# Essays in Labor Economics

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# Curriculum Vitae

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# PREFACE

This dissertation is composed of two self-contained chapters, exploring topics in Labor Economics. Both papers broadly explore the question of how we define labor markets.

The first chapter investigates a new mechanism through which differential competitive pressures faced by in-house and contract workers yield a contracting wage penalty. I study this issue in the context of private security guards, a low-wage and relatively homogeneous occupation where outsourcing is prevalent. I build a unique data set from the near-universe of job vacancy postings from Burning Glass Technologies, and identify jobs for security guards as in-house or contracted. I find that a 1% increase in the Hirschman-Herfindahl index has a differential impact on contract and in-house guards, with contract guards experiencing a relatively larger wage penalty of 9.6%. I provide evidence that contract and in-house guards (1) represent the same occupation given a lack of heterogeneity in skill requirements and (2) operate in the same labor market for nominally different employers. What then explains the differential response to concentration? I propose that, conditional on in-house and contract guards having identical probabilities of transition in to outside occupations, any remaining variation must come from differences in how guards match to other firms within their own occupation. I find that the role of outside options can meaningfully explain why contract workers have a higher elasticity of wages to concentration, and show that outside options are a function of the relative market share of business service firms and private firms, and the average wages for each firm type.

In the second chapter, I take a task-based approach to defining workers' outside options using job vacancy data, bringing together the literatures on job tasks and monopsony. I construct an index of outside options, which considers the skill overlap between two occupations; the more skill overlap between each occupation pair, the more viable the other occupation is as an alternative profession. For each occupation, I calculate the value of outside options as the sum over all occupations of pairwise similarity scores, weighted by the relative employment share of the the alternative occupation and their average wages in an MSA. I find that my outside option index is highly predictive of wages, and picks up an effect of monopsony that is independent from the HHI. I construct alternative versions of my index where I condition on posted education requirements asking for either a high

school or college diploma. I find that outside options matter relatively more for low-skilled occupations than for high-skilled occupations, consistent with the idea that non-routine jobs are more likely to encounter monopsony power. Finally, I explore how predictive each skill category is of the value of outside options. I find that the value of outside options is increasing in social and cognitive skills, but that the return to social skills occurs only conditional on a college degree. This is consistent with a model where social skill intensity decreases in job routineness.

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# CHAPTER 1

# MONOPSONY IN THE MARKET FOR OUTSOURCED WORKERS: EVIDENCE FROM THE SECURITY INDUSTRY

## 1.1 Introduction

The rise of domestic outsourcing[1] has fundamentally restructured how workers are organized into firms. For many low-wage occupations, this has translated to a sustained decline in opportunities to participate in more traditional employer-employee relationships. Instead, the demand for non-traditional employment relationships (including subcontracting, offshoring, and contingent work) is increasingly dominating the hiring market for logistics and services occupations that often lay outside a firm's "core competencies". Growth in business service firms that specialize in providing labor to other private firms has allowed many private firms to contract out entire occupations including food services, cleaning, human resources, trucking, and private security. There is a growing consensus in the economics literature that there exists a within-occupation "contracting penalty" whereby workers in contract jobs earn lower wages relative to their direct-hire or in-house counterparts who perform the same job functions.

This paper investigates a new mechanism through which differential competitive pressures faced by in-house and contract workers yield a contracting wage penalty. Using the near-universe of online job postings from Burning Glass Technologies, I document that the own-occupation Herfindahl-Hirschman index (HHI), a common measure of local labor market concentration, is an insufficient metric of market power for "fissured" occupations. I argue that a 1% change in an HHI may mean something fundamentally different for contract and in-house workers of the same occupation. I provide evidence that added consideration

[1] I refer to jobs that have been subjected to domestic outsourcing as "contract jobs". Importantly, I treat these jobs as distinct from those in the gig economy where workers are self-employed and sell their services directly to the hiring firm. In my setting, business service firms or "contracting firms" hire labor directly and sell that labor to labor buyers. Contract jobs are therefore those where work is not supervised by the firm paying the salary, and contracts for continuing employment relationships may not exist. Contract firms simply act as intermediaries between workers and firms, where the selling firm hires workers as employees, but the buying firm hires labor from the selling firm as contract employees.

for the role of outside options is key to understanding the mechanism by which concentration impacts wages.

The existing literature has largely focused on the loss of firm-specific rents as the source of the contracting wage penalty. For firms with historically high wage premia, the potential for large cost reductions makes outsourcing an attractive option (Goldstein and Schmieder 2017). When wages are no longer subject to equity constraints on within-firm inequality, the wage penalty associated with moving to a firm with lower wage premia can be significant, even when accounting for compensating differentials including health benefits, hours, skill differences, and industry (Dube and Kaplan 2010). That the wage penalty persists suggests the existence of anti-competitive frictions.

However, the existing literature has generally overlooked the competitive consequences of broad changes in employment structure over the past decades. Recent literature documents that domestic outsourcing has contributed to overall occupational assortativeness with the entry of business service firms, with occupations becoming more concentrated across establishments over time (Dube and Kaplan 2010; Goldschmidt and Schmieder 2017; Song et al. 2018). This pattern suggests a novel source of anti-competitive pressure on wages. Felix and Wong (2021) more formally consider the role of job reallocation and employment composition in driving market-level effects on wages and employment, focusing mainly on changes in the age distribution across occupations.

But the composition of the labor market faced by workers in heavily outsourced occupations may shift in other meaningful ways. That outsourcing has become a permanent part of the employment landscape suggests that traditional employer-employee relationships need no longer be the norm. Outsourcing in this context may effectively "fissure" occupations such that in-house and contract workers face different competitive environments. If so, then a more complete picture of competitive differentials driving the contracting penalty would directly account for within-occupation employment structure.

This paper addresses three fundamental questions. First, do contracted and in-house workers with the same job title represent the same occupation? Second, how does the type of employment contract a worker faces dictate the boundaries of their local labor market? And third, can differences in outside options for contracted and in-house workers explain the contracting wage penalty? I argue that if contract and in-house workers exist in the same labor market, then how those workers match to other firms *within* their own occupation can help account for the contracting wage penalty.

I address these questions in the context of private security guards, a security service occupation that provides guarding, monitoring, and patrolling services to establishments. I focus on security guards for three primary reasons. First, the employment landscape for security guards has trended towards the growth and expansion of business service firms, but demand for in-house employment remains substantial. Second, degree and skill requirements for security guards are relatively homogeneous so that job titles are a good proxy for job duties. Third, security guards are an occupation for which jobs are easily identifiable as contracted or in-house using industry and occupation codes.[2]

In the first part of this paper, I investigate whether security guards employed by business service firms are fundamentally different than guards employed in-house by other private firms. I leverage data on skill requirements associated with each job vacancy to highlight the relative homogeneity of security guards across employment types. Although there is some variation in skill demand between the two groups, education and experience requirements are almost identical and reflect a similar candidate pool. I find that accounting for any remaining differences in skill requirements has no meaningful impact on the contracting wage penalty. This suggests that on average, differences between contracted and in-house security guards should merely reflect legal labels associated with their employment contracts and not meaningful differences in their job responsibilities.

Next, I estimate the elasticity of posted wages to concentration for contracted security guards. My baseline specification has the flavor of a difference-in-differences specification in which I compare the elasticity of wages to concentration for contractors to that for in-house guards, controlling for observable confounders. I find that the elasticity of wages to concentration is larger for contractors than for their in-house counterparts. My baseline estimate suggests that on average going from the median to the $95^{th}$ percentile of the HHI would incur a wage penalty that is 5.9 log points larger for contractors than for their in-house counterparts.

[2] Janitors are another low-wage service occupation for which it is straightforward to distinguish between contracted and in-house employment. Janitors are much less well-represented in my data and are subsequently also less suitable for conditioning on merger and acquisition activity, so I do not consider them in my analysis. However, there is no fundamental reason why my analysis should not extend to other low-wage occupations where business service firms are a dominant part of the employment landscape.

The primary empirical issue is endogeneity, most obviously because *many* factors are likely to change both concentration and wages simultaneously. Nearly all of the existing literature documenting a contracting wage penalty relies on mass layoffs and establishment closures as a source of exogenous variation in concentration. My data represents only the demand side of the labor market, and so I cannot observe actual hiring and firing decisions. Instead, I use mergers and acquistions in the security space to address the concerns of regressing one endogenous market outcome on another, and estimate the merger-induced impact of concentration on wages following Arnold (2020). I collect data from the Security Data Company (SDC) Platinum Mergers and Acquisitions database to identify all mergers and acquisitions in my sample period that impact the market for security guards. I match a total of 736 merger events to my main BGT sample using the names of the acquiring and target firms.

To estimate the elasticity of posted wages with respect to concentration for contractors due to merger activity, I use top-ventile merger-induced changes in concentration as an instrument for the HHI. This is motivated by the facts that i) concentration changes due to M&A activity explains relatively little of the variation in observed concentration changes and ii) only the largest merger-induced concentration changes cause a decrease in posted wages. This approach yields a point estimate of -0.187 (SE 0.049). This is substantially larger than my OLS estimate and highly significant, suggesting a mix of omitted variable bias and measurement error in the baseline results. My preferred specification limits the M&A sample to national firms that post vacancies in at least five MSAs over the sample period to alleviate the concern that M&A activity is not random and may be driven by local economic activity. My results suggest that competitive differentials do contribute to the contracting wage penalty.[3]

What explains why local vacancy concentration has an independent effect on the contracting wage penalty? If we believe that (1) contractors and in-house guards are identical conditional on observable skill differences, (2) contractors and in-house guards perform the same job for nominally different employers and subsequently that (3) contractors and in-house guards operate in the same market, then there must be another mechanism through which the HHI would differentially impact these groups.

[3]This result does not rule out the role of rent differentials due to a loss of firm-specific wage premia. Although I do not formally test for this, the effect is likely picked up by the coefficient on contractor status, which exhibits independent explanatory power from the interaction term between HHI and contractor status.

I propose that outside options for security guards must vary at the employment contract-level rather than at the occupation level. Although contract and in-house guards can with some probability transition into other occupations, that probability should be equal for both worker types. Any remaining variation in wages, then, must come from differences in how guards match to other firms within their own occupation. I provide several stylized examples that demonstrate this mechanism in my setting. In particular, I consider that in-house guards earn more in equilibrium than do contracted guards, and that large, business service firms continue to acquire smaller firms and expand their market share. This exercise demonstrates that a difference in the value of outside options generates a larger elasticity of wages to concentration for contracted versus in-house guards.

The rest of this paper proceeds as follows. Section 1.2 discusses the job vacancy data, the institutional background, and Section 1.3 describes skill requirements for security guards. Section 1.4 presents my empirical approach and baseline estimates. Section 1.5 addresses endogeneity concerns and estimates merger-induced changes in concentration on posted wages for contract guards. Section 1.6 discusses outside options as a potential mechanism for my findings. Section 1.7 concludes.

### 1.1.1 Literature Review

**Contracting penalty.** I contribute to a small number of studies that identify a wage penalty associated with contracting or domestic outsourcing.[4] A number of studies use on-site outsourcing events to show that workers in traditional employer-employee relationships systematically earn more than their counterparts who are outsourced or staffed by a temporary employment agency (Bernhardt et al. 2016, Goldschmidt and Schmieder 2017, Felix and Wong 2020, Drenik et al. 2020). Perhaps most closely related to my study, Dube and Kaplan (2017) provide a broader estimate of the effect of outsourcing on wages and find that differences in labor market rents rather than competitive differentials are consistent with the existence of a contracting penalty. By contrast, my study proposes that occupational market structure reflects an additional source of competitive differentials that is indeed consistent with a contracting penalty.

**Defining local labor markets.** I also contribute to an emergent literature that argues for flexibility in defining the scope of a worker's labor market. Most prior studies define

[4]For a broader discussion on the rise of domestic outsourcing, see Weil (2014); Bernhardt et al (2016); Dey et al (2010); Handwerker (2015); and Abraham and Taylor (1996)

a labor market using standard industry-area or occupation-area boundaries. More recent work argues that a worker's labor market is defined not only by their (location-specific) occupation (industry), but also by other occupations (industries) that are reasonable alternatives for the worker's skill set and qualifications (i.e. "outside options") (Nimczik 2018, Macaluso 2019, Schubert, Stansbury and Taska 2022, Arnold 2020). Jarosch et al. (2019) consider that outside options are also a function of market structure, and in particular the size of the firm that workers are bargaining with. I make a theoretically similar argument that outside options and thus wages are a function of market structure, but focus on the relative share of private firms and business service firms that are reasonable alternatives for a worker. Insofar as alternative work arrangements[5] like domestic outsourcing continue to make up sizeable and likely permanent segments of the labor market, I provide evidence that market structure is an important consideration in defining a worker's outside options and thus labor market.

**Inter-industry wage differentials.** My results also highlight why the contracting penalty is not an example of classic inter-industry wage differentials, in which wage premia exist within occupations even after controlling for skill differences, place, local amenities, firm size, and other compensating differentials. (Krueger and Summers 1988, Gibbons and Katz 1992, Card et al. 2013, Song et al. 2019, Kline et al. 2019, Goosbee and Syverson 2019, Qiu and Sojourner 2019). Though business service firms comprise a unique industry, their employees are not working in the business service industry *per se*.[6] Instead, these employees can reasonably be hired by a private firm in *any* industry that has security needs, so that industries are differentiated only by legal designation (Dube and Kapan 2017). This suggests an additional channel by which wage differentials can exist. I discuss a potential mechanism for this finding and suggest that concentration does not map one to one with outside options even within an occupation. How responsive wages are to changes in concentration depends on how outside options shift, which in turn depends on the market's composition of private and business service firms.

**Measuring outside options.** Finally, I contribute to the debate over the usefulness of task- or skill-based approaches to measuring labor market concentration relative to those

[5] See Mas and Pallais (2017) and Katz and Kreuger (2016, 2019) for discussions on the growth of alternative work arrangements.

[6] Of course, business service firms with physical locations may hire their own security guards. I consider this to be a negligible portion of our sample.

that use observed job transitions. Papers that take a task-based approach to measuring concentration argue that models using skill-based measures of HHI are highly correlated with those embedding outside options into HHI using information on worker flows (Arnold 2020, Nimczik 2022) as well as those including outside options as a metric with independent explanatory power from HHI (Schubert, Stansbury and Taska 2020). For example, Dodini (2023) argues that a task-based "occupation clusters" are highly correlated with job transition likelihood, and is less sensitive to underlying labor supply and demand forces as well as promotion issues that arise from observing equilibrium outcomes of job transition. To this literature, I contribute evidence that a skills-based approach may not capture competitive pressures that dictate the likelihood of transition between jobs with identical skills, and subsequently on the value of outside options. Nonetheless, my findings support the growing literature which suggests that a full accounting of labor demand concentration must directly include workers' outside options.

## 1.2 Background

### 1.2.1 Data

I use Burning Glass Technologies' (BGT)[7] job posting data, covering 2013-2017, which tracks the near universe of online vacancy postings in the United States. BGT "spiders" or pulls vacancy postings from over 40,000 online job boards, with no more than 5% of the sample coming from any single site. To ensure that job postings are unique, BGT implements a sophisticated de-duplication algorithm to detect whether any vacancy is listed across multiple job boards. BGT is generally recognized as a good-quality database and for many purposes it provides a consistent picture for similar analyses performed using the Current Population Survey (CPS) or the JOLTS database to track hiring patterns by industry and occupation.[8]

I restrict the data to all job postings in the private sector, not in a military occupation, and without commission pay. The main sample consists of all vacancy postings for private security guards (SOC 33-9032) with populated industry and occupation codes, location, and posted wage data. When vacancies post a wage range, I use the average posted wage.

[7] Burning Glass Technologies is now known as Lightcast.

[8] I refer the reader to a growing literature that provides a more comprehensive assessment of the comparability of BGT data to other data sets. See Hershbein and Kahn (2017); Hazell and Taska (2022); Hazel, Patterson, Sarsons, and Taska (2021); Azar, Marinescu, Steinbaum and Taska (2020)

I also collect information on the employer associated with each job posting, and define an establishment as a collection of vacancies posted by a firm in an MSA. Finally, when available, I include information on salary type, pay frequency, and posted skill requirements, including years of experience and education and a raw text field for all skills or requirements included in the job vacancy. Tables 1.1 and 1.2 summarizes the full sample and the sub-sample of business service firms or contract firms.

### 1.2.2 Market for private security

In this paper I focus on the market for private security guards, a growing low-wage occupation where domestic outsourcing is common. Security guards are employed to provide protective services to establishments by guarding, patrolling, and monitoring, among other public safety services. Over the last 50 years, the number of security guards has increased dramatically from about 200,000 workers in 1970 to nearly 1.1 million workers by 2020. Of all security guards in 2020, approximately 58% were employed in business service firms (i.e. in the private security industry, which contracts out security guards to other private firms with security needs) (BLS OES 2020). Figure 1.1 shows the evolution of job postings for contracted security guards in the Burning Glass data set, which comprise 53% of all vacancies with non-missing industry codes by 2017.

Because security guards typically provide labor services that do not contribute directly to a firm's core competency, the occupation lends itself naturally to domestic outsourcing or contracting. Moreover, that skill requirements for security guards tend to be relatively homogeneous suggests that a business service firm specializing in private security will have an advantage over other private firms in managing their security force. Business service firms may also be able to provide training more efficiently as the landscape for security services changes. For example, these firms may be better able to meet evolving industry standards that place an increased emphasis on skills requiring communication, de-escalation tactics, and minimizing excessive and unnecessary force. Outsourcing may also enable firms to better respond to short-term fluctuations in labor supply due to the larger pool of substitute workers at the contract firm (Houseman 2001). Most literature on the contracting wage penalty focuses on rent-sharing that occurs between all workers at private firms. These firms have an incentive to outsource so that equity concerns do not inflate the wages of "non-essential" employees.

Although contracting firms continue to grow and increasingly dominate the market for private security, the market for in-house security has not disappeared. This is primarily due to client preferences and particular security needs that may vary by industry. The demand for in-house security exits in particular industries that do better with proprietary staff who accumulate firm-specific knowledge. Table 1.2 lists the industries in my sample that post the most vacancies for in-house security guards. In general, firms in the medical, education, and hospitality industries have the most demand for in-house security.[9] These industries are highly client-facing and can require specialized knowledge of firm protocol when there are elevated security needs. Hospitals, for example, may prefer de-escalation tactics between patients and medical professionals that meet the hospital's standards for conduct between doctors and patients.

Among contracting firms, both large and small companies continue to exist and differentiate themselves to clients. Larger security firms have been able to sustain their growth by acquiring smaller, regional firms, allowing them to diversify their product and provide a broader array of services to clients (for example, expansion into electronic security systems or canine services). Small and regional contracting firms, on the other hands, can provide more customized, service-oriented security solutions. These smaller firms also benefit from mergers and acquisitions among larger firms which allow them to acquire talent in the event of layoffs. Although contract firms continue to expand, employers of in-house security guards continue to produce a significant share of employment opportunities in the security space.

### 1.2.3 Measuring outsourcing using industry and occupation codes

The primary empirical challenge to measuring the wage losses associated with outsourcing is in identifying contract jobs; that is, identifying jobs for the same occupation that are paid in-house versus by a contracting firm that provides intermediate services to other firms. To do so, I identify industry-occupation pairs and match 4-digit occupation codes to 5-digit industry NAICS codes reported by BGT.[10] More specifically, I identify private security guards and observe whether the hiring firm is a business service firm or not. I

[9] In my data I cannot observe if firms hire in-house security in addition while also hiring security from a contracting firm. Firms oftentimes use contracted guards to provide temporary services due to employee turnover, a tight hiring market, overtime needs, etc. See Strom et al. (2010). Thus, I cannot infer the degree to which firms rely on in-house versus contracted guards or exploit variation in contracting within firms.

[10] For any firms which have more than one assigned NAICS code, I define the NAICS code as that most frequently linked to the firm. If there is no modal industry assignment I set the NAICS code to missing.

define a contract guard to be a security guard employed by a business service firm, and an in-house or direct-hire guard to be a security guard employed by a private sector firm in any other industry.[11]

There are several limitations to this approach worth noting. Although job vacancy data are a good proxy for hiring demand, it has limited use in exploring the supply side of the labor market. First, there is no way to observe which firms or industries rely on business service firms to supply guards. Any characteristics that influence a firm's decision to contract out cannot be observed. Second, there is the possibility that firms hire more than one worker per posted vacancy, and furthermore that this occurs relatively more often business service firms than for other private sector firms. In this case, we would underestimate the incidence of outsourcing. Finally, it could be the case that business service firms are simply better at hiring online than are other hiring firms given that hiring and contracting out security guards is the core competency of these firms. In this case, we are likely to overestimate the recruiting intensity of business service firms relative to other hiring firms.

## 1.3 Skill requirements for private security guards

It is theoretically possible that the contract wage penalty reflects a classic case of inter-industry wage differentials, such that employers in different industries require distinct skill sets from employees who have only nominally comparable occupations. However, in the case of business service firms, it is instead the *hiring firms* we consider to be only nominally different. We can expect that a security guard hired by a business service firm can and will perform their job at a private firm that has contracted out their in-house security. On average, differences between between contract and direct hire security guards should merely reflect legal labels associated with their employment contracts and not by meaningful differences in their job responsibilities.

I assess this possibility empirically by leveraging the detailed text fields associated with each vacancy from BGT. BGT parses the text of each job posting and extracts any qualifications or skill demands required for the position. This includes education and experience

[11] This is the same method used by Dube and Kaplan (2014), Berlinski (2008), and Abraham (1990, 1996), who use CPS data to estimate the contracting penalty, and by Goldschmidt and Schmieder (2017), who use German administrative data.

requirements, as well as any preferred qualifications (i.e. specific computer or software skills, social skills, physical requirements, etc.). Although I cannot observe the skills or qualifications of workers who were actually hired for any given vacancy, the stated skill demands associated with each job posting provide a reasonable approximation of the occupation's demographic characteristics.[12]

Table 1.3 summarizes the data for my primary sample of job vacancies for private security guards over 2013-2017. Over the sample period, 76% of vacancies had an education requirement. Among those vacancies with an education requirement, only 3% of the sample called for a college degree and a negligible portion of vacancies require an advanced degree. The vast majority of positions required the equivalent of a high school education. As expected, converting degrees to their equivalent years of schooling shows that the average education requirement is just over 12 years, corresponding to the equivalent of a high school education.

In contrast to education requirements, only 22% of the sample had an experience requirement, of with 84% called for between one and five years of schooling, with the remainder being split between less than one year or 5-10 years of experience and a negligible portion requiring more than 11 years of experience. Conditional on having any education requirement, the average vacancy required 2.64 years of experience.

Columns (2) and (3) calculate the within-MSA difference in qualifications and skill requirements for vacancies in the primary sample that correspond to business service firms versus to other private firms. While the contract sample was more likely to post an education requirement, they were less likely to post an experience requirement relative to the direct hire sample. Conditional on posting any education requirement, average vacancies in both samples were highly skewed towards requiring a high school education, but the direct hire sample had a significantly higher portion of vacancies requiring the equivalent of a college degree. The corresponding average years of required schooling was 12.03 years for the contract sample and 12.51 years for the direct hire sample, representing a statistically significant though economically negligible difference in education. Experience requirements follow a similar pattern. Conditional on posting any experience requirement, the majority of vacancies in both samples required between 1-5 years of schooling followed by 5-10 years.

[12] Dube and Kaplan (2014) utilize the panel structure of their CPS data set and control for time invariant skill differentials using individual fixed effects. My approach focuses on controlling for the demand for skill as opposed to the supply.

The average vacancy posting in the contract sample asks for 2.8 years of experience versus 2.5 years in the direct hire sample.

Finally, in contrast to experience and education requirements, skill requirements reveal more variation between the contract and direct hire samples. Both business service firms and other private firms have a propensity to post any skill qualification in over 90% of vacancies. I rely on skill requirements based loosely on Deming and Kahn (2018), who demonstrate that job skills have explanatory power in determining wages. Following Deming and Kahn (2018), I categorize skill requirements found in job vacancies into broad skill categories including cognitive, social, and non-cognitive skill sets.[13] I also supplement these categories with skill categories more specific to the occupation.[14] The contract sample and direct hire samples show significant differences in their propensity to post in most skill generalized skill categories. Social, non-cognitive, and cognitive skills are more likely to appear in vacancies for business service firms. Importantly, skill requirements that ask specifically for security experience are roughly equivalent across samples, with between 6-8% of vacancies that post any preferred skill qualification asking for experience in security, prevention of criminal activity, detection of suspicious behavior, etc.

There are several features of the skills data that should be noted as caveats to this analysis. First, controlling for year and MSA, neither social, cognitive, nor non-cognitive skills are predictive of wages in this sample. Second, for skills that are predictive of higher wages (computer and management skills, in particular), it is the contract sample that has a higher propensity to post said skills. Given that we find a negative contract penalty, this skill mix is likely to attenuate our results. Third, although measuring skill posting as a conditional probability should account for differences in verbosity across firms, it does not eliminate the possibility that differences across subgroups represent permanent differences across firm types and not the jobs themselves.[15] Fourth, we consider private security guards

[13] Specifically, I parse each skill for keywords associated with each skill category. For example, the social skills category captures any skills including keywords like "listening", "engagement", "positive disposition", etc.

[14] Although Deming and Kahn (2018) also use BGT data, they restrict their analysis to SOC codes 11-29 which represent professional occupations that require a college education. This sample notably excludes security guards, which is a non-professional occupation that requires a college degree in a minority of cases. Given the differences in our samples, it is not surprising that broad skill requirements are less predictive of wages in this sample and more likely represent permanent differences across firm types.

[15] With the exception of security-specific skills, many preferred qualifications are likely to align with the firm's core competencies and values. For example, one can imagine that a hotel and resort is more likely than a business service firm to emphasize personal presentation and interpersonal skills given that their core competency focuses on guest experience. A generic vacancy for a business service firm, on the other hand, will often express that working environments and conditions may vary by client site.

to have a relatively homogeneous skill set as demonstrated by the relatively high turnover and low-skilled requirements that are features of this occupation.[16] Finally, differences in posted skill demand are not constant over the sample, reflecting in part fluctuations over time and in the composition of firms posting job vacancies. Education and experience requirements, on the other hand, are relatively stable and reflect a similar candidate pool. To account for any remaining differences, I control for a full set of year, MSA, and skill requirement dummies to absorb the overall difference in skill requirements. Still, controlling for posted skills does rule out that there is remaining unobserved heterogeneity between the two groups. Given the similarity in education and experience requirements as well as the relatively homogenous skill set required for a private security guard, I believe that any outstanding differences are likely to be minimal.

## 1.4 Empirical approach

In this section I first motivate my main empirical approach. I then describe the construction of my measure of market concentration, an employer vacancy-posting Hirschman-Herfindahl Index. I present results from my baseline specification in which I find that on average moving from the median to the $95^{th}$ percentile of HHI would incur a wage penalty that is 5.9 log points lower for contractors than for their in-house counterparts. Finally, I discuss potential endogeneity concerns.

### 1.4.1 Theoretical predictions

Why might contract workers earn less relative to their direct hire counterparts? The literature to date has found empirical support for the role of both rent and competitive differentials. The core intuition for the role of rent differentials is that outsourced workers suffer a loss of firm-specific rents. If, for example, firms pay higher wages to all their employees in order to anchor wages of their workforce to their higher-skilled employees and achieve internal equity, then choosing to outsource a low-skilled occupation will effectively eliminate any wage benefits that were realized due to the firm's compensation scheme. This phenomenon has broad support in the data. Dube and Kaplan (2017) and Goldschmidt and Schmieder (2017) in particular find that outsourcing occurs largely among high-wage firms,

[16] In fact, that a robust market for contracted security guards exists at all is indicative of the homogeneous skills required for the job.

so that the wage loss associated with outsourcing is large. If the contract penalty were driven solely by the loss of firm specific rents, it must be true that the contracting penalty might not exist should the outsourcing firms pay wages comparable to those being paid by the business service firms.[17] Competitive differentials, on the other hand, might take the form of skill differentials or compensating differentials. The former suggests that a difference in skill mix across industries can explain the wage gap (e.g. security guards at private firms have more qualifications, experience, or education than do contracted guards). The latter suggests that the wage gap may be the result of contractors working shorter hours, receiving fewer non-wage benefits, or lacking union protection. In general the existing literature rejects that competitive rather than rent differentials explain the contracting wage penalty.

Despite the benefits that contracting out seem to provide private firms, business service firms and private firms continue to co-exist and compete to fill vacancies for security guards.[18] Although business service firms have continued to grow their market share, posting 53% of all security guard vacancies in 2017, the share of private firms posting vacancies for security guards does not appear to be at risk of converging towards zero. This suggests that another source of competitive differentials may be at play; namely, that (nominally) different firms compete for and hire security guards under distinct employment contracts.

The difference in employment contract between contractors and direct hires can be described as follows. On the one hand, employees hired directly by the singular firm to which they provide labor (i.e. "direct hires") make relationship-specific investments with their employer. On the other hand, workers hired as "contractors" do not enter into relationships with any one firm, as they may work with several firms over a single employment spell.[19][20] Hiring firms in this setting (i.e. "business service firms") act as intermediaries between workers and firms, as they hire labor and sell that labor to labor buyers (i.e. other private

[17]Note that this argument does not suggest that the marginal effect on workers being outsourced is zero

[18]This is true for other occupations that are highly outsourced including janitors and food and labor services.

[19]Baker and Hubbard (2003) in their work on asset ownership and job design refer to these employment relationships as cases of "relational" versus "discrete" work, respectively. They find that better monitoring mechanisms have led to a decline in "discrete work". Instead, the market has moved towards larger and more integrated firms as the incentive to work independently goes down. This phenomenon has parallels in the security industry, where labor is still contracted but under the umbrella of a large firm.

[20]My setting does not consider "gig economy" workers such as ride sharing drivers, food delivery drivers, etc. Relative to gig economy workers, the contractors I consider are more likely to make some degree of relationship-specific investments in their hiring firm, are more often under the protection of employment law, and are more likely to receive benefits. See Strom (2010)

firms with security needs). In other words, the selling firm hires workers as employees, but the buying firm hires workers from the selling firm as contract employees.

This is somewhat distinct from the case in which contractors are "owner-operators" who are responsible for selling and managing their own labor and can be better categorized as "gig economy" workers. Relative to gig economy workers, the contractors in my setting work in a less competitive environment; in particular, the cost of exit may be higher since there is some degree of relationship-specific investment made in the hiring firm who is responsible for selling their labor. On the other hand, relative to direct hires, contractors may *theoretically* operate in a more competitive environment. Direct hires have a high cost of exit due job specific investments so that alternative employers are less likely to compensate them for specific skill-match.

However, it need not be the case that the market for contractors is highly competitive. Since contractors face employment contracts that are in some ways relationship-specific, they face competitive pressures not dissimilar to those faced by direct hires. For example, if there are few hiring business service firms, then (1) the cost of exit increases and (2) business service firms have more labor market power by which to monopsonistically suppress wages.

This landscape suggests that there may or may not be differences in competitive pressured faced by in-house and contracted guards. I explore this possibility and find evidence that there does exist variation in competitive pressures or labor market monopsony *within* occupations where outsourcing is prevalent. I begin by assuming that a routine measure of labor market concentration describes the market for security guards to illustrate this point.

### 1.4.2 Measuring employer concentration

In this paper, I rely on the Herfindahl-Hirschmann concentration index (hereon "HHI") as my primary measure of local labor market power. Although this statistic relies on a binary and somewhat inflexible labor market definition, it is a relevant starting point for measuring labor market power that arises from employer size. Naidu and Posner (2021), for example, show that employer HHI is correlated to the degree of wage suppression under a standard Cournot model. Here, an increase in HHI leads to a proportional increase in the gap between the marginal productivity of labor and wages as the labor supply curve becomes upward-sloping for individual firms.

An HHI captures a number of relevant ideas for my setting: (1) The contractor wage gap derives from the mix of business service firms and other private firms (a function of both relative number and hiring intensity of each firm type) in the local market for security guards. (2) An HHI presupposes that all jobs are perfect substitutes within a local labor market. Should concentration exert different wage pressures on contract and in-house security guards, I can infer that market structure and firm type have important implications for explaining wage variation within a narrowly defined occupation-area. (3) For workers with homogeneous skills working in a the same labor market, outside options should theoretically be identical across workers. This allows me to focus on the change in outside options that can occur *within* the confines of a narrowly defined occupation-area.

To this end, I use employer vacancy HHI across firms within a market (defined as an occupation-MSA pair) as a measure of the concentration of labor demand in a market following Azar, Marinescu, Steinbaum, Taska (2020a). Vacancy HHI is calculated as follows:

$$HHI_{m,t} = \sum_{i=1}^{I} s_{i,m,t}^2$$

where $s_{i,m,t}$ is the market share of firm $i$ in market $m$ at time $t$. I define market share to be the sum of vacancies posted by a given firm in a given market divided by total number of vacancies posted in that market. For the 19% of observations where there is no employer name, I treat each observation as an individual, distinct employer. This choice is likely to underestimate concentration for two reasons: First, it is likely that several vacancies without an employer name belong to the same firm, and so this metric will be provide the lower bound of vacancy concentration. Second, our sample contains several large business service firms, skewing the employer size distribution. If large firms or business service firms are more likely to make multiple hires per post, vacancy concentration will underestimate true concentration.

**Descriptive HHI for private security guards.** Figure 1.2 plots the distribution of the HHI for private security guards over 2013-2017 for both the unweighted and employment weighed samples. In general, the market for private security guards is relatively concentrated, with a mean (unweighted) HHI of 0.14. The Horizontal Merger Guidelines used by the United States Department of Justice consider a market with an HHI below 0.15 to be unconcentrated, an HHI between 0.15 and 0.25 to be moderately concentrated, and an HHI above 0.25 to be highly concentrated. I denote an HHI of 0.25 with the dashed vertical line in Figure 1.2, which corresponds to roughly the $80^{th}$ percentile of my sample. Schubert, Stansbury and Taska (2022) find that 92% of security guards work in a market with an estimated wage penalty of at least 2% due to employer concentration, the second highest of all occupations covered in their sample.

### 1.4.3 Elasticity of wages to changes in concentration

I estimate the elasticity of posted wages with respect to concentration for contracted security guards as follows:

$$w_{i,m,t} = \alpha_m + \rho_t + \beta_1 C_{i,m,t} + \beta_2 HHI_{m,t} \tag{1.1}$$

$$+ \beta_3 \left[HHI_{m,t} \times C_{i,m,t}\right] + X_{i,m,t} + \epsilon_{i,m,t} \tag{1.2}$$

where subscripts refer to the vacancy post $i$, metropolitan statistical area (MSA) $m$, and year $t$. $\rho$ and $\alpha$ are year and MSA fixed effects, respectively. Log wages $w$ are average hourly wages that are posted in a given job vacancy, when available.[21] I construct the HHI from my job vacancy data for each MSA-year; construction is detailed in Section 1.4.3. The indicator variable $C$ is equal to 1 if the hiring firm is a business service firm (NAICS 5616), i.e. the job vacancy is for a contract position as opposed to an in-house position for a private firms. Importantly, I allow the impact of the HHI to vary by contractor status, interacting HHI with the indicator. The full sample for the baseline regressions consists of 144,215 vacancies over 4,685 MSA-years. The vector $X$ controls for observable education requirements, experience requirements, and skill requirements including non-cognitive skills, cognitive skills, social skills, computer skills, and security experience. I weight all regressions by MSA employment and cluster my standard errors at the MSA-level.

My baseline specification has the flavor of a difference-in-differences specification in which I compare the elasticity of wages to concentration for contractors to that for direct hires, controlling for observable confounding variables. The primary coefficient of interest is $\beta_3$.

[21] Where only annual earnings are posted, I obtain the hourly equivalent by dividing earnings by 2080.

### 1.4.4 Baseline results

The OLS estimates of my baseline specification suggests that not only does a strong negative correlation exist between concentration and wages, but that the associated wage penalty differs for contract and in-house security guards. My estimates indicate that moving from an unconcentrated market with an HHI of 0.15 to a highly concentrated market with an HHI of 0.25 would incur a wage penalty that is 3 log points lower for contractors than for their in-house counterparts.

In Table 1.5, I find that both HHI and contractor status are independently associated with a wage penalty. In column (1), HHI has a coefficient of -0.03.[22] In column (2), contractor status has a statistically significant and economically meaningful coefficient of -0.409, corroborating findings from the existing literature that a contracting wage penalty exists.[23] Notably, the addition of covariates made no meaningful change to the magnitude or significance of the coefficient. Combining HHI and contractor status in column (3), I find that the coefficient on contractor status is virtually unchanged and the coefficient on HHI drops by about one half but remains highly statistically significant.

Columns (4) and (5) of Table 1.5 present the findings of my baseline specification, where my preferred specification is in column (5) with the addition of skill controls. The interaction term between HHI and contractor status has a statistically significant coefficient of -0.057, suggesting that on average going from the median to the 95th percentile of HHI (from an HHI of 0.12 to an HHI of 0.34) would incur a wage penalty that is 5.9 log points lower for contractors than for their in-house counterparts.[24]

### 1.4.5 Addressing endogeneity between wages and concentration

My finding that own-occupation vacancy concentration lead to a reduction in wages is likely to suffer from a variety of endogeneity concerns. The most obvious issue is that *many* factors are likely to change both concentration and wages simultaneously. For example,

[22] Hershbein et al. (2020) and Schubert, Stansbury and Taska (2022) use comparable wage measures and find a coefficient between -0.014 and -0.015 on HHI. My coefficient is substantially larger than those estimates, which likely reflects that the market for security guards is highly concentrated. Evidence that wage penalty is largest in most concentrated markets

[23] This estimate is significantly larger than that found in Dube and Kaplan (2017). Their results suggest that contracted guards earn 19% less than do in-house guards, while mine suggests a 33% difference. However, our sample time differs substantially, and my main dataset suggests a much larger raw wage gap between contractors and direct hires relative to that found in Dube and Kaplan (2017).

[24] Alternatively, the point estimate suggests that on average a 10% increase in concentration leads to a 0.57% decrease in wages for contractors relative to their direct hire counterparts.

an expanding firm will both mechanically increase concentration while also becoming more productive, lending ambiguity to the overall effect on wages. Increasing employment, in fact, is counterintutive to the idea that an increase in market share also increases the firm's market power.

A second challenge is that concentration requires a market definition. To date most literature has relied on a market definition that is defined at the occupation- or industry-area. A more recent literature has allowed for additional flexibility, considering other occupations or industries that are reasonable alternatives for the worker's skill set and qualifications, and directly accounting for probabilities that a worker can transition between "binary" markets. My setting does not directly account for available outside options, and I instead rely on a measure of vacancy concentration defined at the occupation-MSA level. My results so far demonstrate that this definition may not be reasonable since there is evidence of a contracting penalty that exists *within* an occupation at the MSA level.

In the following section I address these endogeneity concerns. My results show that endogeneity concerns are well-founded, but that the effect remains substantial and significant. I provide additional evidence that the HHI does not capture the competitive differences facing in-house and contract security guards.

## 1.5 Mergers and acquisitions

In this section I provide evidence to support my finding that contractors and in house security guards experience a differential reduction in posted wages due to market concentration. My results suggest that an HHI may be an insufficient description of the monopsonistic determinants of wages.

### 1.5.1 Overview

As previously noted, there are outstanding concerns that my baseline specification suffers from endogeneity issues. First, there are many factors I do not account for that may change wages and concentration simultaneously. Second, my market definition may be insufficiently flexible and does not account for the role that outside options play in wage determination. Identifying exogenous variation in concentration that cannot be conflated with differences in outside options may help account for my finding that the elasticity of wages with respect to concentration differs for contract and in house security guards. Nearly all of the existing literature documenting a contracting wage penalty relies on mass layoffs and establishment closures as a source of exogenous variation in concentration. My data represents only the demand side of the labor market, and so I cannot observe actual hiring and firing decisions of any given firm.

To address this concern, I explore merger and acquisition (M&A) activity as a source of variation in market concentration. In particular, I follow Arnold (2020) in using M&A activity as an instrument for concentration. I first show that expected concentration changes due to ownership change are predictive of realized concentration changes, but they explain relatively little of the variation in concentration changes. I then use M&A activity as an instrument for concentration and estimate the elasticity of posted wages to vacancy concentration. This approach conditions on markets that have experienced at least one M&A event over the sample period and estimates the impact of *merger-induced* changes in concentration on posted wages. Finally, to ensure I am isolating variation that is not driven by local economic conditions, I validate the results by limiting my sample to firms that operate in multiple MSAs, or that operate as "national wage setters".

### 1.5.2 Data

I collect data on mergers and acquisitions in the United States between 2013 and 2017 from the Securities Data Company (SDC) Platinum Mergers and Acquisitions database, and merge the data with my main sample of job vacancy postings from BGT.[25] SDC Platinum is a high-quality database that provides details on activity in the global financial marketplace, including comprehensive coverage on mergers and acquisition. I use the SDC database to identify all mergers and acquisitions with announcement dates between January 1, 2013 and December 31, 2017. I require that (1) the target is US company, (2) acquisitions be completed, (3) that 100% of the target be acquired after the transaction, (4) that the acquiror is not the same firm as the target firm, and (5) the transaction is not a leveraged buy-out. I obtain relevant data from SDC including the announcement and effective date, the name and industry of both the target and acquiror, and deal value when available. This

[25] An alternative approach taken by Arnold (2020) is to identify M&A activity from the Longitudinal Business Database establishment-level data. This approach has the advantage of including both establishment- and enterprise-level identifiers and of mapping to worker-level data, so that identifying M&A events and market outcomes is relatively straightforward. Although the SDC data contain various characteristics of the M&A itself, resulting in some advantages relative to the LBD, matching M&A events to my main dataset necessitates that I rely on firm names so that the process is more subjective.

yields a total of 60,396 M&A events, of which 54,573 M&A events have target firms in industries represented in my main BGT sample.

My analysis requires that the target firm be present in the main BGT sample. I use an extensive cleaning process by which I match firm names in the SDC data to firm names in the BGT data using a fuzzy match algorithm. Finally, I manually exclude observations for which I cannot be sure that the target firm has a true match in the BGT data. I ultimately match 736 target firms to the main BGT sample.[26][27] The resulting dataset constitutes my main M&A sample.

The final sample consists of 736 mergers and acquisitions in which both the acquirer and the target are US companies between 2013 and 2017. Panel (a) of Figure 1.3 shows the number of acquisitions by year. Panel (b) reports the six industries which experience the most M&A activity in my sample.

### 1.5.3 Empirical approach

To motivate the choice of M&A activity as an instrument for concentration, I illustrate that correlations between concentration and wages may not be an informative estimate of the impact of changes in market structure on labor market outcomes including posted wages.

I match each M&A event in my sample to the primary BGT dataset by target and acquiring firm name to calculate a merger-induced counterfactual HHI. The counterfactual HHI in time $t$ holds the number of vacancy posts for each firm fixed to its $t-1$ level but assigning time $t$ employers (i.e. vacancies from acquired firms are reassigned to their acquiror). I calculate the change in HHI from time $t$ to $t+1$ for both my actual and counterfactual HHIs. Table 1.6 shows the correlation between the counterfactual or predicted change in HHI due to merger activity on the realized change in HHI. The predicted change in HHI tends to be significantly smaller than the realized change between times $t$ and $t+1$, due in part to the relatively small number of vacancy postings relative to employment levels at each posting firm. Still, the change in concentration based on my counterfactual HHI is highly predictive of the observed change in HHI.

[26] Approximately 65% of the main BGT sample falls under the business services industry for security guards, and so the majority of M&A events do not map into this sample.

[27] I also perform a sanity check to make sure that any new firms formed through a merger are only listed as firms in the BGT dataset in the years since the merger.

Despite the M&A-induced change in HHI being highly predictive of the observed change in HHI, it explains relatively little of the variation in concentration changes with an $R^2$ of 0.078. This suggests that the correlation between posted wages and concentration tells us little about the anti-competitive impacts of M&A (via changes in market structure) on posted wages, given that most variation in concentration is not driven by merger activity. This motivates the use of merger activity as an instrument for HHI. Like Arnold (2020), I find a relationship between (absolute) changes in HHI and log wages that suggests significant (negative) shifts in posted wages are generated only for concentration changes in the top ventile. A concentration change equal to roughly 1.2 log points corresponds to the $95^{th}$ percentile of concentration changes; concentration changes below that have no significant effect on log wages.

### 1.5.4 Elasticity of earnings with respect to vacancy concentration

To estimate the elasticity of posted wages with respect to concentration due to merger activity, I use two-stage least squares regression of the form:

$$\widehat{HHI}_{m,t} = \alpha_m + \rho_t + \beta\left[Q20_m \times Post_{m,t}\right] + X_{i,m,t} + \epsilon_{m,t} \tag{1.3}$$

$$w_{i,m,t} = \alpha_m + \rho_t + \beta_1 C_{i,m,t} + \beta_2 \widehat{HHI}_{m,t} + \beta_3\left[\widehat{HHI}_{m,t} \times C_{i,m,t}\right] + X_{i,m,t} + \epsilon_{m,t} \tag{1.4}$$

where equation (1.3) is the first stage regression. HHI and the interaction of HHI and contractor status $C$ is instrumented by a top ventile concentration change $Q20_m$ interacted with an indicator $Post$ for whether time $t$ is post-merger. Equation (1.4) is the second stage regression on posted wages of non-merger firms. My analysis conditions on markets that had any M&A activity over the sample period, comprising 40% of all markets in the main BGT sample. Of markets that had at least one M&A event over the sample period, 25% of markets had just one event. Conditional on having some merger activity, the identifying variation comes from differences in the size of the concentration changes across MSAs. I follow Arnold (2020) and Lafortune et al. (2018) and create duplicate observations for each market that experiences multiple M&A events.

**National firms.** Because M&A activity is likely not random, my analysis above still allows for the possibility that local economic conditions are driving M&A activity through endogenous decisions by firms. For example, a local demand shock might simultaneously decrease employment while increasing M&A activity if that shock lowers the threshold above which firms are willing to sell. To account for this possibility, I limit the M&A sample to firms that operate in at least five MSAs over the sample period under the reasonable assumption that M&A activity by a firm that operates in multiple MSAs is less likely to be driven by local economic conditions at any one establishment. This restriction drops approximately 15% of the sample

One way to alleviate this concern is to focus my analysis on mergers that are less likely to have been triggered by local economic conditions. To do this, I limit my sample to "national firms", defined as those target firms and acquiring firms that operate in at least five MSAs. Merger decisions, then, are less likely to be tied to the local conditions of any single establishment. This alleviates cases where, for example, a negative productivity shock occurs in an MSA contemporaneously with an M&A event. In this example, we might spuriously attribute any negative impact on wages to the M&A event rather than to the negative productivity shock. Dropping observations where the target and acquiror post vacancies in fewer than five MSAs drops 367,480 vacancies from the estimation sample.

### 1.5.5 Results

Table 1.7 provides regression results for our first stage equation. Top-ventile mergers appear to be a strong instrument for HHI, with a corresponding $F$-statistic of 29.5 found in column *2*. The coefficient suggests that top-ventile mergers increase log vacancy concentration by 0.411.

When instrumenting for the HHI, I find that the elasticity of wages to concentration for contractors is highly significant and substantially larger than my OLS estimate with a coefficient of -0.205 (Table 1.8, column *4*). This suggests that the OLS coefficients likely suffer from a large degree of omitted variable bias or measurement error. The coefficient on the contractor dummy remains large and statistically significant, lending support to the finding that a contracting penalty exists and is not driven only by differences in market structure. Instead, my results suggest that both rent differentials and competitive differentials independently contribute to the contracting penalty.

Table 1.8, columns *5* and *6* present my estimates from the sub-sample of national firms, which should alleviate bias in the full sample estimates that arises from endogenous merger decisions that are made based on local labor market conditions. Compared to the full sample, the national firm sample estimates are only marginally attenuated. The coefficient on the instrumented interaction between contractor status and HHI is negative and highly statistically significant, confirming that the contracting penalty reflects competitive differentials, at least in part. As in the OLS and full sample IV specifications, controlling for observable differences in skill has little impact on the coefficients.

To summarize, I find that mergers which significantly increase HHI have a negative impact on posted wages for non-merging firms. In particular, the wage penalty is larger for job postings for contract versus in-house security guards. I interpret this as evidence for the role of competitive differentials in driving the contracting wage penalty.

## 1.6 The role of outside options

### 1.6.1 Overview

In the previous section, I find that competitive differentials contribute to the contracting wage penalty. My findings suggest that a 1% increase in the HHI has a differential impact on contracted and in-house security guards, with contracted security guards experiencing a relatively larger wage penalty due to an increase in concentration.

My results do not rule out the role of rent differentials, whereby the wage penalty is due to a loss of firm-specific rents driven by firms with high wage premia choosing to outsource. This effect is likely picked up by the coefficient on $C$ in my instrumented specification in Table 1.8, which exhibits independent explanatory power from the interaction term between HHI and $C$.

What then explains why local vacancy concentration has an independent effect on the contracting wage penalty? If we believe that (1) contract and in-house guards are identical conditional on observable skill differences and (2) that contractors and in-house guards perform the same job for nominally different employers, then there must be another mechanism through which HHI would differentially impact these groups.

A prominent idea in recent economic literature suggests that a standard HHI may be overly simplistic and does not appropriately account for competitive pressures faced within a market. Schubert, Stansbury, and Taska (2022) interact an HHI with their measure of an occupation's outside options, and suggest that only occupations with the lowest mobility (i.e. the fewest outside options) experience negative pressure on wages due to local concentration. Their empirical approach does not explicitly account for the wages in other firms in a worker's own occupation, although they find theoretical support for this mechanism. Handwerker (2022) makes a similar point in the context of low-wage occupations where outsourcing is prevalent and calculates a standard HHI separately for business service firms and all other private firms that employ a given occupation.[28] This has the flavor of treating business service firms and other private firms as two distinct markets. However, this approach fails to capture the high degree of skill substitutability between contract and in-house guards, as well as the interaction between business service firms and private firms.

These approaches each reveal an important consideration in explaining the mechanism through which competitive differentials may drive the contracting wage penalty. Namely, that if contract and in-house guards exist in the same market, then outside options must vary at the employment contract-level rather than at the occupation level. Although both contract and in-house guards can with some probability transition into other occupations, that probability should be the equal for both worker types. Any remaining variation in wages, then, must come from differences in how guards match to other firms *within* their own occupation.

### 1.6.2 A stylized example

Consider the following thought experiment that illustrates this idea. Suppose there are 1000 firms in each of two markets. In Market A, Firm 1 is a huge contracting firm with 50% market share, and Firms 2-1000 are all small firms who hire in-house labor. In Market B, Firm 1 is a huge contracting firm with 60% market share, and Firms 2-1000 are all small firms who hire in-house labor. Market A has an HHI of 0.25, while Market B is relatively more concentrated with an HHI of 0.36. Going from Market A to Market B implies little change in outside options for the workers at the contracting firm. For the in-house hires, however, the increase in HHI implies a much bigger (positive) change in outside options. Since we would expect an increase in outside options to result in a better bargaining position and thus higher wages, we might expect that the impact of increased concentration results in wages that are reduced relatively more for the contract workers compared to those of the in-house workers.[29]

[28] In fact, Handwerker (2020) finds that security guards who work for business service firms face the highest degree of concentration for all occupation-firm type pairs she considers.

[29] Consider a similar example in which the contractors as opposed to the in-house workers experience a larger change in outside options that still results in a contracting wage penalty. Suppose there are two markets where Market A has 10 firms and Market B has six firms. In Market A, Firm 1 is a huge contracting firm with 30% market share, and Firms 2-10 are smaller firms who hire in-house labor. In Market B, Firm

To express this formally, consider business service firms $b$ and other private firms $p$ to be analagous to two distinct "firm types" so that a guard can either be employed at a business service firm or at a private firm with security needs. Their local market consists of firm types $b$ and $p$ where the sum of market shares over firm types $b$ and $p$ equals one. The value of outside options for a contractor $c$ employed at a type $b$ firm can be expressed as

$$OOI_c = \sum_{b \neq \_b} \left[ (\pi_{c \to b}) \times \left( \frac{s_{b,t}}{s'_t} \right) \times (\widehat{w_{b,t}}) \right] + \sum_{p} \left[ (\pi_{c \to p}) \times \left( \frac{s_{p,t}}{s'_t} \right) \times (\widehat{w_{p,t}}) \right].$$

Analogously, the value of outside options for an in-house guard $d$ at a type $p$ firm can be defined as

$$OOI_d = \sum_{b} \left[ (\pi_{d \to b}) \times \left( \frac{s_{b,t}}{s'_t} \right) \times (\widehat{w_{b,t}}) \right] + \sum_{p \neq \_p} \left[ (\pi_{d \to p}) \times \left( \frac{s_{p,t}}{s'_t} \right) \times (\widehat{w_{p,t}}) \right].$$

That is, for each contractor (direct hire), the value of within-occupation outside options is the weighted average of wages in all other firms of each type. $s_{b,t}$ ($s_{p,t}$) is the market share of firm $b$ ($p$) and $s'_t$ is the sum of the market shares of each firm less the market share of the firm that the contractor (direct hire) currently works at, reflecting that one's own firm is not a viable outside option (Jarosch et al 2023). Probabilities $\pi$ reflect the likelihood of that a contractor (direct hire) at a firm of type $b$ ($p$) can transition to a firm of type $p$ ($b$). For simplicity, we can assume that these probabilities are equal to one given that contractors and direct hires perform the same job at nominally different firm types.[30]

In Appendix A I provide a stylized numerical example using the framework above. The context is a market $A$ where a large business service firm and several smaller, private firms hire security guards, and a market $B$ where the large business service firm expands and displaces hiring by private firms. This example confirms the intuition of the thought experiment above: moving from a low to a high concentration market decreases the value of outside options for contract guards relatively more than for in-house guards, resulting in a larger wage penalty.

1 is a huge contracting firm with 50% market share, and Firms 2-6 are smaller firms who hire in-house labor. Market A has an HHI of 0.16, while Market B is relatively more concentrated with an HHI of 0.30. Going from Market A to Market B implies no change in outside options for the in-house workers. For the contractors, however, the increase in HHI implies a much bigger (negative) change in outside options. Since we would expect a decrease in outside options to result in a worse bargaining position and thus lower wages, we might expect that the impact of increased concentration results in wages that are reduced relatively more for the contract workers compared to those of the in-house workers.

[30] This need not be the case in practice if there is unobserved heterogeneity between contract and in-house security guards.

One important caveat of this simplistic approach is that it does not consider general equilibrium effects. Rather, it conditions on observable characteristics of the market for private security, including the increasing dominance of business service firms and the existing contracting wage penalty. Of course, as market composition shifts, we would expect relative wages to shift as well. My theory captures only partial equilibrium effects, and does not purport to represent the marginal effect on wages of security guards when these firms expand or in-house guards are contracted out. A more rigorous approach would account for both effects.

## 1.7 Conclusion

In this paper I investigate a new mechanism through which market competition yields a contracting wage penalty for domestically outsourced workers. I show that, in the context of private security guards, moving from the median to the $95^{th}$ percentile HHI would generate a wage penalty that is 9.5 log points larger for contracted security guards relative to their in-house counterparts. This finding is robust to using merger-induced concentration changes to isolate exogenous variation in concentration. Most critically, I show that conditional on (1) contract and in-house guards representing the same occupation with a similar skill set and on (2) that contract and in-house guards perform the same job for nominally different employers, then the HHI must not fully capture competitive pressures that impact the market for security guards.

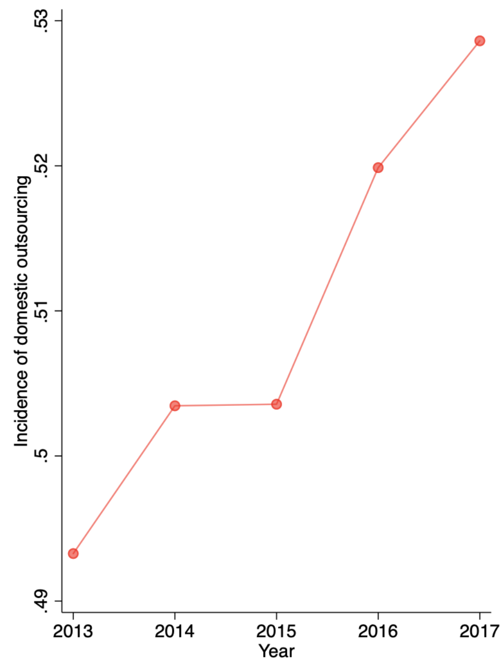
The growth of business service firms tells us that while "fissured" occupations do not disappear from the private workplace, they are re-organized and restructured under different terms. In occupational settings that lend themselves to outsourcing, it is therefore no longer the case that in-house employment relationships need be the norm. Wage differentials that exist between workers of the same occupation in the same local labor market suggest that other sources of monopsony power must differ between worker types. I show that outside options, and in particular own-occupation outside options, may be an important source of monopsony power. A more flexible labor market definition that includes within-occupation outside options can help account for the differential elasticity of wages to concentration for contract versus in house security guards.

One way to think about the role of outside options is through the lens of return to job search effort. As business service firms continue to grow, there are decreasing alternatives for workers at other firms in their own occupation. The degree of downward wage pressure imposed on contractors might compel those workers to seek employment opportunities outside their own occupation. If so, what are the relevant alternatives for firms? The fact that the majority of workers in low-wage occupations subject to domestic outsourcing are employed by business service firms suggests that that this is a relevant policy question. Business service firms may ultimately need to provide better compensation to remain competitive, and future work should be directed at understanding how to optimally allocate workers in this setting.

Finally, this paper presents a case study of one specific occupation. Although occupations that are subject to domestic outsourcing tend to have similar attributes (including low wages, low education requirements, and relative homogeneity of task content), my approach can and should be modified to accommodate a wider variety of occupations and employment contract types. A matched employer-employee data set would be more suitable for these purposes.

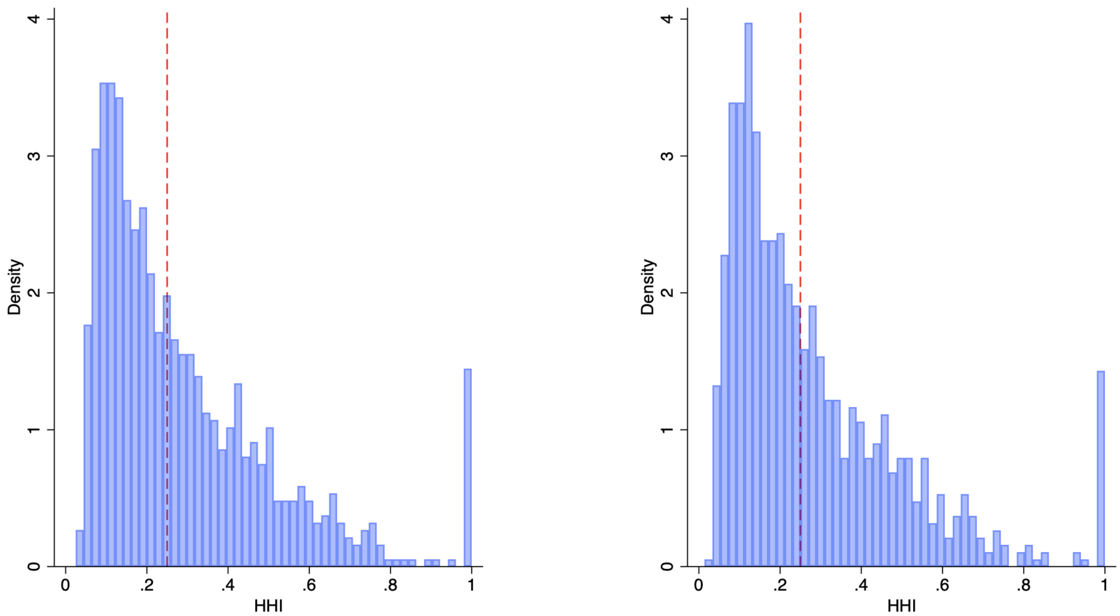
## 1.8 Tables and Figures

**Figure 1.1:** *Incidence of domestic outsourcing for security guards*




Note:

**Figure 1.2:** *Herfindahl-Hirschman Index*

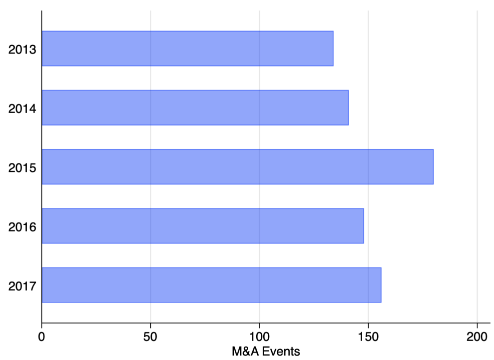



**(a)** *Full sample*

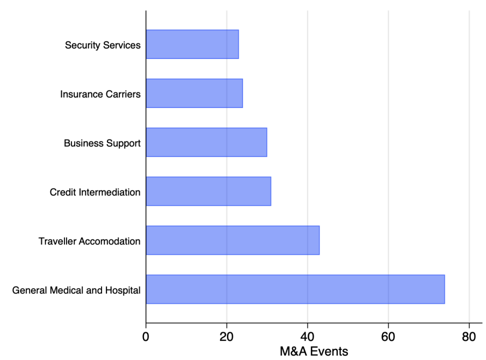
**(b)** *Full sample, employment weighted*

Note: This figure plots the distribution of the Herfindahl-Hirschman Index (HHI) for private security guards for each MSA-year observation over 2013-2017. The vertical red line indicates the HHI above which a market is considered to be highly concentrated according to the Horizontal Merger Guidelines used by the antitrust division of the US Department of Justice. See Section X for details on index construction.

**Figure 1.3:** *M&A Activity*




**(a)** *M&A activity*




**(b)** *M&A activity by industry*

Note: This figure plots M&A activity for my main merger sample. Data comes from the Security Data Company (SDC) Platinum Mergers and Acquisitions database and is matched by target and acquiring firm name to my dataset of job vacancies from BGT. Panel A plots the distribution of events over the sample period 2013-2017. Panel B shows the six industries that experience the most M&A activity in my sample.

**Table 1.1:** *Cell counts for private security guards (2013-2017)*

| | Mean | |
|---|---|---|
| | Full Sample | Contract Firm Sample |
| **Total Vacancies** | 443,000 | 294,717 |
| Number of MSAs | 956 | 906.00 |
| Number of Firms | 16,597 | 1,794 |
| Wage Posting | 26% | 20% |
| Posts per MSA-Year | 98.8 | 74.4 |
| Posts per Firm-MSA-Year | 5.9 | 9.2 |

Notes: This table presents an overview of the BGT job vacancy data for private security guards (SOC 33-9032). Column (1) summarizes the full sample and Column (2) summarizes the sample for security guards who are employed by a business service firm (NACIS 5616).

**Table 1.2:** *Summary statistics: private security guards (2013-2017)*

| Percentile | 1 | 5 | 10 | 25 | 50 | 75 | 90 | 95 | 99 |
|---|---|---|---|---|---|---|---|---|---|
| | *Panel A: MSA-occupation employment and wages* | | | | | | | | |
| *Employment* | 9 | 28 | 54 | 207 | 1009 | 2754 | 4417 | 7168 | 8672 |
| *Employment (emp-wt)* | 183 | 633 | 1123 | 2131 | 3632 | 6627 | 8292 | 8672 | 8672 |
| *Mean hourly wage* | 8.0 | 9.0 | 9.5 | 10.5 | 12.0 | 15.0 | 23.7 | 33.8 | 62.5 |
| *Mean hourly wage (emp-wt)* | 8.5 | 9.5 | 10.0 | 11.0 | 12.45 | 15.0 | 24.0 | 33.8 | 63.5 |
| | *Panel B: Employer Concentration HHI* | | | | | | | | |
| *HHI* | 0.02 | 0.03 | 0.05 | 0.07 | 0.12 | 0.19 | 0.27 | 0.34 | 0.52 |
| *HHI (emp-wt)* | 0.02 | 0.03 | 0.04 | 0.08 | 0.11 | 0.19 | 0.27 | 0.28 | 0.34 |

Notes: This table reports summary statistics for private security guards (SOC 33-9032) in my main sample of BGT vacancy data for which I have wage data and a vacancy HHI. The HHI measures employer vacancy concentration at the MSA-year level and treats each vacancy with no employer information as belonging to a unique firm. Rows that are employment-weighted ("emp-wt") show the percentiles weighted by MSA-level employment.

**Table 1.3:** *Industries directly hiring security guards*

| Industry (4-digit NAICS) | Number of vacancy postings | % of direct hires |
|---|---|---|
| General Medical and Services Hospital | 26,068 | 18.7 |
| Traveller Accommodation | 16,767 | 12.0 |
| Software Publishers | 8,443 | 6.06 |
| Justice, Public Order, and Safety Activities | 7,232 | 5.19 |
| Colleges, Universities, and Professional Schools | 7,086 | 5.08 |
| Management, Scientific, and Technical Consulting Services | 4,567 | 3.28 |
| Elementary and Secondary Schools | 4,414 | 3.17 |
| Depository Credit Intermediation | 3,877 | 2.78 |
| National Security and International Affairs | 3,548 | 2.55 |
| Business Support Services | 3,520 | 2.52 |
| Executive, Legislative, and Other General Government Support | 2,913 | 2.09 |
| Services to Buildings and Dwellings | 2,841 | 2.04 |
| Gambling Industries | 2,761 | 1.98 |
| Department Stores | 2,578 | 1.85 |
| Computer Systems Design and Related Services | 2,111 | 1.51 |
| Insurance Carriers | 2,004 | 1.44 |
| Continuing Care Retirement and Assisted Living Facilities | 1,941 | 1.39 |
| Aerospace Product and Parts Manufacturing | 1,817 | 1.30 |
| Architectural, Engineering, and Related Services | 1,583 | 1.14 |
| Restaurants and Other Eating Places | 1,171 | 0.84 |
| Scientific Research and Development Services | 1,103 | 0.79 |
| Individual and Family Services | 1,054 | 0.76 |
| Business, Professional, Labor, Political, and Similar Organizations | 1,009 | 0.72 |
| Other Amusement and Recreation Industries | 966 | 0.69 |
| Junior Colleges | 952 | 0.68 |

**Table 1.4:** *Skill requirements*

| | Mean | | |
|---|---|---|---|
| | Full sample | Contract sample | Direct hire sample |
| *Education requirements* | | | |
| Any education requirement | 0.76 | 0.82 | 0.62 |
| | (0.43) | (0.39) | (0.49) |
| High school | 0.96 | 0.99 | 0.86 |
| | (0.19) | (0.09) | (0.34) |
| College | 0.03 | 0.01 | 0.11 |
| | (0.17) | (0.07) | (0.31) |
| Advanced degree | 0.00 | 0.00 | 0.01 |
| | (0.04) | (0.01) | (0.08) |
| Years of schooling | 12.14 | 12.03 | 12.51 |
| | (0.75) | (0.32) | (1.35) |
| *Experience requirements* | | | |
| Any experience requirement | 0.22 | 0.15 | 0.40 |
| | 0.42 | 0.36 | 0.49 |
| Less than one year | 0.08 | 0.05 | 0.10 |
| | 0.27 | 0.23 | 0.31 |
| 1-5 | 0.84 | 0.87 | 0.81 |
| | 0.37 | 0.33 | 0.39 |
| 5-10 | 0.06 | 0.06 | 0.07 |
| | 0.25 | 0.23 | 0.26 |
| 11+ | 0.02 | 0.02 | 0.01 |
| | 0.12 | 0.13 | 0.11 |
| Years of experience | 2.64 | 2.84 | 2.47 |
| | 2.60 | 2.73 | 2.46 |
| *Skill requirements* | | | |
| Any posted skill | 0.92 | 0.93 | 0.90 |
| | 0.27 | 0.25 | 0.30 |
| Computer skills | 0.33 | 0.37 | 0.24 |
| | 0.47 | 0.48 | 0.43 |
| Physical skills | 0.61 | 0.75 | 0.25 |
| | 0.49 | 0.43 | 0.43 |
| Social skills | 0.64 | 0.71 | 0.46 |
| | 0.48 | 0.46 | 0.50 |
| Cognitive skills | 0.47 | 0.57 | 0.23 |
| | 0.50 | 0.50 | 0.42 |
| Security experience | 0.07 | 0.06 | 0.08 |
| | 0.25 | 0.24 | 0.28 |
| Noncognitive skills | 0.39 | 0.48 | 0.16 |
| | 0.49 | 0.50 | 0.37 |
| Social-cognitive skills | 0.40 | 0.50 | 0.16 |
| | 0.49 | 0.50 | 0.36 |

Notes: This table reports summary statistics from the main sample of job vacancies from BGT over 2013-2017. Mean education and experience requirements are conditional on posting any education requirement and any experience requirement, respectively. Skill requirements are conditional on posting any skill requirement, noting that any vacancy can post multiple skills. Column (1) provides mean skill requirements for the full sample. Columns (2) and (3) provide mean skill requirements for contractors and direct hires, respectively. Standard deviations are in parentheses.

**Table 1.5:** *Baseline regression of wages on HHI*

| | Log wage | Log wage | Log wage | Log wage | Log wage |
|---|---|---|---|---|---|
| HHI (log) | -0.045 | | -0.021 | 0.024 | 0.023 |
| | (0.009) | | (0.006) | (0.014) | (0.014) |
| Contractor | | -0.409 | -0.409 | -0.567 | -0.543 |
| | | (0.011) | (0.011) | (0.036) | (0.034) |
| Contractor × HHI (log) | | | | -0.060 | -0.057 |
| | | | | (0.015) | (0.015) |
| Year FE | Y | Y | Y | Y | Y |
| MSA FE | Y | Y | Y | Y | Y |
| Skill controls | N | Y | Y | N | Y |
| $R^2$ | 0.091 | 0.305 | 0.305 | 0.289 | 0.307 |
| Obs | 144215 | 129181 | 129181 | 129181 | 129181 |

Notes: This table reports baseline estimates of the effect of concentration on wages for private security guards who are employed by business service firms and contracted out to private firms. The HHI measures employer vacancy concentration at the MSA-year level and treats each vacancy with no employer information as belonging to a unique firm. Contract status is equal to one if a private security guard (SOC 33-9032) is hired by a business service firm (NAICS 5616). Specifications with skill controls account for experience requirements, education requirements, and skill requirements including social skills, non-cognitive skills, cognitive skills, computer skills, and security experience. The regressions are estimated on my primary sample of job vacancies from BGT. All results are weighted by the local MSA employment. Standard errors are clustered at the MSA level.

**Table 1.6:** *Predicted vs actual changes in local labor market concentration*

| | Observed change in HHI |
|---|---|
| Predicted change in HHI | 11.526 |
| | (3.869) |
| Year FE | Y |
| MSA FE | Y |
| $R^2$ | 0.078 |
| Market-Years | 1501 |

Notes: This table reports the correlation between the actual change in vacancy concentration and the predicted change in vacancy concentration due to merger activity. The HHI measures employer vacancy concentration at the MSA-year level and treats each vacancy with no employer information as belonging to a unique firm. I calculate the predicted change in vacancy HHI that would occur at time $t$ in MSA $m$ if employment at every establishement (firm-MSA pair) remained at *t-1* levels but the owners set to time $t$ firms (i.e. assumes the acquiror posts exactly as many vacancies as the target firm posted pre-acquisition). The regressions are estimated on my primary sample of job vacancies from BGT. Standard errors appear in parentheses, and are clustered at the MSA level.

**Table 1.7:** *First stage impact of top-ventile concentration increase on log HHI*

| | HHI (log) | HHI (log) |
|---|---|---|
| Q20 × Post Merger | 0.411 | 0.411 |
| | (0.055) | (0.055) |
| Year FE | Y | Y |
| MSA FE | Y | Y |
| Skill controls | N | Y |
| F-statistic | 55.07 | 29.46 |

Notes: This table reports the first stage estimates of the impact of a top-ventile concentration increase due to merger activity on log HHI for private security guards. The HHI measures employer vacancy concentration at the MSA-year level and treats each vacancy with no employer information as belonging to a unique firm. Specifications with skill controls account for experience requirements, education requirements, and skill requirements including social skills, non-cognitive skills, cognitive skills, computer skills, and security experience. The regressions are estimated on my primary sample of job vacancies from BGT. All results are weighted by MSA employment. Standard errors appear in parentheses, and are clustered at the MSA level.

**Table 1.8:** *Instrumental Variables estimates of the elasticity of earnings with respect to HHI*

| | Full sample | | Full sample | | National Firms | |
|---|---|---|---|---|---|---|
| | OLS | OLS | 2SLS | 2SLS | 2SLS | 2SLS |
| Contractor | -0.485 | -0.463 | -0.936 | -0.896 | -0.992 | -0.970 |
| | (0.059) | (0.055) | (0.176) | (0.148) | (0.118) | (0.095) |
| HHI (log) | -0.002 | 0.000 | 0.142 | 0.119 | 0.147 | 0.139 |
| | (0.025) | (0.024) | (0.092) | (0.081) | (0.092) | (0.074) |
| Contractor × HHI (log) | -0.020 | -0.018 | -0.212 | -0.205 | -0.198 | -0.187 |
| | (0.026) | (0.024) | (0.088) | (0.077) | (0.059) | (0.049) |
| Year FE | Y | Y | Y | Y | Y | Y |
| MSA FE | Y | Y | Y | Y | Y | Y |
| Skill controls | N | Y | N | Y | N | Y |
| $R^2$ | 0.250 | 0.270 | 0.163 | 0.185 | 0.203 | 0.222 |

Notes: This table reports the instrumental variable estimates of the effect of concentration on wages for private security guards who are employed by business service firms and contracted out to private firms. The instrument for HHI is an indicator for a top-ventile concentration increase due to merger activity. Columns (1) and (2) present the baseline OLS estimates for the full sample. Columns (3) and (4) present the IV estimates for the full sample. Columns (5) and (6) present the IV estimates for the restricted sample of national firms, where a national firm is defined as posting vacancies in at least five MSAs over the sample. The HHI measures employer vacancy concentration at the MSA-year level and treats each vacancy with no employer information as belonging to a unique firm. Specifications with skill controls account for experience requirements, education requirements, and skill requirements including social skills, non-cognitive skills, cognitive skills, computer skills, and security experience. The regressions are estimated on my primary sample of job vacancies from BGT. All results are weighted by MSA employment. Standard errors appear in parentheses, and are clustered at the MSA level.

# Appendix

### 1.8.1 Data construction

**Main sample.** My main sample includes all vacancies for security guards (SOC 33-9032) over 2013-2017 collected by Burning Glass Technologies. I exclude vacancies with missing wage data, missing industry or occupation data, or missing location information. I also exclude vacancies that are for military occupations, that have commission pay, and that are not in the private sector.

To identify cases where security guards are employed by business service firms rather than by other private firms, I use a combination of the 6-digit SOC code and 4-digit NAICS code. I identify all vacancies associated with the NAICS code 5616 ("Investigation and Security Services") as contract jobs. All other vacancies not associated with NAICS 5616 are identified as non-contract/in-house security positions.

There are many cases in which single firms are associated multiple NAICS codes. I assign to each firm the industry in which it posts most vacancies over the sample period. In cases where there is no modal industry across vacancies, I replace those observations to have a missing NAICS code. This affects very little of the sample; for example, in 2013 only 1.21% of vacancies had no identifiable modal industry.

**Cleaning firm names.** The BGT dataset provides an employer name associated with each vacancy when available. This data field is cleaned so as to standardize firm names. For example, this procedure makes sure that "Allied Universal", "Allied Univ", and "Allied Universal Inc" are not treated as separate firms. I undertake an additional cleaning procedure in two steps.

First, I use the procedure outlined in Schubert, Stansbury and Taska (2021) and Hazell et al. (2021) to clean and harmonize firm names from the BGT dataset of online vacancies. Their crosswalk maps from raw firm names in the Burning Glass data to cleaned and harmonized firm names using a combination of cleaning code and then a machine learning de-duplication algorithm.

Second, I impose an additional cleaning procedure on all firm names regardless of their match to the crosswalk, given the many instances in which the algorithm does not accurately group firms. For example, the crosswalk classifies "Allied Barton/Allied Universal", "Allied Universal Security", "Allied Universal Formerly Known as Allied Barton", and "Allied Universal Security and Investigations" (among many other variations) as separate firms when they should not be. This issue is independent of distinguishing between establishments, which is not necessary for my purposes.

### 1.8.2 Outside options

**Numerical example.** Here, I provide a brief numerical example in which differences in outside options can result in a larger elasticity of wages with respect to vacancy concentration for contractors than for in-house workers in the same market. This example is supported by my data, which suggests that large contracting firms tend to have the highest market share in a given MSA.

Consider the two markets for private security guards $A$ and $B$ illustrated in Figure 1.4. In Market $A$, a huge contracting firm has 30% market share and seven private firms each have 10% market share so that the market HHI is 0.185. In Market $B$, a huge contracting firm has 50% market share and five private firms each have 10% market share so that the market HHI is 0.358. In both markets, wages for security guards are \$15/hour at the private firms and \$10/hour at the contracting firm. I assume that contracted and in house security guards have an equal likelihood of transitioning into other occupations, so that it is sufficient to think of employment opportunities that exist at firms in a worker's own local market, excluding his current employer.

Consider business service firms $b$ and other private firms $p$ to be analagous to two distinct "firm types" or "industries" so that a worker can either be employed at a business service firm or a private firm with security needs. A local market consists of firm types $b$ and $p$ where the sum of market shares of each firm of type $b$ and each firm of type $p$ equals one. The value of outside options for a contractor $c$ employed at a type $b$ firm can be defined as follows:

$$OOI_c = \sum_{b \neq \_b} \left[ (\pi_{c \to b}) \times \left( \frac{s_{b,t}}{s'_t} \right) \times (\widehat{w_{b,t}}) \right] + \sum_{p} \left[ (\pi_{c \to p}) \times \left( \frac{s_{p,t}}{s'_t} \right) \times (\widehat{w_{p,t}}) \right].$$

Analogously, the value of outside options for a direct hire $d$ at a type $p$ firm can be defined as

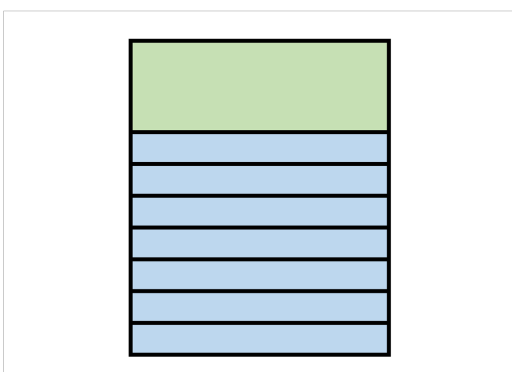
$$OOI_d = \sum_{b} \left[ (\pi_{d \to b}) \times \left( \frac{s_{b,t}}{s'_t} \right) \times (\widehat{w_{b,t}}) \right] + \sum_{p \neq \_p} \left[ (\pi_{d \to p}) \times \left( \frac{s_{p,t}}{s'_t} \right) \times (\widehat{w_{p,t}}) \right].$$

That is, for each contractor (direct hire), the value of outside options is the weighted average of wages in all other firms of each type. $s_{b,t}$ ($s_{p,t}$) is the market share of firm $b$ ($p$) and $s'_t$ is the sum of the market shares of each firm less the market share of the firm that the contractor (direct hire) currently works at, reflecting that one's own firm is not a viable outside option. Probabilities $\pi$ reflect the likelihood of that a contractor (direct hire) at a firm of type $b$ ($p$) can transition to a firm of type $p$ ($b$). For simplicity, I assume that these probabilities are equal to one given that contractors and direct hires perform the same job at nominally different firm types.[31]

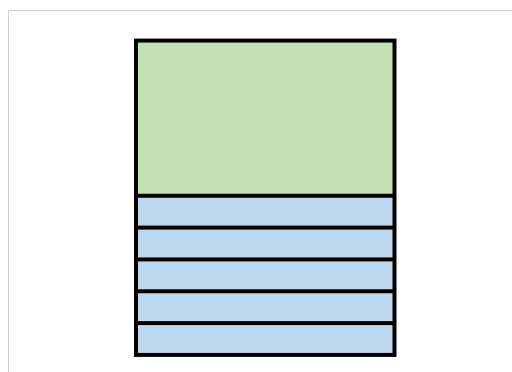
In Market $A$, in-house security guards have a value of outside options equal to 13.33, while contracts have a value of outside options equal to 10.5. Going from Market $A$ to $B$ implies reduction in the value of outside options of 21.2% for in-house workers, but a reduction in the value of outside options of nearly 60% for contract workers. Conditional on the HHI being the same for contract and in-house security guards in the same market, the greater reduction in outside options for contract workers implies a relatively larger wage penalty for contractors than for in-house security guards.

### 1.8.3 Appendix Figures

**Figure 1.4:** *Markets for security guards*



**(a)** *Market A*



**(b)** *Market B*

Note: This figure shows two different markets for security guards. The green boxes represent business service firms, and the blue boxes represent other private firms that hire security guards in-house. Relative to Market A, Market B shows an increased market share for the business service firm as fewer private firms choose to hire their own in-house guards.

[31] This need not be the case in practice if there is unobserved heterogeneity between contract and in-house security guards.

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# CHAPTER 2

# JOB DIFFERENTIATION AND MONOPOLISTIC COMPETITION: EVIDENCE FROM ONLINE VACANCY POSTINGS

## 2.1 Introduction

A burgeoning empirical literature on monopsony in the labor market has attempted to quantify the margins along which employers can assert wage-setting power (Azar, Marinescu, and Steinbaum 2020; Azar, Berry, and Marinescu 2019; Qiu and Sojourner 2019; Rinz 2018; Hershbein, Macaluso, and Yeh 2018). For reasons of data availability and computational feasibility, an outsize share of this literature has focused on estimating labor market concentration using a binary definition of the labor market (i.e. industry-area, occupation-area, etc.) (Schubert, Stansbury and Taska 2020; Hershbein et al. 2019; Dube and Kaplan 2017). However, there is little reason to suspect that monopsony is just concentration, or that its reach is neatly bounded by narrowly-defined markets. Dynamic monopsony (i.e. search frictions) and job differentiation, for example, are two broad ways to think about monopolistic competition in a way that is distinct from market concentration.

Two broad approaches to measuring monopsony power based on a more flexible concept of the labor market have attempted in the literature. The first approach is to embed a more flexible market definition into the more "traditional" metric of labor market concentration, the Hirschman-Herfindahl Index (hereon HHI) (Dodini et al. 2023; Nimczik (2022); Manning and Petrongolo (2017)). The second is to construct a second, distinct metric that captures workers' abilities to move across firms, occupations, and industries. These alternative employment opportunities are commonly referred to as "outside options".

In this paper I take a task-based approach to explore the role of job differentiation in determining own-occupation wages, bringing together literatures on job tasks and monopsony. Broadly, one can think about job differentiation as differences competitive differentials such as non-wage amenities ranging from services (e.g. free childcare, work from home flexibility) to preferences (e.g. "I like this neighborhood"; "I get along with my boss"). A separate dimension of job differentation is the task content or skill requirements of jobs. In practice we observe workers moving across occupations and industries, and so it is natural to think about what a worker's options are outside their current occupation or industry. Skill content is one such way to measure the likelihood of transition between jobs. For example, consider an administrative assistant. They can perform their job role in many industries if the skill content of their job is relatively homogenous. But the administrative assistant might also have skills that make them a good candidate for other occupations. For example, they may have accumulated good management skills that are desirable in many other positions. Clearly, feasible employment opportunities extend well beyond the current job title, suggesting that causal effects of monopsony may be overstated. I follow the literature and refer to the set of feasible alternative employment opportunities as *outside options*.

Standard theories of wage determination in labor markets allow for wages to depend on a worker's outside options (Pissarides 2000; Diamond 1982; Rogerson, Shimer, and Wright 2005). However, differences in the composition of local labor markets will determine both whether those outside options exist, and how they are valued by potential employers. Importantly, outside options will be a function of industry composition, occupation composition, firm composition and equilibrium wages that vary across labor markets. To quantify the outside options of jobs in detailed occupation cells, I collect data on the near-universe of online job vacancy postings from Burning Glass Technologies (hereon BGT). BGT parses the text of online vacancy posts from 40,000+ online job boards and extracts detailed information on the employer, industry, occupation, location, and various requirements associated with each job. I focus on posted skill requirements and assume that stated demand for skill is a good proxy of actual job content.

To meaningfully compare jobs across place, I define the task content of each job vacancy with a vector of skill categories that capture requirements or preferred qualifications that employers value for job performance, and aggregate up to the 6-digit Standard Occupational Classification (SOC) code. I measure the distance between occupations in each MSA over 2010-2017 using an uncentered, normalized Pearson correlation that runs between 0 and 1. Occupations with identical skill content will have a similarity score of 1 and will be upweighted in an outside option index. Occupations that have no transferrable skills between them will have a similarity score of 0, formalizing that there is approximately zero likelihood of transferring between those occupations. I measure the value of outside options for each occupation by summing over distances to all other occupations, weighted by local employment shares and average wages.

Using a basic regression of log wages on the outside option index at the year by MSA by occupation level, I find that the outside options of an occupation do inform own-occupation wages independently of market concentration. To address bias in the point estimate on concentration, I construct an instrument to isolate the variation in vacancy concentration that is driven by national changes in occupation concentration instead of by local labor market dynamics, following Azar et al. (2019). To address concerns that industry shocks may affect both own-occupation wages and outside options simultaneously, I also construct a standard "shift-share" Bartik shock and at it as a control to my baseline regressions. I find that my naive estimates are stable to instrumenting for concentration and controlling for log Bartik shocks. In my preferred specification, I find that controlling for concentration, a one unit increase in the outside option index translates into a roughly 19 log point increase in hourly wages.

To explore heterogeneity in the value of outside options, I limit my main sample to a subset of firms that post education requirements. I find that outside options matter relatively more for own-occupation wages in jobs requiring only a high school degree than for those requiring a bachelor's degree. Looking at the HHI, the relationship is reversed: vacancy concentration matters relatively more for wage determination among jobs requiring a bachelors' degree than for those requiring only a high school degree.

This finding is consistent with the idea that at the occupation level, the returns to skill vary with job task. Specifically, that outside options matter relatively more for high school degree holders is consistent with evidence that non-routine jobs are more likely to encounter monopsony power (Bachmann, Demir, and Frings 2020). This also suggests that skill requirements are an important signal of job compatibility when educational attainment is low. If high-skilled workers possess more specialized skills that fewer firms demand, or if their degree signals more about underlying productivity than does the task content of their employment history, then monopsonistic employers may hold wages below the marginal productivity of labor.

Finally, I investigate which skill categories predict returns on the value of outside options. I find that outside options increase in social and cognitive skills, though cognitive skills play a much larger role. Furthermore, conditioning on education requirement, I find that the return of social skills on the value of outside options matters only conditional on a bachelor's degree, but not on a high school diploma. Again, this is consistent with a model where social skill intensity decreases in job routineness. Since low-skilled jobs have more routine tasks, there are fewer returns to social skills relative to jobs that require a degree of social skill intensity.

My paper is closely related to two recent papers measuring outside options. Schubert et al. (2020) use resume data also from BGT to measure the probability of occupation to occupation transitions. Caldwell and Danieli (2018) use matched employer-employee data to measure the joint distribution of firm and worker characteristics based on observed employment relationships. While my approach has the drawback of not relying on observed matches, and I only observe stated demand, I nonetheless maintain much of the insight of these more micro-founded approaches. I address concerns that skill-based matching may not be informative about the task content of an occupation.

The paper proceeds as follows. In Section 2.2 I describe the data from Burning Glass Technologies. In Section 2.3 I outline my empirical strategy, and Section 2.4 discusses my results. Section 2.5 explores the returns to skill, and Section 6 concludes.

## 2.2 Data

### 2.2.1 Burning Glass Technologies

My primary data source comes from Burning Glass Technologies (BGT), and contains the near-universe of online vacancy postings in the United States over 2007 and 2010-present. BGT "spiders" or pulls vacancy postings from over 40,000 online job boards; no more than 5% of the sample comes from any single site. To ensure that job postings are unique, a sophisticated de-duplication algorithm detects whether any vacancy is listed across multiple job boards. Unique vacancy postings are parsed to extract relevant characteristics of each job. Detailed information on each job's title, employer, industry, occupation, location, wages, hours, and education and experience requirements are compiled and classified at various degrees of aggregation. The data are fine enough to be able to define a job as a job-title by establishment (employer-MSA) by salary type by pay frequency observation; for example, an Auto Damage Appraiser for Liberty Mutual in the Phoenix-Mesa-Scottsdale, AZ MSA with annual base pay.

BGT also collects posted skill requirements for each vacancy. For example, an employer might include a mix of "soft" skills (e.g. good communicator, ability to work well in a team, self-starter) and more specialized skills (e.g. Python, Microsoft Office, electrical wiring) in a vacancy posting in order to provide a complete description of job demands for potential applicants. Each skill is classified according to BGT's own skill categorization scheme such that each individual skill belongs to a broader skill family or skill family cluster.

The resulting dataset provides a rich description of labor demand across industries, occupations, and employers throughout the US. The BGT data has the advantage over comparable representative labor market surveys (for example, the BLS's Job Openings and Labor Turnover Survey (JOLTS)) of being high-frequency, with new vacancies added daily. Insofar as individual employers, industries, occupations or even place have evolving demands for skill, the BGT data is well-suited for precise, real-time analysis of labor demand. I refer the reader to Hershbein and Kahn (2018) who provide a comprehensive assessment of the comparability of BGT's online job vacancy postings to other data sets.

There are several limitations of the data that are worth noting. First, while job vacancy postings are a good proxy for firm demand, they contain little insight into the supply-side of the labor market. Hires are not observed, and there is no scope to understand hiring motives in the context of other modes of labor input adjustment, including separations, promotions, or fires. Second, online vacancies may not be representative of all job openings. Promotions, job-to-job transitions, and hiring based on referral networks are not observed. Third, recruitment intensity is not observed and only the job posting date is available.[1] Finally, vacancy postings have highly incomplete coverage of employer names and wages. The majority of vacancy postings that do not list an employer name come from recruitment agencies who often do not disclose the hiring firm until potential recruits have been identified. On the wage side, only 16% of online vacancies posted wages over 2010-2018, although the share has been growing over time (13% in 2010 versus 22% in 2018). Still, even administrative data has drawbacks; for example, only Unemployment Insurance payroll tax records in Minnesota, Washington, Oregon and Rhode Island contain detailed information

[1] It is not unusual for vacancy postings to remain online after the job has been filled, or if the employer suspended the hiring process. Other vacancies may expire according to guidelines of individual posting boards. As such, recruitment intensity is notoriously difficult to measure accurately.

on both wages and hours. When available, the BGT data contain information on both wages and hours and may provide a useful snapshot of local wages.[2]

I restrict my main analysis to a 10% random sample of job vacancies in each year over 2013-2017. My unit of analysis is a market, defined as a year by MSA by 6-digit SOC observation. The main sample includes all job vacancies for which I have a posted wage, an associated Herfindahl–Hirschman Index, and an outside options index.

**Skill classification.** My main analysis leverages detailed skill requirements that accompany each job vacancy in my main data set. Over all vacancies, the BGT data has over 15,000 distinct skills that employers include with their job descriptions. In order to meaningfully compare skills across vacancies, I rely on two classification schemes to parse and categorize the open text field for skills.

First, I start by defining skill categories using BGT-defined skill clusters. These clusters attempt to group individual skills into subsets of broadly similar skills. For example, skills such as "farming", "soil analysis", and "tending to livestock" might be included in a skill cluster for agriculture. In total, BGT defines 27 distinct skill clusters.

Second, for the many skills for which BGT does not define a skill cluster, I build on the skill categories frequently used in the routine-biased technical change literature. Deming (2017) and Deming and Kahn (2018), for example, consider the "routineness" of tasks as used in Autory, Levy and Murname (2003) and again parse BGT's open text field for skills that are compatible with either social, cognitive, or non-cognitive skills. I adopt their classification scheme and add to it a number of other skill categories (e.g. creative, management, AI, etc.). In total I consider 42 distinct skill categories. Finally, to facilitate my analysis of heterogeneity in demand for skill, I rely on posted degree and experience requirements. This allows me to identify jobs that are more or less suited to workers with different levels of educational attainment and experience on the job.

### 2.2.2 Employment statistics

I collect data on employment by 4-digit NAICS industry code and 6-digit SOC occupation code from the Census Bureau's County Business Patterns (CBP) database. For finer

[2]Hazel (2019) discusses wage-posting behavior in job vacancy postings in depth, and importantly finds no evidence of cyclicality in wage posting; Marinescu and Wolthoff (2015) provide corroborating evidence that wage posting is correlated with some invariant firm characteristics.

geographical variation I collect employment data by industry at the MSA-level from the BLS's Occupational Employment Statistics (OES) database.

For data on average wages in each MSA I use the OES database. Relative to the OES database, the coverage of wages in the BGT data set is less complete and subject to measurement error, particularly for markets with few wage observations. Figure 1 shows the relationship between posted wages in the BGT dataset and wages from the OES. In general, for a given market, OES wages tend to be somewhat higher than BGT's average posted wages, but the two series are nonetheless highly correlated. That posted wages are lower than wage data from the OES database is consistent with a worker bargaining channel through which a job applicant may leverage their skills to increase the salary offer. I condition on experience to eliminate a portion of this gap.

### 2.2.3 Distance between occupations

Consider an occupation $O$ that requires a combination of skills to perform successfully. Let vector $s = [s_1, s_2, ..., s_S]$ of skill categories $s_i$ for $i \in 1, ..., S$ represent the required skill mix. Each skill category $s_i$ contains a group of broadly similar skills, combining more than 15,000 skills from BGT's job vacancy data into $S$ distinct skill categories. I am interested in how similar occupation $O$ is to all other occupations. Because the realized task content of jobs is unobservable, I assume that $s$ accurately represents the skill requirements of occupation $O$.

To measure the degree of similarity between occupations, I define the distance between "skill requirements" of occupations $a$ and $b$ using an absolute un-centered Pearson correlation. The symmetric similarity score $Simil_{a,b}$ between occupations $a$ and $b$ is

$$Simil_{a,b} = \frac{\sum_{j=1}^{J} skillcat_{a,j} \times skillcat_{b,j}}{\left[\left(\sum_{j=1}^{J} skillcat_{a,j}^2\right) \times \left(\sum_{j=1}^{J} skillcat_{b,j}^2\right)\right]^{1/2}} \tag{2.1}$$

where

$$skillcat_{j,k} = \frac{\text{\# of job postings assigned to skill category } j \text{ in occupation } k}{\text{total \# of job postings in occupation } k}. \tag{2.2}$$

$Simil_{a,b}$ is normalized and takes a value $= 1$ if the vector of skill categories between occupations is identical, and $= 0$ if skill categories are completely disjoint. A larger relative to a smaller similarity score suggests that the two occupations are relatively more substitutable for each other. If occupations are close substitutes, then a worker in occupation $a$ has a high probability of being hired in occupation $b$.

This definition has a number of limitations. First, I have no ability to rank the relative importance of skill categories if multiple categories are listed in a job posting. One can imagine a scenario in which, say, all vacancy postings for software engineers list "teamwork" or "collaboration" as desired skills in addition to specialized software skills. As the demand for social skills increases across or within occupations, it becomes difficult to discern by this measure whether teamwork or Javascript is more important for success (we might assume it is the latter, which is more observable). Second, all skill categories are treated as equally distinct. In practice, "management" and "people skills" may be more similar to each other than "writing" is to "natural language processing", but I cannot make the distinction. Finally, the measure treats the distance between occupations as symmetric; that is, occupation $a$ is just as similar to occupation $b$ as $b$ is to $a$. Insofar as the similarity score is meant to capture the probability of transition between occupations, this assumption is unlikely to be the case in practice. For example, it is much more likely that that a laid-off hedge fund manager would find a job in retail than would a laid-off retail worker find a job at a hedge fund.

It is difficult if not impossible to address these problems, in particular the issue of symmetry, using vacancy postings alone. Several solutions have been successful. Caldwell and Danieli (2018) use matched employer-employee data to observe the employment options of workers with similar observables. Schubert, Stansbury and Taska (2020) parse a large sample of resumes to measure occupation-to-occupation transition probabilities directly. Each of these approaches relies on observable firm-worker matches to let the distribution of workers across jobs inform their measures of outside options. In contrast, I can say less about whether the distance between skill vectors is predictive of job-to-job transitions. Without observable matches my distance measure has the flavor of measuring the distance between *jobs* and not the distance between workers per se. In this way I leverage the strengths of the BGT dataset and focus on the rich account of labor demand. I find that in fact much of the information content from observed firm-worker matches is captured by my measure of similarity, which I return to later.

### 2.2.4 Value of outside options

For an occupation that uses transferable skills (i.e. has skill content relatively "similar" to that of other occupations), the value of those skills will depend on both (1) local wages of alternative occupations and (2) the employment share of alternative occupations, or "outside options". I construct an outside option index (OOI) for occupation $j$ as the weighted average of local wages in other occupations as follows:

$$OOI_{j,m,t} = \frac{1}{J-1} \sum_{k \neq j} \left[ (Simil_{j,k}) \times \left( \frac{s_{k,m,t}}{s_{k,t}} \right) \times (wage_{k,m,t}) \right] \tag{2.3}$$

$J$ is the number of occupations. $Simil_{j,k}$ is weighted by averages wages in occupation $k$ $wage_{k,m,t}$ and by $s_{j,m,t}/s_{j,t}$, the relative employment share of occupation $j$ in MSA $m$ to its national employment share. For example, if the national share of occupation $j$ is 0.05 but 0.10 in a given MSA, the relative employment share will be equal to 2. This captures the relative return to job search in one MSA versus another. The OOI is bounded below by 0, and takes a value = 0 when skills in occupation $j$ are completely disjoint from all other occupations within an MSA. An OOI = 1 suggests that the occupation is a perfect substitute for all other occupations. A larger OOI suggests that there are more possible occupational transitions within an MSA relative to a lower OOI.

### 2.2.5 Heterogeneity by skill group

An outstanding concern is that certain skill groups may simply be noisy measures of unobserved qualifications. For example, we might expect that cognitive skills and years of schooling are highly correlated, and so my outside options index may be spuriously picking up something other than returns to skill.

To address this issue, I limit my main sample to the subset of job vacancies in each occupation that posts an education requirement. Failure to condition on an education requirement assumes that all job postings without this qualification require zero years of schooling, which is highly unlikely.[3] I identify the subset of my main sample of vacancies

[3] I perform an alternative exercise where I assign a minimum of ten years of schooling, corresponding to some high school, to all vacancies without an education requirement. My results are robust to this alternative specification.

that require a minimum of a high school diploma, and the subset that requires a college degree. For each education level $educ \in$ (high school diploma, bachelor's degree), I modify my definition of *skillcat* such that:

$$skillcat_{j,k} = \frac{\#\text{ of job postings assigned to skill category } j \text{ in occupation } k \mid \mathbb{1}[educ]}{\text{total }\#\text{ of job postings in occupation } k}. \tag{2.4}$$

In essence, for someone with a high school degree, jobs for which minimum education requirements are not met effectively have no relevant skills. I therefore treat jobs with identical skill vectors but different education requirements as completely disjoint. For example, consider two occupations $a$ and $b$ that have identical skill vectors, but every job in occupation $a$ requires only a high school diploma while every job in occupation $b$ requires a bachelor's degree. In this case, despite the identical skill vectors, the distance between occupations $a$ and $b$ would be equal to 0 since there is no scope to move from $a$ to $b$ with only a high school diploma.

One caveat to this analysis deriving from the symmetry of the outside option index is that this does not allow for jobs with a minimum of a high school diploma to be feasible outside options for workers with a college degree. I perform a robustness check where I allow any vacancies that require less than a college degree to be viable outside options for occupations that require a college education. My results are virtually unchanged. This may reflect that in practice there are few transitions between occupations with different educational requirements. In particular, jobs requiring a high school degree are much more routine than those that require a college degree, and the returns to skill may be minimal. I return to this possibility later.

## 2.3 Empirical approach

I am interested in whether firms set wages in response to workers' outside options. If there exists imperfect competition in the labor market, we would expect to find evidence that own-occupation wages increase in the value of outside options as firms exercise wage-setting power.

Much of the empirical literature on monopsony in the labor market has focused on concentration, which is relatively straightforward to estimate in a narrowly-defined labor market. However, concentration is only one source of labor market monopsony. The inability of concentration indexes to fully account for observable wage premia (across place, firm, industry, education, etc.) suggests that there are other working mechanisms.

I focus instead on an occupation's outside options where, conditional on the HHI, non-wage differences across jobs reflect job differentiation whereby employers vary in their preferences for skill.

### 2.3.1 Baseline specification

To estimate the effect of outside options on own-occupation wages, I run the following OLS regression at the market-level:

$$\ln(wage_{j,m,t}) = \alpha + \beta_1 \ln(OOI_{j,m,t}) + \beta_2 \ln(HHI_{j,m,t}) + \alpha_{j,t} + \alpha_{m,t} + \epsilon_{j,m,t}. \tag{2.5}$$

Observations are indexed by 6-digit SOC code $j$ in MSA $m$ in year $t$, where $t$ spans 2010-2017. Log average wages are regressed on the log OOI for each occupation, conditioned on a full set of year-by-MSA and year-by-SOC fixed effects. Standard errors are clustered at the year-by-MSA-level. I control for vacancy concentration *HHI*, which I estimate by identifying unique employers in the BGT data and calculating market share. If outside options are a relevant consideration for wage-setting behavior, the outside option index should have explanatory power for own-occupation wages beyond what concentration accounts for.

### 2.3.2 Identification

**Instrumenting for concentration.** Vacancy concentration is likely to be endogenous and to bias $\widehat{\beta_2}$. An increase in market concentration might reflect an increase in relative productivity for a firm, such that an increase in the marginal product of labor is rewarded with higher wages. However, the simultaneous increase in monopsony power would allow that firm to assert downward pressure on wages. That the net effect is ambiguous suggests that my estimate may be biased by correlations between concentration and wages driven by changes in local labor demand.

To isolate the variation in vacancy concentration that is driven by national changes in occupation concentration instead of by local labor market dynamics, I follow Azar et al. (2019) and instrument the HHI in each market with the average of the natural log of the reciprocal number of firms across all other MSAs in the same occupation and year.[4] This provides variation in the HHI that is driven only by national-level changes in the occupation. This instrument does not account for the possibility that national changes in labor demand might simultaneously affect both concentration and productivity (and therefore wages) of an occupation. Formally, the instrument can be written as

$$HHI^{inst}_{j,m,t} = \frac{\sum_{n \neq m} ln(1/N_{j,n,t})}{\sum_{n \neq m} N_{j,n,t}}. \tag{2.6}$$

The first stage and structural equations of my baseline specification are as follows.

$$\ln(HHI_{j,m,t}) = \alpha + \beta_3 HHI^{inst}_{j,m,t} + \alpha_{j,t} + \alpha_{m,t} + \tau_{j,m,t} \tag{2.7}$$

$$\ln(wages_{j,m,t}) = \alpha + \beta_4 \ln(HHI_{j,m,t}) + \alpha_{j,t} + \alpha_{m,t} + \epsilon_{j,m,t}. \tag{2.8}$$

If $\widehat{\beta_4}$ is an unbiased estimator and can be interpreted as the causal effect of concentration on wages, we can speak to the relative importance of outside options in explaining wage-setting behavior.[5]

**Industry Bartik.** Similar endogeneity concerns arise when estimating the effect of outside options on wages due to differences in the occupation composition of each industry. Depending on the exposure of an MSA to an industry, trends in productivity and wages by industry may differentially affect occupations across place. Furthermore, own-occupation wages and outside options may simultaneously move in the same direction in response to a local shock. To account for this I construct a standard shift-share Bartik shock, and add it as a control to my baseline regressions. In particular, the Bartik shock should account for the fact that industry shocks effect both own-occupation wages and outside options simultaneously, depending on local industry composition. The instrument is defined as

[4] See also Nevo (2001), Autor, Dorn and Hanson (2013), Sojourner and Qiu (2019), Marinescu, Ouss and Pape (2020). Rinz (2018) takes a similar approach but uses average HHIs within the same industry across other commuting zones in the same year, weighted by employment. Using the number of firms instead of HHIs is less likely to be endogenous and does not rely on market shares.

[5] In a robustness check I instrument for the outside option index, substituting in (3) the the initial employment share in 2006 relative to the national employment share in 2006, weighted by the national leave-one out mean wage in the occupation. Coefficients on the regression using an instrumented HHI are substantively unchanged. See Schubert, Stansbury and Taska (2020) for further details.

$$B_{j,m,t} = \sum_{i}^{I} \left[ \frac{\frac{s_{i,j,t-1}}{s_{j,t-1}} \times \frac{s_{i,m,t-1}}{s_{m,t-1}} \times wages_{i,t}}{\frac{s_{i,j,t-1}}{s_{j,t-1}} \times \frac{s_{i,m,t-1}}{s_{m,t-1}}} \right] \tag{2.9}$$

where average industry wages at time $t$ are weighted by the employment share of industry $i$ in occupation $j$ and the employment share of industry $i$ in MSA $m$, lagged to avoid endogenous employment responses and summed over all 4-digit NAICS industries.[6]

## 2.4 Results

### 2.4.1 Outside Options Index

To compute the OOI I collapse the skill content of each online vacancy posting into 42 distinct skill groups, using 10% random samples of BGT data in each year over 2010-2017. Skill vectors are computed at the year-MSA-occupation level, where an occupation is defined as a 6-digit SOC, and used to generate pairwise similarity scores between each occupation.[7]

Figure 2.2 plots the distribution of pairwise similarity scores between occupations at the 6-digit SOC by MSA level. The distribution is highly stable over time, and so plot the I average over 2010-2017. The distribution has a long left tail, suggesting that most occupations have a weak overlap of skill requirements. Table 2.1 ranks the closest and furthest occupation families by similarity score. The results are rather intuitive. Occupations that require highly specialized skills show up at either extreme of the distribution. For example, consider health-related occupations. Among the smallest similarity scores, I find a large overlap of skill requirements between healthcare practitioners and technical operations, healthcare support, community and social services, and personal care and services. Health occupations are otherwise represented at the other extreme of the distribution, and are broadly dissimilar to other occupations, suggesting that skill requirements are highly specialized and particular to the occupational setting. Computer and mathematical occupations, which are again highly technical, also fall at the high end of the distribution. On the low end, we find a close match between food preparation and serving and building, grounds cleaning and maintenance, two low-skilled occupations. These results are broadly

[6]See Goldsmith-Pinkham, Sorkin, and Swift (2019) for common identification issues associated with Bartik shocks.

[7]Not every occupation has employment and wage data for each MSA, and so the panel is unbalanced.

consistent with the occupation transition probabilities derived from observable transitions between occupations calculated in Schubert, Stansbury and Taska (2020).

Figure 2.3 plots the distribution of the outside option index for the full sample and for the sub-sample that conditions on whether a job has posted an education requirement. The two distributions are roughly equivalent, suggesting that the latter is a representative sample. Again, there is a small mass at very small values of the outside option index, suggesting a large degree of dissimilarity between occupations. Figure 2.4 replicates Figure 2.3 but splits the sample by education requirement according to the procedure outlined in section 3.3. While the two distributions display a large degree of similarity, the figure is nonetheless suggestive that jobs requiring a Bachelor's degree have an overall larger number of transferable skills than do jobs requiring only a high school diploma, which we expect.

### 2.4.2 Outside options and wages

I now turn to my main results. I start by estimating equation (2.5) for the 10% random samples over 2010-2017. The results can be found in Table 2.2. Regressing HHI on log wages yields a highly significant point estimate of -0.014, suggesting that on average wages decrease with industry concentration. Reassuringly, the point estimate is identical to that found in Hershbein et al. (2019) and Schubert et al. (2020), who also calculate own-occupation vacancy concentration using job vacancy postings, thus making the coefficients comparable. Introducing the log outside option index decreases the point estimate on concentration to -0.011 and enters with significance. This implies that for ten point higher outside option index corresponds to a 1 log point increase in own-occupation wages. This is consistent with employers setting wages based on outside options. That the concentration coefficient decreases on the introduction of the OOI is suggestive of omitted variable bias, and that outside options may be an important aspect of imperfect competition in the labor market. Importantly, the outside option index has independent explanatory power from the HHI, suggesting that there are distinct channels through which each metric impacts wages.

In order to account for endogeneity bias in the point estimate on concentration, Table 2.3 repeats the original exercise but instruments for HHI. The point estimate remains significant and increases somewhat, suggesting that bias was indeed present. Again, the outside options index enters with significance and the point estimate on HHI falls. Table 2.4 introduces the Bartik control, which enters with significance across all specifications. Results are largely unchanged.

Although the distribution of outside options appears stable over time, I explore the possibility that the role of outside options in employer wage setting varies by skill group. Hershbein and Kahn (2017) find no evidence that increased demand for high school (college) degrees occur in occupations traditionally reliant on high-skilled (low-skilled) labor, implying that over time the occupational composition of jobs requiring a high school or college degree has remained constant. This finding leaves as an open question why wages have not grown in high-skill occupations despite increasing demand for skill.

There are a few ways in which the stability of the occupational distribution does not rule out that the distance between occupations across or within skill groups could still evolve. First, if conditional on degree requirement, upskilling could occur differentially across occupations. One could imagine that more productive MSAs might demand workers to have a richer skill profile conditional on education, creating variation across place. Similarly, due to variation in occupational task content, skill requirements may change more rapidly in some occupations than in others (e.g. occupations closer to the technological frontier). This idea is the subject of a large literature on routine-biased technological change (RBTC), such that the task content of relatively more "routine" occupations is susceptible to automation, thereby changing the composition of skill demand once some tasks become obsolete.[8]

To understand the role of outside options by skill group, I repeat my baseline analysis separately for each education level in the conditional sub-sample. Table 2.5 lists the results without instrumenting for HHI. The estimates in columns *1* and *2* are identical to those in the full sample, suggesting that the sub-sample is informative. Moving to columns *3* and *4*, I regress log wages on the OOI specific to each education group, controlling for HHI. I find that the OOI matters relatively more for wage determination among jobs requiring a high school degree than for those requiring a bachelor's degree, with respective point estimates of 0.127 and 0.079. Looking at the HHI, the relationship is reversed; vacancy concentration matters relatively more for wage determination among jobs requiring a bachelor's degree than for jobs requiring a high school degree. Table 2.6 repeats the analysis instrumenting for HHI; Table 2.7 both instruments for HHI and controls for Bartik shocks, which is the preferred specification. The Bartik shock enters with significance, and the point estimates are stable across specifications.

[8]See Autor, Levy and Murname (2003) for a full review of occupational classification based on routineness.

Although I find evidence that jobs requiring a bachelor's degree provide relatively better outside options, there are several lines of intuition that are compatible with the results in Table 2.7. First, my findings are consistent with the idea that at the occupation level, skill requirements are an important signal of job match when educational attainment is low. This reflects that occupations with lower educational requirements on average tend to be more routine, such that the return to soft skills is relatively low. A bachelor's degree, on the other hand, may signal some degree of confidence in ability that is not captured by an observable skill, and so outside options translate relatively less into wages.

Second, in a sample of German workers, Caldwell and Danieli (2017) find a similar result and argue that high-skilled workers tend to have relatively more specialized skills that are valued by fewer employees. However, this story may or may not be consistent with my finding that outside options matter more for low-skilled workers, who have relatively more generalist skills. To distinguish between these two channels, I return to the contribution of individual skill categories to my outside options index.

## 2.5 Returns to skill

What skill categories predict the value of outside options? To answer this question, I explore the relative contribution of distinct skill categories to my task-based measure of outside options. I focus on four broad skill categories following Deming (2017): social skills, cognitive skills, non-cognitive skills, and social-cognitive skills.

I run a regression of the following form:

$$\begin{aligned} \ln Dep_{j,m,t} = \alpha &+ \beta_1 \text{Social}_{j,m,t} \\ &+ \beta_2 \text{Cognitive}_{j,m,t} + \beta_3 \text{Non-cognitive}_{j,m,t} \\ &+ \beta_4 \text{Social-cognitive}_{j,m,t} + \alpha_{j,t} + \alpha_{m,t} \\ &+ \epsilon_{j,m,t} \end{aligned} \tag{2.10}$$

where *Social*, *Cognitive*, *Social-cognitive*, and *Non-cognitive* are the percentage of vacancy postings for each occupation that require the relevant skill in an MSA-year. My dependent variable *Dep* is either log wages or the log OOI.

The results for the return to skill on wages can be found in Table 2.8. The baseline model includes year by MSA and year by SOC fixed effects, and standard errors are clustered at the

MSA-year level. Column *1* shows that the return to social skills is positive and statistically significant, with a coefficient of 0.005 (SE 0.002) suggesting that a one percentage point increase in social skill intensity will increase wages by 0.5 log points. Column *2* adds the measure of cognitive skills. The addition of cognitive skills lowers the coefficient on social skills, which does not remain significant, but the coefficient on cognitive skills is large and more than double the coefficient on social skills. Column *3* adds non-cognitive skills with enter only with marginal significance. Curiously, the coefficient on non-cognitive skills is negative. Column *4* tests for the complementarity of social and cognitive skills by including an interaction term between the two groups. The coefficient is insignificant and has no meaningful impact on the coefficients for social and cognitive skills, suggesting that social and cognitive skills are complementary skill sets.

Turning to outside options, Table 2.9 shows that the effect of each skill category on outside options mimics my findings in Table 2.8. That is, cognitive and social skills are complements but cognitive skills are much more predictive of the value of outside options. Again, non-cognitive skills enter counter intuitively with a negative coefficient. Table 2.10 repeats this specification on a subsample of the main data set that conditions on having a posted education requirement. The results are largely unchanged.

Finally, I turn to Table 2.11 which estimates the returns to skill on the value of outside options conditional on a high school diploma or college degree. My results suggest that the value of outside options increases in social skills conditional on jobs that require a bachelor's degree, but not conditional on a high school diploma. This is consistent with a model where social skill intensity decreases in job routineness. Because low-skilled jobs are more routine, there are fewer opportunities for social skills to be important. This finding is consistent with Autor, Levy, and Murname (2003) who draw a distinction between skills and job tasks and find that the return to skill is increasing only in certain job tasks (e.g. routine task intensity versus social skill task intensity).

## 2.6 Conclusion

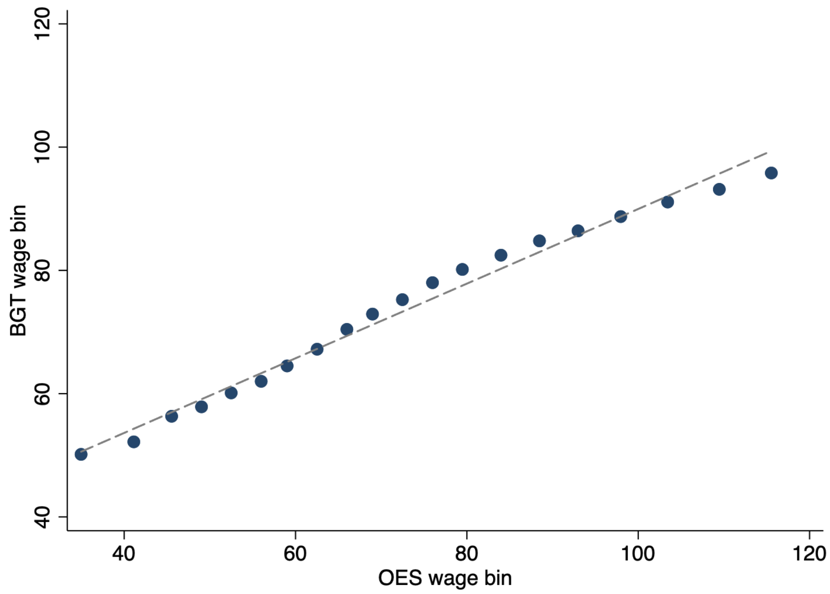
In this paper I estimate the impact of outside options on own-occupation wages using online vacancy posting data. I use stated firm demand for skill to estimate an outside options index for each 6-digit SOC industry at the year-MSA level. My results suggest that wage setting based on outside options is an important feature of monopsony in the labor market. In particular, I find that a ten percent increase in the outside options index corresponds to 1 log point increase in wages.

I find evidence that wage setting based on outside options is heterogeneous across skill groups. For jobs that require only a high school diploma, outside options are a relatively stronger predictor of own-industry wages than they are for jobs requiring a bachelors degree. This finding is consistent with the idea that skill requirements are an important signal of productivity when educational attainment is low. My results are also consistent with the literature that suggests there are lower returns to social skills in occupations that have high routine intensity.

My results are comparable to those in the literature that rely on observed worker-firm matches to measure outside options, suggesting that there is a wealth of evidence to be found in skill requirements. My metric also has the benefit of being more flexible than embedding skill content into the HHI; indeed, I find evidence that the outside option index has an independent effect on wages from concentration. Overall, I provide evidence that task-based measures are informative and highly predictive of returns to skill.

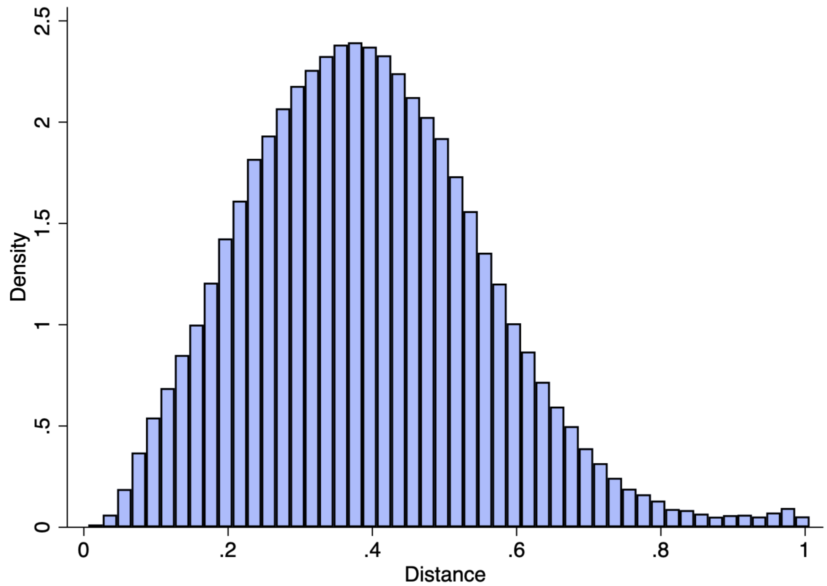
## 2.7 Tables and figures

**Figure 2.1:** *Wages from BGT and the BLS*




Note: This figure the relationship between hourly wages from the OES database and posted wages from BGT, conditional on posting an experience requirement in BGT. Average hourly wages by MSA and 6-digit SOC are grouped in \$0.25 (nominal) wage bins and weighted by total vacancy postings. A wage bin of 40 corresponds to an hourly wage of \$10.50-\$10.75, and a wage bin of 120 corresponds to an hourly wage of \$30.25-\$30.50.

**Figure 2.2:** *Outside option index, 10% sample*

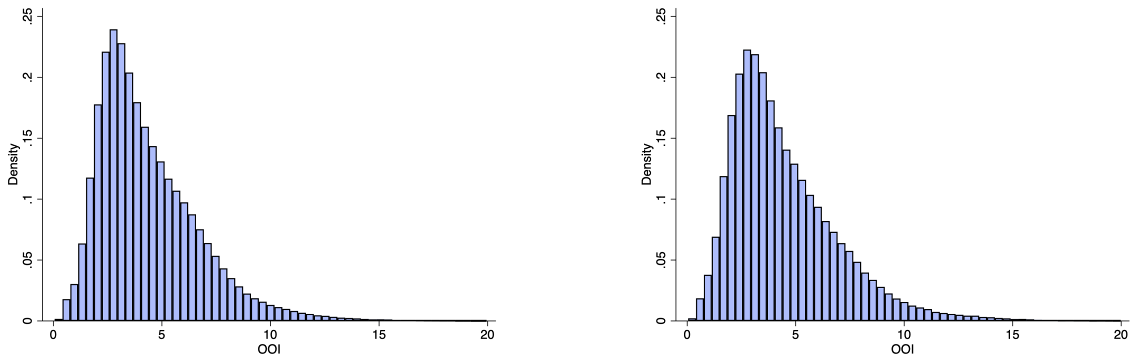



Note: This figure plots the distribution of pairwise distances between each 6-digit SOC within each MSA, averaged over 2010, 2013, and 2017. See section 3 for details on index construction. Data on skills comes from BGT's online vacancy postings database.

**Table 2.1:** *Distance between occupations*

| **Occupation *a*** | **Occupation *b*** | **Distance** |
|---|---|---|
| Healthcare practitioners and technical operations | Healthcare support | 0.006 |
| Community and social services | Healthcare practitioners and technical operations | 0.030 |
| Community and social services | Healthcare support | 0.042 |
| Construction and extraction | Installation, maintenance and repair | 0.085 |
| Food preparation and serving | Building, grounds cleaning and maintenance | 0.086 |
| Management | Business and financial operations | 0.097 |
| Community and social services | Personal care and services | 0.114 |
| Building, grounds cleaning and maintenance | Farming, fishing and forestry | 0.149 |
| Healthcare support | Personal care and services | 0.159 |
| Healthcare practitioners and technical operations | Personal care and services | 0.174 |
| Business and financial operations | Office and administrative support | 0.208 |
| Management | Office and administrative support | 0.227 |
| ... | ... | ... |
| Sales and related | Construction and extraction | 0.805 |
| Business and financial operations | Healthcare support | 0.811 |
| Healthcare support | Installation, maintenance and repair | 0.814 |
| Healthcare practitioners and technical operations | Installation, maintenance and repair | 0.815 |
| Computer and mathematical | Building, grounds cleaning and maintenance | 0.819 |
| Computer and mathematical | Transportation and material moving | 0.820 |
| Computer and mathematical | Personal care and services | 0.823 |
| Education, training and library | Construction and extraction | 0.824 |
| Computer and mathematical | Construction and extraction | 0.825 |
| Community and social services | Construction and extraction | 0.831 |
| Computer and mathematical | Food preparation and serving | 0.832 |
| Architecture and engineering | Healthcare practitioners and technical operations | 0.850 |
| Architecture and engineering | Healthcare support | 0.872 |
| Healthcare practitioners and technical operations | Construction and extraction | 0.886 |
| Healthcare support | Construction and extraction | 0.890 |
| Computer and mathematical | Healthcare practitioners and technical operations | 0.911 |
| Computer and mathematical | Healthcare support | 0.928 |

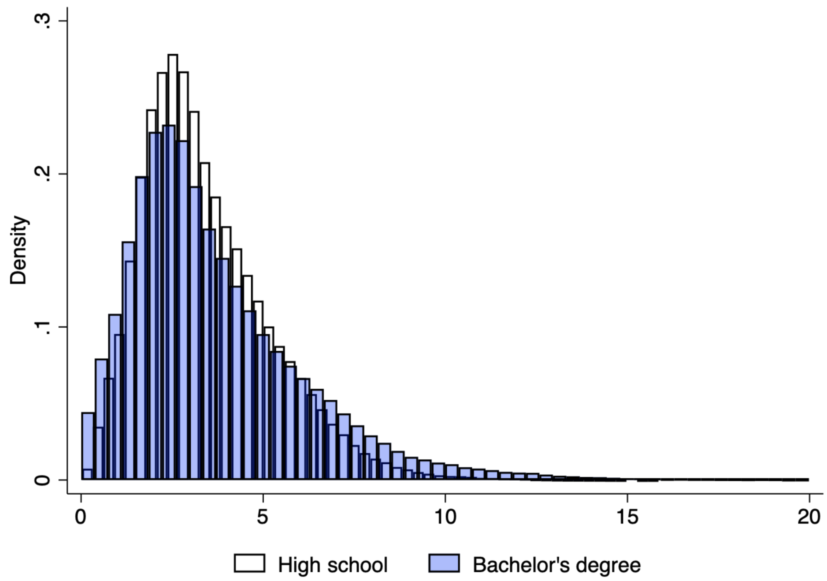
**Figure 2.3:** *Outside option index, 10% sample*




**(a)** *Full sample*  **(b)** *Conditional on education requirement*

Note: This figure plots the distribution of the outside option index for each year by MSA by occupation observation, averaged over 2010, 2013, and 2017. See section 3 for details on index construction. Data on skills comes from BGT's online vacancy postings database; data on wages and employment by 6-digit SOC code and MSA come from the BLS's OES database.

**Figure 2.4:** *Outside option index by educational attainment, 10% sample*




Note: This figure plots the distribution of the outside option index for each year by MSA by occupation observation, averaged over 2010, 2013, and 2017, and split by educational attainment. The sample is limited to vacancies that post education requirements. See section 3 for details on index construction. Data on skills comes from BGT's online vacancy postings database; data on wages and employment by 6-digit SOC code and MSA come from the BLS's OES database.

**Table 2.2:** *OLS regression of posted wages on the outside options index*

| | Log wage | Log wage |
|---|---|---|
| Herfindahl-Hirschman index (log) | -0.014 | -0.011 |
| | (0.001) | (0.001) |
| Outside option index (log) | | 0.099 |
| | | (0.007) |
| Year × MSA | Y | Y |
| Year × SOC | Y | Y |
| $R^2$ | 0.93 | 0.93 |
| Obs | 282489 | 282468 |

Notes: Average occupational wages by MSA are collected from the BLS's Occupational Employment Statistics (OES) database. Data to estimate the Herfindahl-Hirschman Index (HHI) and outside option index (OOI) come from a 10% random sample of vacancy postings data from Burning Glass Technologies over 2010-2017. The HHI measures employer vacancy concentration at the year-MSA-occupation level. Details on the construction of the OOI can be found in section 3.

**Table 2.3:** *2SLS regression of posted wages on the outside options index*

| | Log wage | Log wage |
|---|---|---|
| Herfindahl-Hirschman index (log) | -0.019 | -0.016 |
| | (0.001) | (0.001) |
| Outside option index (log) | | 0.096 |
| | | (0.003) |
| Year × MSA | Y | Y |
| Year × SOC | Y | Y |
| Obs | 282489.00 | 282468.00 |

Notes: Vacancy concentration is instrumented by own occupation concentration in other MSAs. Average occupational wages by MSA are collected from the BLS's Occupational Employment Statistics (OES) database. Data to estimate the Herfindahl-Hirschman Index (HHI) and outside option index (OOI) come from a 10% random sample of vacancy postings data from Burning Glass Technologies over 2010-2017. The HHI measures employer vacancy concentration at the year-MSA-occupation level. Details on the construction of the OOI can be found in section 3.

**Table 2.4:** *2SLS regression of wages on the OOI controlling for Bartik shock*

| | Log wage | Log wage | Log wage |
|---|---|---|---|
| Herfindahl-Hirschman index (log) | -0.018 | -0.015 | -0.015 |
| | (0.001) | (0.001) | (0.001) |
| Outside option index (log) | | 0.097 | 0.097 |
| | | (0.003) | (0.004) |
| Year × MSA | Y | Y | Y |
| Year × SOC | Y | Y | Y |
| Bartik shock | | | Y |
| Obs | 193472 | 193470 | 179787 |

Notes: Vacancy concentration is instrumented by own occupation concentration in other MSAs. Industry shift-share Bartik shocks are constructed from data on industry-level wages and employment from the County Business Patterns database and from the BLS. Average occupational wages by MSA are collected from the BLS's Occupational Employment Statistics (OES) database. Data to estimate the Herfindahl-Hirschman Index (HHI) and outside option index (OOI) come from a 10% random sample of vacancy postings data from Burning Glass Technologies over 2010-2017. The HHI measures employer vacancy concentration at the year-MSA-occupation level. Details on the construction of the OOI can be found in section 3

**Table 2.5:** *OLS regression of posted wages on the OOI, conditional on education requirement*

| | Log wage | Log wage | Log wage | Log wage |
|---|---|---|---|---|
| **Herfindahl-Hirschman index (log)** | -0.014 | -0.011 | -0.011 | -0.015 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| **Outside option index (log)** | | | | |
| Full (conditional) sample | | 0.104 | | |
| | | (0.007) | | |
| High school degree | | | 0.127 | |
| | | | (0.009) | |
| Bachelor's degree | | | | 0.079 |
| | | | | (0.007) |
| Year × MSA | Y | Y | Y | Y |
| Year × SOC | Y | Y | Y | Y |
| $R^2$ | 0.93 | 0.93 | 0.92 | 0.92 |
| Obs | 282314 | 282250 | 242548 | 211193 |

Notes: Average occupational wages by MSA are collected from the BLS's Occupational Employment Statistics (OES) database. Data to estimate the Herfindahl-Hirschman Index (HHI) and outside option index (OOI) come from a 10% random sample of vacancy postings data from Burning Glass Technologies over 2010-2017. The HHI measures employer vacancy concentration at the year-MSA-occupation level. Details on the construction of the conditional OOI can be found in section 3. Here the OOI is constructed conditional on vacancies posting an education requirement.

**Table 2.6:** *2SLS regression of posted wages on the OOI, conditional on education requirement*

| | Log wage | Log wage | Log wage | Log wage |
|---|---|---|---|---|
| **Herfindahl-Hirschman index (log)** | -0.019 | -0.016 | -0.013 | -0.023 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| **Outside option index (log)** | | | | |
| Full (conditional) sample | | 0.101 | | |
| | | (0.003) | | |
| High school degree | | | 0.124 | |
| | | | (0.004) | |
| Bachelor's degree | | | | 0.075 |
| | | | | (0.004) |
| Year × MSA | Y | Y | Y | Y |
| Year × SOC | Y | Y | Y | Y |
| Obs | 282314.00 | 282250.00 | 242548.00 | 211193.00 |

Notes: Vacancy concentration is instrumented by own occupation concentration in other MSAs. Average occupational wages by MSA are collected from the BLS's Occupational Employment Statistics (OES) database. Data to estimate the Herfindahl-Hirschman Index (HHI) and outside option index (OOI) come from a 10% random sample of vacancy postings data from Burning Glass Technologies for the years 2010, 2013, and 2017, conditional on posting an education requirement. The HHI measures employer vacancy concentration at the year-MSA-occupation level. Details on the construction of the OOI can be found in section 3.

**Table 2.7:** *2SLS regression of wages on the OOI controlling for Bartik shock, conditional on education requirement*

| | Log wage | Log wage | Log wage | Log wage | Log wage |
|---|---|---|---|---|---|
| **Herfindahl-Hirschman index (log)** | -0.018 | -0.018 | -0.015 | -0.013 | -0.022 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| **Outside option index (log)** | | | | | |
| Full (conditional) sample | | | 0.104 | | |
| | | | (0.004) | | |
| High school degree | | | | 0.130 | |
| | | | | (0.005) | |
| Bachelor's degree | | | | | 0.077 |
| | | | | | (0.005) |
| Year × MSA | Y | Y | Y | Y | Y |
| Year × SOC | Y | Y | Y | Y | Y |
| Bartik shock | N | Y | Y | Y | Y |
| Obs | 193443 | 179760 | 179727 | 154848 | 135544 |

Notes: Vacancy concentration is instrumented by own-occupation concentration in other MSAs. Industry shift-share Bartik shocks are constructed using data on industry-level employment and wages from the County Business Patterns database and the BLS. Average occupational wages by MSA are collected from the BLS's Occupational Employment Statistics (OES) database. Data to estimate the Herfindahl-Hirschman Index (HHI) and outside option index (OOI) come from a 10% random sample of vacancy postings data from Burning Glass Technologies over 2010-2017. The HHI measures employer vacancy concentration at the year-MSA-occupation level. Details on the construction of the OOI can be found in section 3.

**Table 2.8:** *Returns to skill to posted wages*

| | Log wage | Log wage | Log wage | Log wage |
|---|---|---|---|---|
| Social skills | 0.005 | 0.003 | 0.004 | 0.004 |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Cognitive skills | | 0.010 | 0.010 | 0.010 |
| | | (0.002) | (0.002) | (0.003) |
| Non-cognitive skills | | | -0.004 | -0.004 |
| | | | (0.002) | (0.002) |
| Social-cognitive skills | | | | 0.001 |
| | | | | (0.004) |
| Year × MSA | Y | Y | Y | Y |
| Year × SOC | Y | Y | Y | Y |
| Obs | 206542 | 206542 | 206542 | 206542 |

Notes: Average occupational wages by MSA are collected from the BLS's Occupational Employment Statistics (OES) database. Data on skill requirements comes from BGT's job vacancy postings over 2010-2017, and are grouped into skill categories based on Deming (2017). Results are clustered at the MSA-year level.

**Table 2.9:** *Returns to skill on outside options index*

| | OOI | OOI | OOI | OOI |
|---|---|---|---|---|
| Social skills | 0.005 | 0.002 | 0.004 | 0.004 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Cognitive skills | | 0.012 | 0.013 | 0.013 |
| | | (0.001) | (0.001) | (0.001) |
| Non-cognitive skills | | | -0.005 | -0.005 |
| | | | (0.001) | (0.001) |
| Social-cognitive skills | | | | -0.002 |
| | | | | (0.002) |
| Year × MSA | Y | Y | Y | Y |
| Year × SOC | Y | Y | Y | Y |
| Obs | 369204 | 369204 | 369204 | 369204 |

Notes: Average occupational wages by MSA are collected from the BLS's Occupational Employment Statistics (OES) database. Data to estimate the outside options index (HHI) come from a 10% random sample of vacancy postings data from Burning Glass Technologies over 2010-2017. Data on skill requirements comes from BGT's job vacancy postings over 2010-2017, and are grouped into skill categories based on Deming (2017). Results are clustered at the MSA-year level.

**Table 2.10:** *Returns to skill on outside options index, conditional on education requirement*

| | Conditional on years of education | | | |
|---|---|---|---|---|
| | OOI | OOI | OOI | OOI |
| Social skills | 0.005 | 0.002 | 0.003 | 0.004 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Cognitive skills | | 0.012 | 0.012 | 0.013 |
| | | (0.001) | (0.001) | (0.001) |
| Non-cognitive skills | | | -0.004 | -0.004 |
| | | | (0.001) | (0.001) |
| Social-cognitive skills | | | | -0.001 |
| | | | | (0.002) |
| Year × MSA | Y | Y | Y | Y |
| Year × SOC | Y | Y | Y | Y |
| Obs | 368467 | 368467 | 368467 | 368467 |

Notes: Average occupational wages by MSA are collected from the BLS's Occupational Employment Statistics (OES) database. Data to estimate the outside options index (HHI) come from a 10% random sample of vacancy postings data from Burning Glass Technologies over 2010-2017, and conditions on having a posted education requirement. Data on skill requirements comes from BGT's job vacancy postings over 2010-2017, and are grouped into skill categories based on Deming (2017). Results are clustered at the MSA-year level.

**Table 2.11:** *Returns to skill on outside options index, conditional on educational attainment*

| | High school diploma | | | | Bachelor's degree | | | |
|---|---|---|---|---|---|---|---|---|
| | OOI | OOI | OOI | OOI | OOI | OOI | OOI | OOI |
| Social skills | 0.001 | -0.000 | 0.001 | 0.001 | 0.003 | 0.002 | 0.002 | 0.002 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Cognitive skills | | 0.007 | 0.007 | 0.008 | | 0.007 | 0.008 | 0.007 |
| | | (0.001) | (0.001) | (0.001) | | (0.001) | (0.001) | (0.001) |
| Non-cognitive skills | | | -0.003 | -0.003 | | | -0.003 | -0.003 |
| | | | (0.001) | (0.001) | | | (0.001) | (0.001) |
| Social-cognitive skills | | | | -0.001 | | | | 0.002 |
| | | | | (0.002) | | | | (0.002) |
| Year × MSA | Y | Y | Y | Y | Y | Y | Y | Y |
| Year × SOC | Y | Y | Y | Y | Y | Y | Y | Y |
| Obs | 288959 | 288959 | 288959 | 288959 | 297327 | 297327 | 297327 | 297327 |

Notes: Average occupational wages by MSA are collected from the BLS's Occupational Employment Statistics (OES) database. Data to estimate the outside options index (HHI) come from a 10% random sample of vacancy postings data from Burning Glass Technologies over 2010-2017, and conditions on having a posted education requirement for either a high school diploma or a bachelor's degree. Data on skill requirements comes from BGT's job vacancy postings over 2010-2017, and are grouped into skill categories based on Deming (2017). Results are clustered at the MSA-year level.

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