of a given company in a specific location. The data include more than 214,000 distinct employers that have submitted LCAs for more than 4 million different positions. Most LCAs (72 percent) are associated with computer-related occupations, 10 percent with business occupations, 6 percent with engineer occupations, and 3 percent with management positions.

I assemble a balanced panel structured across cells. Each cell is defined by year, employer, and occupation as measured by six-digit SOC codes. The panel includes every employer that has ever submitted an LCA to obtain government permission to recruit an H-1B worker. The main outcome I consider in this paper is the log number of positions associated with LCA petitions by cell. Employers also have to report the indicative wage offered for these positions in their LCA petitions. In additional specifications, I consider the log of wages advertised in LCAs as another outcome.

LCAs are different from actual H-1B applications as they only correspond to the first step of the H-1B visa application process and some LCAs are not followed by an actual H-1B application (Doran et al., 2022). Therefore, LCAs represent an imperfect indicator of the aggregate demand for H-1B workers. However, they represent a second-best approximation, for two reasons. First, exhaustive data on H-1B applications are not available.[2] Second, distinguishing between H-1B applications and LCAs is not problematic in the context of this paper. Submitting an LCA represents a first signal of the employer's interest for H-1B workers. This interpretation holds even if the LCA is not followed by an actual H-1B application. I explore the sensitivity of the results to this approximation in robustness analyses.

[2] The H-1B Employer Data Hub of the US Citizenship and Immigration Services only includes information on H-1B visa applications that are selected in the lottery, while the rejected applications are returned unopened to the employers.

2.2 Data on Online Job Vacancies

The second source of data gathers online job vacancies advertised on US job boards between 2010 and 2019. The data are from Burning Glass Technologies (BGT) and arguably cover the near-universe of job vacancies advertised in the United States (Hershbein and Kahn, 2018). They enable me to measure the number of job postings advertised by start-ups in each local labor market (defined by county and six-digit SOC code) each year. I use this measure, standardized at the local labor market level, as a proxy for recruitment competition.

Start-ups are defined as employers that are included in both BGT and Crunchbase data, the third and last source of data described below. I identify start-ups included in both data sets using a fuzzy matching algorithm based on company names. This sample includes almost 10,000 distinct start-ups distributed across the United States. The average number of start-ups per local labor market is 41, and half of these companies advertise more than 9 vacancies annually in these markets.

2.3 Data on VC Investments

The third and last source of data details VC investments in US start-ups. The data come from Crunchbase.com, the largest crowdsourcing platform for US start-ups. Crunchbase is a VC analytics company whose database represents the "premier data asset on the tech/start up world" used by the capital venture industry (Dalle et al., 2017). The company collects data through its partnership with "more than 3,700 investment firms that submit monthly portfolio updates."[3] The data collection process is completed by 500,000 executives, entrepreneurs, and investors belonging to the community of Crunchbase data users, data analysts working for Crunchbase, and machine learning algorithms that validate data accuracy and scan for anomalies.

Crunchbase data include information on more than 150,000 rounds of VC investments in more than 75,000 distinct innovative companies from start-ups to the Fortune 1000 between 2010 and 2019. The data gather information on most types of VC investments from seeds to post-IPO equity and report, in most cases, the amount of capital involved. I restrict the sample to start-ups by only including companies that have not yet initiated an IPO at the time they are observed in the data. I use this data set to measure VC investments in start-ups and instrument yearly variation in recruitment competition at the local labor market level.

[3]A description of the data is made available by Crunchbase at the following address: https://about.crunchbase.com/products/the-crunchbase-difference/, accessed on December 28, 2022.

3 Identification Strategy

In this section I present the identification strategy. I first detail and formalize the hypothesis to be tested, and then present the IV strategy and discuss the interpretation of the estimates. Finally, I highlight the potential limits of the identification and what I do to address these issues.

3.1 Test Hypothesis

Employers that try to recruit in tight sections of the US labor market can expand their pool of potential candidates by considering foreign workers in addition to US nationals. Many foreign candidates already live in the United States. Some are enrolled in US colleges under F-1 student visas, while others already work in the US labor market with an optional practical training (OPT) employment authorization, an extension of their F-1 student visa. More than OPTs, the H-1B visa program represents the main program of temporary visas for skilled foreign workers who have attained at least a bachelor's degree. Visas are issued for three years and can be renewed once. Over the last few years, a very large majority of H-1B visa recipients were previously working in the United States with an OPT employment authorization (Beine et al., 2023).[4]

In contrast with recruiting US citizens, recruiting workers under H-1B visas requires employers to sponsor foreign candidates, which involves administrative and pecuniary costs. Even if both US and foreign workers graduated from US universities, these costs may negatively affect the relative preference for the latter. However, when the labor market becomes tighter and the labor supply of US workers becomes scarcer, the benefit of recruiting an H-1B worker compared to leaving the vacancy unfilled might offset these costs. An increase in recruitment competition might therefore increase employers' labor demand for H-1B workers.

This is consistent with a simple search model where employers choose between considering only US citizens in their recruitment or considering both US and H-1B workers. Employers' choice relies on comparing the expected present values associated with each option. The model suggests that employers prefer the second option when the additional cost associated with recruiting H-1B workers is smaller than a given threshold. This threshold decreases with the employer's ability to find a US worker to fill the vacancy in the next period, a decreasing function of the recruitment competition in the market. Within this framework, an increase in recruitment competition increases the threshold below which employers consider both types of workers in their recruitment.

Figure 1 illustrates this situation with the cumulative distribution function of employers that differ in their costs to recruit foreign workers. For simplicity, I assume that each employer only seeks to fill one vacancy and additional costs associated with recruiting H-1B workers are normally distributed across employers. The vertical black lines correspond to the thresholds where employers are indifferent between the two recruitment options. Only those whose cost is below the threshold consider both US and H-1B workers in their recruitment. The difference between the left and right panels shows the increase in the threshold associated with an increase in recruitment competition. This highlights the positive impact on the number of employers willing to consider both types of workers in their recruitment.

[4] H-1B visa holders were not necessarily working for the same employer when previously working under OPT.

Figure 1. Increase in Recruitment Competition and Search for H-1B Workers

Notes: The graph illustrates how an increase in recruitment competition from RC to RC' affects employers' labor demand for H-1B workers. Each panel represents the cumulative distribution function of employers that differ in the additional cost they face to recruit H-1B workers. The black vertical lines highlight the thresholds below which employers consider both US and H-1B workers in their recruitment.

3.2 IV Strategy

To measure how employers respond to changes in recruitment competition, I regress the log number of LCAs ($\log(LCAs_{iot})$) submitted by employer i, for occupation o (measured by six-digit SOC code), in year t on the number of job postings ($JP_{c(i)ot}$) advertised by start-ups in the same county c as employer i, for the same occupation o, in the same year t. I focus on the relationship between LCA submissions and job postings advertised only by start-ups in order to maintain consistency with the identification strategy presented below.

The estimate capturing this relationship exploits yearly variations across local labor markets, the data allow me to include more granularity in the analysis. I take advantage of this data feature and use cells defined by employer, occupation, and year as the unit of observation.

This enables me to eliminate variation associated with time-constant employer-occupation specificities. This approach will also be useful to consider heterogeneous responses across employers, later in the analysis. The main specification is the following:

$$\log(LCAs_{iot}) = \beta_1 JP_{c(i)ot} + \beta_{io} + \beta_t + \varepsilon_{iot}, \tag{1}$$

where β_{io} is a set of employer-by-occupation fixed effects and β_t is a set of year fixed effects. In robustness specifications, I also include a set of state $\times$ four-digit SOC code $\times$ year fixed effects to eliminate variation associated with state-specific time trends in the labor supply.

The estimated β_1 from Equation (1) intends to capture the average response from employers to an increase in the local recruitment competition resulting from the labor demand of start-ups. However, omitted variables in Equation (1) can bias the estimation of β_1. To address this issue, I instrument the number of job postings advertised by local start-ups with variations in VC investments in these start-ups.

The choice of the IV relies on two results of the literature. First, Haltiwanger et al. (2013) show that start-up recruitment plays an important role in US job creation.[5] Second, Bertoni et al. (2011) document the positive causal effect of VC investments on start-ups' employment growth. These two results support the relevance of the instrument.

In addition, I only consider a subset of the variation in VC investments that are not correlated with changes in the local labor market. This approach builds on Borusyak and Hull (2021) and Beine et al. (2023). The former suggests controlling for nonrandom variations in the instrument and testing whether the remaining variation can be interpreted as quasi-random. The latter provides an example of such an identification strategy. Accordingly, my approach follows a two-step procedure.

In the first step, I extract residual variation in VC investments in start-ups. This specification is estimated at the start-up level to eliminate variation associated with average changes in the local labor market. I regress VC investments (VCI_{st}) in each start-up s on each year t on a set of county-by-year fixed effects ($\eta_{c(s)t}$):

$$VCI_{st} = \eta_{c(s)t} + \upsilon_{st}. \tag{2}$$

The residuals obtained from this specification (υ_{st}) depend on start-ups' specificities, but they are orthogonal with time-specific shocks affecting the local economy. I interpret these residuals as a measure of the "quasi-random" VC investments in start-ups.[6]

In the second step, I aggregate the residuals from Equation (2) by county c and year t and use this measure as an instrument to predict $JP_{c(i)ot}$, the number of job postings advertised by the corresponding start-ups in county c for occupation o in year t. This corresponds to the estimation of the following first-step equation:

$$JP_{c(i)ot} = \alpha_1 \sum_{s \in c} \hat{\upsilon_{st}} + \alpha_{io} + \alpha_t + \epsilon_{iot}. \tag{3}$$

The estimation of Equation (3) only exploits yearly changes across local labor markets. However, Equations (1) and (3) are simultaneously estimated with a two-stage least-squares regression (2SLS) procedure. The units of observation must be the same in both specifications and correspond to cells defined by employer i, occupation o, and year t. Consequently, job posting residuals in Equation (3) are likely to be correlated across employers located in the same local labor market. I account for this issue by clustering standard errors by county and occupation. Finally, the 2SLS procedure also requires me to include similar control variables in both specifications. α_{io} corresponds to a set of employer-by-occupation fixed effects, and α_t is a set of year fixed effects.

[5] Using BGT data, I find that for management, business, computer, and engineering occupations, vacancies from start-ups represent 10 percent of the job postings advertised by local labor markets, on average.

[6] "Quasi-random" must be understood as quasi-random regarding local labor market changes.

These specifications only consider local variation in recruitment competition, a restriction motivated by the IV research design. Recruitment competition at the local level is particularly relevant as most US and international graduates stay in the same metropolitan area as their university upon entering the labor market (Conzelmann et al., 2022; Beine et al., 2023). However, this restriction might prevent me from capturing the complete relationship between employers' LCA submissions and other sources of friction affecting the labor market on a broader scale. In addition, an increase in labor demand in one specific county might also increase the recruitment competition faced by employers elsewhere, especially if recruiting transcends county boundaries. Therefore, I might underestimate the differences in relationships between recruitment competition and the number of LCAs submitted by employers located in different counties. Considering these two reasons, my results should be interpreted as lower-bound estimates.

3.3 Limits of the Identification Strategy

In addition to the identification challenges previously mentioned, there are three potential alternative channels between VC investments and the number of LCAs submitted that might alter the causal interpretation associated with recruitment competition. The first channel relates to competition in funding opportunities among start-ups. Consider the following example involving an employer A and a start-up B to illustrate this potential issue. If VC investments in start-up B reduce funding opportunities for employer A, it might also affect the number of LCAs submitted by employer A through a channel other than recruitment competition. In the next section, I present descriptive evidence that nuances the plausibility of this alternative channel.

The second channel relates to the unobserved potential cooperation between employer A and start-up B. For example, if employer A is a subcontractor of start-up B, VC investments in B might also boost labor demand from A, including the demand for H-1B workers. In one robustness analysis, I control for this alternative channel by including the yearly number of vacancies advertised by employer A in my specification.

The last channel relates to the unobserved potential monopsony power of employer A in the local labor market. In this situation, a reverse causality channel might emerge where changes in the labor demand of employer A affect VC investments in start-up B. I investigate whether this alternative channel is likely to drive the results by replicating the main specification on a subsample excluding the largest employers from each local labor market. The results of these robustness tests are presented in the following section and in the online appendix. They all support the causal interpretation associated with the recruitment competition channel.

4 Results

I first present empirical evidence in support of the relevance of the instrument. Table 1 presents start-up-level regression results of the relationship between VC investments and the number of online job vacancies advertised. These specifications only exploit within-firm variation over years by controlling for year and employer × six-digit SOC code fixed effects. The results show a positive and significant association between the amount of VC investments received by start-ups and their number of advertised vacancies across most types of occupations. However, the only exception is for engineer occupations, where the correlation is positive but not statistically significant. The IV strategy builds on these results but only exploits some of the variation captured in these estimates. Variations of the instrument are aggregated at the local labor market level and do not account for time-specific local shocks in VC investments.

Table 1. Relationship between VC Investment in Each Start-Up and Its Number of Online Job Vacancies Advertised

Dependent Variable:	Number of Vacancies by Start-Up					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	All Occupations	Main Occupations	Management	Business	Computer	Engineer
VC Investments by Start-Up	0.0173*** (0.0046)	0.0139*** (0.0035)	0.0067*** (0.0012)	0.0030*** (0.0006)	0.0034** (0.0016)	0.0009 (0.0005)
Observations	79,910	79,910	79,910	79,910	79,910	79,910
Employer FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the relationship between VC investments in each start-up and its number of online job vacancies advertised. Column (1) considers all types of occupations. Column (2) restricts the analysis to management, business, computer, and engineer occupations. The rest of the columns successively focus on each one of these occupations. Standard errors are clustered by start-up. Sources: BGT, Crunchbase, and the US Department of Labor.

I then assess the validity of the IV estimates with three empirical exercises presented in Table 2. Panel A investigates one of the alternative channels previously mentioned: competition in funding opportunities. It presents descriptive evidence suggesting that VC investments in start-ups do not significantly relate to VC investments in similar start-ups where similarity is successively defined by county, state, or industry. The first three columns focus on start-ups included in the main analysis. The results hold when I expand the analysis to all start-ups with funding information included in Crunchbase, as shown in the last three columns. These results suggest that this alternative channel should not alter the causal interpretation of the IV estimates.

Panel B presents the results of another falsification exercise. To be valid, residual VC investments should only predict the number of vacancies advertised by the corresponding start-ups but should not (directly) affect other companies. The panel shows that residual VC investments in start-ups do not significantly predict the number of vacancies advertised by other companies recruiting on the same local labor market. The coefficients are not significant across several specifications where standard errors are clustered in different ways. This result supports the exogeneity of the instrument concerning local labor market shocks.

Table 2. Three Tests of Validity of the Instrument

Panel A: Relationship between Changes in VC Investments in Start-Ups and Changes in VC Investments in Similar Start-Ups

Dependent Variable:	Changes in VC Investment by Start-Up					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	Start-Ups Included in BGT Data			All Start-Ups		
Changes in VC Investments in Start-Ups from the Same County	0.0003 (0.0002)			0.0003 (0.0002)		
Changes in VC Investments in Start-Ups from the Same State		-0.0000 (0.0002)			-0.0000 (0.0002)	
Changes in VC Investments in Start-Ups from the Same Industry			0.0002 (0.0004)			0.0002 (0.0004)
Observations	70,999	71,001	71,001	71,377	71,379	71,379
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Additional FE by	County	State	Industry	County	State	Industry
Std Errors Clustered by	County	State	Industry	County	State	Industry

Panel B: Relationship between IV and Number of Vacancies Advertised by Nonstart-ups

Dependent Variable:	Number of Vacancies Advertised					
	(1)	(2)	(3)	(4)	(5)	(6)
Residual VC Investments	-0.0511 (0.0400)	0.0127 (0.0423)	0.0127 (0.0482)	0.0127 (0.0322)	0.0127 (0.0343)	0.0127 (0.1220)
Observations	591,381	534,073	534,073	534,073	534,073	534,073
Employer-SOC FE	Yes	Yes	Yes	Yes	Yes	Yes
State x SOC4 x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Std Errors Clustered by	county-SOC	employer-SOC	county	employer	6-digit SOC	no clustering

Panel C: Relationship between IV and Past Measures of Recruitment Competition

Dependent Variable:	Residual VC Investments			Total VC Investments		
	(1)	(2)	(3)	(4)	(5)	(6)
Recruitment Competition (1-Year Lag)	28,774.9387 (26,992.3947)			23,392.8513 (26,769.6266)		
Recruitment Competition (2-Year Lag)		-12,305.5231 (16,682.7966)			-19,717.2538 (17,577.2199)	
Recruitment Competition (3-Year Lag)			-6,887.8631 (28,407.2672)			-8,340.9146 (28,585.7726)
Observations	70,742	62,881	55,020	71,919	63,928	55,937
Employer-SOC FE	Yes	Yes	Yes	Yes	Yes	Yes
State x SOC4 x Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Panel A estimates the relationship between changes in VC investments in start-ups and changes in VC investments in similar start-ups. Industries are defined by two-digit NAICS codes. Panel B studies the relationship between the instrument and the number of vacancies advertised by nonstart-ups. Panel C shows nonsignificant relationships between the IV and past measures of recruitment competition. The average standard deviation in the number of job postings is 14. Standard errors are clustered by employer in Panel C. Sources: BGT, Crunchbase, and the US Department of Labor.

The last falsification exercise presented in Panel C investigates the relationship between the instrument and past measures of recruitment competition. To be relevant, the IV must strongly predict the number of vacancies advertised by start-ups when they receive the funding. But to be valid, the IV should not be affected by the number of vacancies advertised in previous years. I test this relationship at the start-up level by regressing residual (and total) VC investments in each start-up on the number of vacancies they advertised in the one, two, and three previous years. All the coefficients are nonsignificant and support therefore the validity of the instrument.

Table 3 presents the main set of results. First-stage coefficients highlight positive relationships between residual VC investments and recruitment competition from start-ups. First-stage F-statistics, ranging between 33 and 78, support the strength of the instrument. Columns (1) and (2) compare the results obtained with OLS and IV estimations, with the main result reported in column (2). It shows that, on average, employers submit 8 percent more LCAs in response to a one standard deviation increase in recruitment competition. Eight percent of the employers' average yearly number of LCAs submitted aggregates to 48,000, which represents more than half of the annual quota for H-1B visas.

Table 3. Causal Effect of Recruitment Competition on the Number of LCAs Submitted by Employer

Dependent Variable:	log(Number of LCAs Submitted)				
	OLS	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)
Sample:	All Occupations			Computer Occupations	Other Occupations
Job Postings Advertised by Local Start-Ups	0.0099***	0.0842***	0.1117***	0.1368***	0.0039
	(0.0019)	(0.0198)	(0.0220)	(0.0296)	(0.0143)
First Stage					
Residual VC Investments in Local Start-Ups	-	0.1006***	0.0897***	0.1173***	0.0854***
		(0.0114)	(0.0108)	(0.0202)	(0.0108)
Observations	1,260,165	1,260,165	1,259,595	734,870	525,295
Employer-SOC FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes		Yes	Yes
State × SOC4 × Year			Yes		
First-Stage F-Statistic		78.24	69.11	33.76	62.02

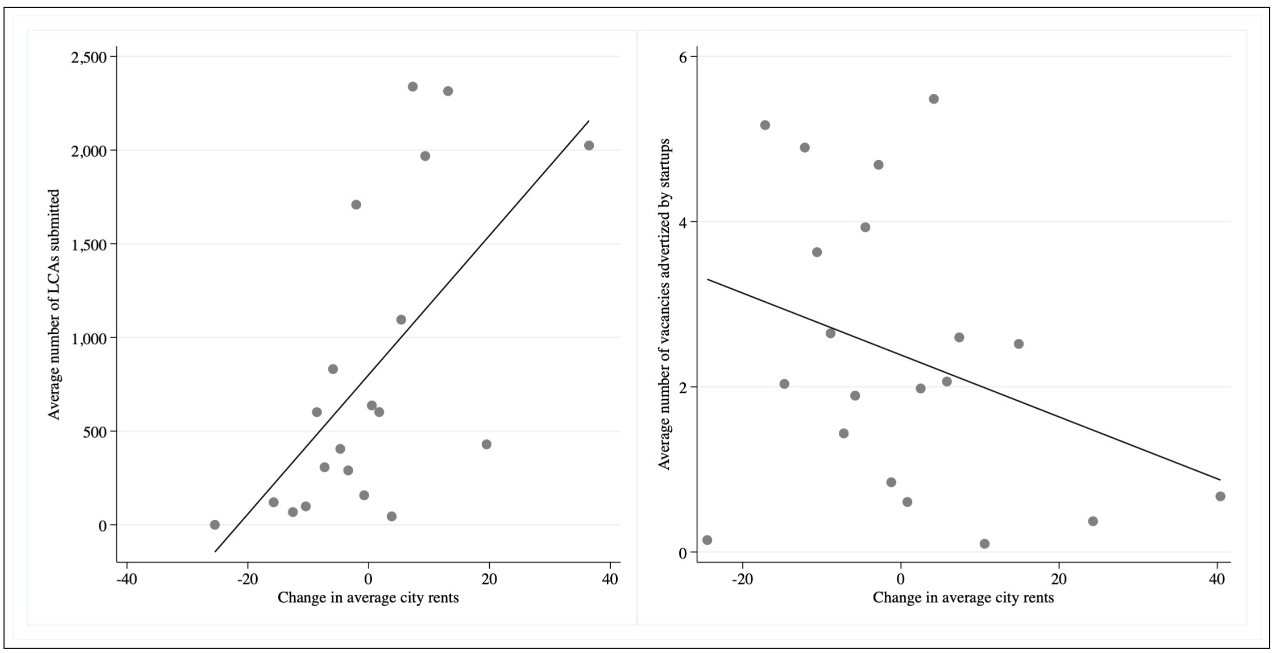
Note: This table presents OLS and IV estimates of the relationship between the standardized number of job postings advertised by start-ups on the local labor market and the number of LCAs submitted by employers. The average standard deviation in the number of job postings is 14. Standard errors are clustered by county and six-digit SOC codes. Sources: BGT, Crunchbase, and the US Department of Labor.

In the next column, I control for state × four-digit SOC codes × year fixed effects to eliminate variation associated with state-specific time trends in the labor supply.[7] Compared to column (2), the point estimate is slightly larger but not statistically different. This suggests that unobserved changes in the labor supply should not be a concern for this analysis.

Columns (4) and (5) highlight heterogeneous results across occupational labor markets. I separately estimate the causal effect of recruitment competition on cells associated with computer occupations and cells associated with other positions. Only the former reports a significant estimate, consistent with the immigration debate that mostly focuses on shortages for STEM occupations (Teitelbaum, 2014).

The comparison of OLS and IV estimates presented in the first two columns of Table 3 suggests that endogeneity issues introduce a negative bias into the former. One explanation for this negative bias might be that start-ups advertise fewer vacancies in booming areas. If start-ups, all else equal, tend to use other recruitment techniques than advertising vacancies in booming labor markets, while simultaneously submitting a larger number of LCAs in these places, this might generate a negative bias in OLS estimations. I provide descriptive evidence consistent with this explanation, and explore this hypothesis in Figure 2 by using changes in average city rents as a proxy for the dynamics of the local economy. The left panel shows a positive correlation between the average number of LCAs submitted by city and year-to-year changes in the average city rents, while the right panel shows a negative relationship with the average number of vacancies advertised by local start-ups.

Figure 2. Relationship between Housing Rents and Number of LCAs Submitted, Number of Vacancies Advertised



Notes: The left panel of the figure represents the relationship between the average number of LCAs submitted in city c and the year-to-year change in the average rents in this city. The right panel represents the relationship between the average number of online job vacancies advertised in city c and the year-to-year change in the average rents in this city. Observations are grouped into equal-sized bins, where x and y values correspond to the average values computed within each bin. Both values of x and y are demeaned to eliminate variation associated with year fixed effects. Sources: BGT and the US Department of Labor.

[7] Appendix Table B1 reports the different levels of precision across occupations defined at the four- and six-digit SOC codes.

Table 4. Causal Effect of Recruitment Competition on Wages Advertised in LCAs

Dependent Variable:	log(Wage Advertised in LCAs)					
	OLS	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	All Occupations				Computer Occupations	Other Occupations
Job Postings Advertised by Local Start-Ups	0.0015**	0.0273***	0.0105	0.0291***	0.0302***	0.0185
	(0.0007)	(0.0068)	(0.0098)	(0.0080)	(0.0068)	(0.0126)
First Stage						
Residual VC Investments in Local Start-Ups	-	0.0823***	0.0789***	0.0805***	0.0834***	0.0800***
		(0.0160)	(0.0159)	(0.0173)	(0.0223)	(0.0153)
Observations	169,625	169,625	168,394	132,814	106,736	62,889
Employer-SOC FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes		Yes	Yes	Yes
State x SOC4 x Year FE			Yes			
Controls for Prevailing Wage				Yes		
First-Stage F-Statistic		26.57	24.73	21.75	13.96	27.47

Note: This table presents OLS and IV estimates of the relationship between the standardized number of job postings advertised by start-ups on the local labor market and wages advertised in submitted LCAs. The average standard deviation in the number of job postings is 14. Standard errors are clustered by county and six-digit SOC codes. Sources: BGT, Crunchbase, and the US Department of Labor.

Table 4 replicates the specifications presented in Table 3 but considers the wages advertised in LCAs as the dependent variable. Column (2) shows that in response to a one standard deviation increase in the number of job postings advertised by local start-ups, employers not only submit more LCAs but also increase the wages advertised in these LCAs by 3 percent. The comparison between OLS and IV estimates and the heterogeneity analysis exhibits the same pattern of results as those reported in Table 3. However, the estimate obtained with the specification controlling for state $\times$ four-digit SOC codes $\times$ year fixed effects is positive but not statistically significant. In addition, column (4) controls for prevailing wages, defined yearly by county and six-digit SOC code. Since H-1B workers cannot be paid below prevailing wages, this specification reports an estimate that is not statistically different from the main specification reported in column (2). This robustness test ensures that the effect does not reflect changes in these wage floors.

These two sets of results are robust to several robustness tests presented in the appendix. In Appendix Table C1, I explore the two remaining alternative channels presented in Section 3. Column (1) shows that the results also hold when replicating the main specification on a subsample excluding the top 1 percent of the largest employers of each local labor market. Column (2) replicates the main specification on a subsample where LCA and BGT data are matched at the cell level, allowing me to control for the total number of vacancies advertised by cell. The results are similar to the main specification reported in column (2) of Table 3. They are also robust to excluding start-ups from the pool of employers submitting LCAs, as shown in column (3) of Appendix Table C1.[8]

As previously mentioned, LCAs correspond only to the first step of the administrative process to obtain H-1B visas. Doran et al. (2022) note that some employers do not always proceed with the second step of the application process once their LCAs are approved by the US Department of Labor. To explore this issue in the measure of the labor demand for H-1Bs, I replicate the analysis on subsamples of employers that have regularly submitted LCAs between 2010 and 2019.

Columns (3) and (4) of Appendix Table C1 report similar results when focusing on employers that have submitted at least 1 LCA in two different years over the period and when focusing on employers that have submitted at least 1 LCA annually over the period, respectively. While the probability of proceeding with the entire application process might vary across these different groups of employers, the point estimates are fairly similar. The estimate reported in column (5) loses statistical significance, potentially due to the smaller sample size. Conversely, column (6) reports a similar effect to the main specification while excluding employers submitting more than 127 LCAs per year. This corresponds to the top 1 percent of employers in terms of LCA submissions. This result addresses the potential concerns about employers possibly submitting many LCAs to increase their chances of obtaining a visa through the lottery.

Appendix Table C2 shows that the results reported with the main specification do not change across several specifications clustering standard errors differently. In Appendix Tables C3 and C4, I consider wages advertised in LCAs as a dependent variable and replicate these robustness analyses. The results report similar patterns to those in Appendix Tables C1 and C2.

5 Conclusion

In contrast with the predictions from the canonical model of competitive labor supply and labor demand, previous literature has not find empirical evidence to support the existence of a crowding-out effect from H-1B workers against close native substitutes. The labor market tightness narrative highlighted by US employers might partly explain this absence of empirical evidence. Despite this narrative's importance in the immigration debate, this paper provides the first causal evidence of the effect of recruitment competition on employers' labor demand for H-1B workers. The contribution of this paper lies in its identification strategy that builds on two inputs. First, it combines three data sources, including exhaustive administrative data on LCAs—submitted as a first step to obtain H-1B visas—and large data sets on online job vacancies and VC investments in start-ups. Second, the new IV strategy enables me to estimate the causal impact of recruitment competition on H-1B labor demand while addressing endogeneity issues.

I find that employers respond to a one standard deviation increase in recruitment competition from local start-ups by increasing the number of LCAs they submit by 8 percent and increasing the wages advertised in these LCAs by 3 percent. These results are driven by the labor demand for computer occupations. The estimates show that part of the H-1B labor demand responds to tight labor markets, where filling vacancies with only US workers might be difficult. My results support the hypothesis that labor market tightness partly explains the absence of the crowding-out effect from H-1B workers against close native substitutes. However, they are silent about the potential implications for natives' wages. This dimension is beyond the scope of this paper but should be explored in future research.

[8] LCAs submitted by start-ups included in Crunchbase represent, on average, 13 percent of all LCAs submitted by local labor markets.

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A Theoretical Framework

This section details the theoretical framework mentioned in Section 3.1. This simple search model rationalizes the hypothesis tested in the empirical analysis. In this framework, employers have an open vacancy and must choose between considering only US citizens in their recruitment or considering both US and H-1B workers. For simplicity, I assume that each employer only opens one vacancy.

Employers' make their choice based on a comparison of the expected present values associated with each option. The following equation describes the situation where employers are indifferent between both options:

$$P_{US}V + (1 - P_{US})U_{US} = P_{US\cup H1B}(V - C) + (1 - P_{US\cup H1B})U_{US\cup H1B}. \tag{A1}$$

The left-hand side formula corresponds to the expected present value of considering only US workers in their recruitment. V is the value of filling the vacancy, and P_{US} is the probability of finding a US worker to fill the vacancy. U_{US} is the value of leaving the vacancy unfilled for employers that only consider US workers in their recruitment. The right-hand side formula corresponds to the expected present value of considering both US and H-1B workers in their recruitment. $P_{US\cup H1B}$ is the joint probability of either finding a US worker or finding an H-1B worker and obtaining an H-1B visa for this worker to fill the vacancy. $U_{US\cup H1B}$ is the expected value of leaving the vacancy unfilled for employers considering both US and H-1B workers. C is the additional pecuniary and administrative cost associated with recruiting an H-1B worker.

Equation (A1) simply indicates that employers prefer the second option when the additional cost associated with recruiting H-1B workers C is smaller than the following threshold:

$$C \quad < \quad \frac{[(1 - P_{US\cup H1B})U_{US\cup H1B} - (1 - P_{US})U_{US} + V(P_{US\cup H1B} - P_{US})]}{P_{US\cup H1B}}, \tag{A2}$$

where $U_{US\cup H1B}$ and U_{US} are both increasing with employers' probability of finding a US worker to fill the vacancy (P_{US}) in the next period. $U_{US\cup H1B}$ is also increasing with the probability of finding an H-1B worker to fill the vacancy in the next period. Therefore, I assume that $\frac{\partial U_{US}}{\partial P_{US}}$ is larger than or equal to $\frac{\partial U_{US\cup H1B}}{\partial P_{US}}$. For simplicity, I simply refer to this right-hand side threshold as T in the following.

I explore the coevolution of threshold T with the probability of finding a US worker (P_{US}) in the following calculus. I first study the sign of the partial derivative of the numerator with respect to P_{US}:

$$\begin{aligned} \frac{\partial U_{US\cup H1B}}{\partial P_{US}}(1 - P_{US\cup H1B}) - \frac{\partial U_{US}}{\partial P_{US}}(1 - P_{US}) - (1 - \frac{\partial P_{US\cup H1B}}{\partial P_{US}})V \\ -U_{US} - U_{US\cup H1B}\frac{\partial P_{US\cup H1B}}{\partial P_{US}}. \end{aligned} \tag{A3}$$

As previously mentioned, I assume that

$$\frac{\partial U_{US\cup H1B}}{\partial P_{US}} \leq \frac{\partial U_{US}}{\partial P_{US}}.$$

In addition, one should note that the pool of US workers is nested in the pool of US and H-1B workers. This has two implications. First, it implies that the probability of finding a US worker is necessarily smaller than or equal to the probability of finding either a US or an H-1B worker (i.e., $P_{US} \leq P_{US \cap H1B}$). Second, it implies that the probability of finding a US or an H-1B worker is increasing with the probability of finding a US worker (i.e., $\frac{\partial P_{US \cup H1B}}{\partial P_{US}} > 0$). Therefore, I can deduce the sign of the following component:

$$\frac{\partial U_{US \cup H1B}}{\partial P_{US}}(1 - P_{US \cup H1B}) - \frac{\partial U_{US}}{\partial P_{US}}(1 - P_{US}) \quad \leq \quad 0.$$

The three last components included in Equation A3 are positive or null:

$$\begin{aligned}
(1 - \frac{\partial P_{US \cup H1B}}{\partial P_{US}})V &\geq 0; \\
U_{US} &\geq 0; \\
U_{US \cup H1B}\frac{\partial P_{US \cup H1B}}{\partial P_{US}} &\geq 0.
\end{aligned}$$

Therefore, the numerator of the threshold T decreases with the probability of finding a US worker (P_{US}). In addition, the denominator of T is positive and increases with this probability. As a consequence, T decreases with the probability of finding a US worker:

$$\frac{\partial T}{\partial P_{US}} \quad \leq \quad 0.$$

I assumed earlier that the expected present values of leaving the vacancy unfilled differ across recruitment choices (i.e., $U_{US \cup H1B} \neq U_{US}$). The coevolution of the threshold T with the probability of finding a US worker (P_{US}) does not change if I relax this assumption.

Most importantly, the probability of finding a US worker to fill the vacancy is a decreasing function of the recruitment competition in the market. Therefore, within this framework, an increase in recruitment competition will increase the threshold below which employers consider both US and H-1B workers in their recruitment.

Figure A1 illustrates this situation with the cumulative distribution function of employers that differ in their costs to recruit foreign workers. For simplicity, I assume that additional costs associated with recruiting H-1B workers are normally distributed across employers. The vertical black lines correspond to the thresholds where employers are indifferent between the two recruitment options. Only employers whose cost is below the threshold consider both US and H-1B workers in their recruitment. The difference between the left and right panels shows the increase in the threshold associated with an increase in recruitment competition. This highlights the increase in the number of employers willing to consider both types of workers in their recruitment.

Figure A1. Increase in Recruitment Competition and Search for H-1B Workers

Notes: The graph illustrates how an increase in recruitment competition from RC to RC' affects employers' labor demand for H-1B workers. Each panel represents the cumulative distribution function of employers that differ in the additional cost they face to recruit H-1B workers. The black vertical lines highlight the thresholds below which employers consider both US and H-1B workers in their recruitment.

B Additional Table

Table B1. List of Four- and Six-Digit SOC Codes for Computer and Mathematical Science Occupations

4-Digit SOC Codes	4-Digit SOC Names	6-Digit SOC Codes	6-Digit SOC Names
15-12	Computer Occupations	15-1210	Computer and Information Analysts
15-12	Computer Occupations	15-1211	Computer Systems Analysts
15-12	Computer Occupations	15-1212	Information Security Analysts
15-12	Computer Occupations	15-1220	Computer and Information Research Scientists
15-12	Computer Occupations	15-1221	Computer and Information Research Scientists
15-12	Computer Occupations	15-1231	Computer Network Support Specialists
15-12	Computer Occupations	15-1232	Computer User Support Specialists
15-12	Computer Occupations	15-1241	Computer Network Architects
15-12	Computer Occupations	15-1242	Database Administrators
15-12	Computer Occupations	15-1243	Database Architects
15-12	Computer Occupations	15-1244	Network and Computer Systems Administrators
15-12	Computer Occupations	15-1251	Computer Programmers
15-12	Computer Occupations	15-1252	Software Developers
15-12	Computer Occupations	15-1253	Software Quality Assurance Analysts and Testers
15-12	Computer Occupations	15-1254	Web Developers
15-12	Computer Occupations	15-1255	Web and Digital Interface Designers
15-12	Computer Occupations	15-1299	Computer Occupations, All Other
15-20	Mathematical Science Occupations	15-2011	Actuaries
15-20	Mathematical Science Occupations	15-2021	Mathematicians
15-20	Mathematical Science Occupations	15-2031	Operations Research Analysts
15-20	Mathematical Science Occupations	15-2041	Statisticians
15-20	Mathematical Science Occupations	15-2051	Data Scientists
15-20	Mathematical Science Occupations	15-2099	Mathematical Science Occupations, All Other

Notes: This table lists all computer and mathematical science occupations and details their four- and six-digit SOC codes and names. Source: US Department of Labor.

C Additional Results

Table C1. Comparison of Causal Effects of Recruitment Competition on the Number of LCAs Estimated on Different Subsamples

Dependent Variable:	log(Number of LCAs Submitted)					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	Excluding Largest Employers	Employers Also Included in BGT	Excluding Start-Ups	LCA Subsample 1	LCA Subsample 2	LCA Subsample 3
Job Postings Advertised by Local Start-Ups	0.0828*** (0.0193)	0.0870*** (0.0200)	0.0821*** (0.0226)	0.1068*** (0.0263)	0.1251*** (0.0449)	0.0725*** (0.0172)
Observations	1,198,696	1,154,226	1,076,149	1,116,940	150,510	1,175,488
Employer-SOC FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Additional Control:	No	Yes	No	No	No	No
First-Stage F-Statistic	76.52	79.59	74.13	76.70	80.89	76.65

Notes: This table compares the causal effects of the number of job postings advertised by local start-ups on the number of LCAs submitted, estimated on several subsamples. Column (1) excludes employers that have submitted more than 19 vacancies for a specific occupation. Column (2) focuses on employers included in both the LCA and BGT data, and it controls for the total yearly number of vacancies advertised by each employer. Column (3) excludes employers included in both the LCA and Crunchbase data. Columns (4) and (5) restrict the sample to employers that have submitted at least 1 LCA in two different years and to employers that have submitted at least 1 LCA in each year, respectively. Column (6) excludes employers that have submitted more than 127 LCAs per year. The average standard deviation in the number of job postings is 14. Sources: BGT, Crunchbase, and the US Department of Labor.

Table C2. Comparison of Causal Effects of Recruitment Competition on the Number of LCAs Estimated across Specifications Where Standard Errors Are Clustered Differently

Dependent Variable:	log(Number of LCAs Submitted)				
	(1)	(2)	(3)	(4)	(5)
Job Postings Advertised	0.0842***	0.0842***	0.0842***	0.0842***	0.0842**
	(0.0198)	(0.0068)	(0.0073)	(0.0180)	(0.0357)
First Stage					
Residual VC Investments in Local Start-Ups	0.1006***	0.1006***	0.1006***	0.1006***	0.1006***
	(0.0114)	(0.0009)	(0.0010)	(0.0176)	(0.0118)
Observations	1,260,165	1,260,165	1,260,165	1,260,165	1,260,165
Employer-SOC FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
First-Stage F-Statistic	78.24	12692	9259	32.73	72.60
Std Errors Clustered by	county × SOC	employer × SOC	employer	county	SOC

Notes: This table compares the causal effects of the number of job postings advertised by local start-ups on the number of LCAs submitted across several specifications where standard errors are clustered differently. The average standard deviation in the number of job postings is 14. Sources: BGT, Crunchbase, and the US Department of Labor.

Table C3. Comparison of Causal Effects of Recruitment Competition on Wages Advertised in LCAs Estimated on Different Subsamples

Dependent Variable:	log(Wage Advertised in LCAs)					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	Excluding Largest Employers	Employers Also Included in BGT	Excluding Start-Ups	LCA Subsample 1	LCA Subsample 2	LCA Subsample 3
Job Postings Advertised by Local Start-Ups	0.0270***	0.0259***	0.0228***	0.0262***	0.0345***	0.0276***
	(0.0072)	(0.0069)	(0.0078)	(0.0075)	(0.0128)	(0.0071)
Observations	154,937	157,174	143,051	159,875	27,825	151,247
Employer-SOC FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Additional Control:	No	Yes	No	No	No	No
First-Stage F-Statistic	24.34	24.86	22.97	26.81	38.61	22.64

Notes: This table compares the causal effects of the number of job postings advertised by local start-ups on wages advertised in LCAs, estimated on several subsamples. Column (1) excludes employers that have submitted more than 19 vacancies for a specific occupation. Column (2) focuses on employers included in both the LCA and BGT data, and it controls for the total yearly number of vacancies advertised by each employer. Column (3) excludes employers included in both the LCA and Crunchbase data. Columns (4) and (5) restrict the sample to employers that have submitted at least one LCA in two different years and employers that have submitted at least one LCA in each year, respectively. The average standard deviation in the number of job postings is equal to 14. Sources: BGT, Crunchbase, and the US Department of Labor.

Table C4. Comparison of Causal Effects of Recruitment Competition on Wages Advertised in LCAs Estimated across Specifications Where Standard Errors Are Clustered Differently

Dependent Variable:	log(Wage Advertised in LCAs)				
	(1)	(2)	(3)	(4)	(5)
Recruitment Competition	0.0273***	0.0273***	0.0273***	0.0273***	0.0273**
	(0.0068)	(0.0054)	(0.0054)	(0.0058)	(0.0122)
Observations	169,625	169,625	169,625	169,625	169,625
Employer-SOC FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
First-Stage F-Statistic	26.57	1474	1263	15.48	54.52
Std Errors Clustered by	county $\times$ SOC	employer $\times$ SOC	employer	county	SOC

Notes: This table compares the causal effects of the number of job postings advertised by local start-ups on wages advertised in LCAs across several specifications where standard errors are clustered differently. The average standard deviation in the number of job postings is 14. Sources: BGT, Crunchbase, and the US Department of Labor.